The Environmental Impact on Facility-Treated Pediatric Asthma Exacerbation: A Secondary Study

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Abstract

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Pediatric asthma is a leading chronic disease in America; however, it is best thought of as a syndrome of airway symptoms with various etiological origins. As a result, there are numerous combinations of "triggers" that can precipitate an exacerbation in individuals who have asthma. Categorically, these triggers can range from psychosocial, such as stress and anxiety, to physical, such as pollen and pet dander. Family geographic relocations are events that can expose a child with asthma to many of these triggers simultaneously. Ecological transition is a concept within Bronfenbrenner's ecological system theory of human development, where individuals and their environments interact to produce change. The ecological transition concept accounts for aspects of the individual and the broadening layers of the environmental interaction (microsystem, mesosystem, exosystem, macrosystem, and chronosystem) in a holistic approach that allows for

seemingly indirect factors to be incorporated in the development process. Through the lens of ecological transition upon the foundation of ecological systems theory, two studies were devised to examine different environmental effects on facility-treated pediatric asthma exacerbations. First, a secondary cross-sectional multilevel binomial regression (n=10,401) suggested there was no significant correlation between children of veteran parents and the likelihood of facility-treated asthma exacerbation (OR 0.96, p= .452). Second, a secondary longitudinal multilevel binomial regression (n=1,055,742) identified a significant correlation between the month of relocation and the first several months following a geographic relocation and the increased likelihood of facility-treated asthma exacerbation. Month of relocation (OR 2.10, p <.001), which is consistent with predictions from ecological transition and ecological systems theory.

Dedication

To my wife, Katie, and daughter, Izzie, I could not have done this without your love and support.

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Disclaimer

The views and information presented are those of the authors and do not represent the official position of the U.S. Army Medical Center of Excellence, the U.S. Army Training and Doctrine Command, or the Department of Army, Department of Defense, or U.S. Government.

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Chapter 1: Introduction to Dissertation

Background and Significance

Military Geographic Relocation

On average, in the United States, individuals move eleven times throughout their lives or about once every seven years and three months (Tredinnick, 2024). In contrast, Military Families relocate or experience a Permanent Change of Station (PCS) every two to three years. Some may PCS as many as five times in six years to locations all over the world. These moves can be stressful for the child and caregiver, disrupt routines and support networks, and expose children to new allergens and weather patterns, all of which may be contributing factors to an asthma exacerbation.

Military Healthcare and Insurance

The military provides active-duty service members and their dependent family members worldwide healthcare through either "direct care" as the healthcare provider in Military Treatment Facilities (MTFs) or "purchased care" as the insurer through TRICARE Prime (Bond & Schwab, 2019). MTFs are bound by strict access to care timelines, so each Primary Care Manager (PCM) has a limit to the number of patients that can be empaneled to them (Bond & Schwab, 2019). Beneficiaries are enrolled in an MTF upon arrival at a new location if they fall within the facility's catchment area and if there is room in the facility's empanelment. Dependents not enrolled in an MTF will be enrolled in a civilian healthcare provider. Also, any beneficiary requiring care that exceeds either the capacity or capability of their MTF will be treated at the closest facility able to provide care (Bond & Schwab, 2019). TRICARE Prime

beneficiaries receive the care they need from either direct or purchased care for free with no premiums, deductibles, or coverage caps, regardless of location. This allows patients to seek the care they need without worrying about what it will cost or rationing care to meet their budget. This essentially eliminates protracted access to care issues. The military captures and stores all billing data on the 9.5 million beneficiaries who have received direct or purchased care over the last few decades (Bond & Schwab, 2019).

Protection of Military Dependents with Medical Needs

The Exceptional Family Member Program (EFMP) is an additional layer of scrutiny added to the typical assignment process for military personnel (Mendez, 2021). Suppose a service member has a family member who requires additional services (e.g., an individual education plan or a diagnosis requiring a primary care visit more frequently than once per year or any specialty visits). In that case, they must be screened for enrollment into EFMP (Mendez, 2021). This program will assess the family member's needs and ensure that any potential assigned location has the capability and capacity of the required services to care for that family member properly. If the necessary services are unavailable, then the assignment must be changed. Asthma is one of the most common medical reasons for child EFMP enrollment (Mendez, 2021).

Military Personnel as a Population to Study the Health Effects of Relocation

Given the frequency of relocations, the unwavering health insurance coverage, the lack of financial barriers to access healthcare, and the systematic capture and warehousing of all health insurance billing data, military personnel and their covered family members are an ideal

population for a retrospective study of the comprehensive health effects associated with geographic relocations.

Pediatric Asthma

Pediatric asthma is one of the most prevalent chronic childhood diseases in the United States, affecting more than 4.68 million children in 2021 (CDC, 2023). According to the Centers for Disease Control and Prevention (CDC), asthma exacerbations in children have declined by 15.6% from 2010 through 2020 (from 58.3% to 42.7%) (CDC, 2023). Despite this significant improvement, much can and must be done to protect those two-fifths of children who experience at least one asthma exacerbation each year. Even though asthma has a high prevalence and high incidence of exacerbation, the geographic and demographic distribution of asthma and asthma exacerbations are not uniform and are poorly understood (Grunwell et al., 2022). Contributing to its misunderstood nature is that asthma is not a simple condition but a collection of airway symptoms, chiefly 1) inflammation of the airways, 2) the accumulation of mucus that obstructs the airways, and 3) airway hyperresponsiveness or tightening of the muscles that surround the airways (AAFA, 2021; Link, 2014). Recent research into asthma phenotypes sheds light on the heterogeneous nature of asthma symptoms, treatment effectiveness, and prognosis (Kaplan et al., 2019). Importantly, asthma triggers vary widely, ranging from sociopsychological to physiological, and as such, treatment regimens must be tailored to each patient.

Prevailing Causes of Asthma Exacerbations

Many factors contribute to or trigger asthma exacerbation, including, but not limited to, psychological stress (Chipps et al., 2017; Das et al., 2022; Miyasaka et al., 2018; Wood et al.,

2018), air pollution (Link, 2014; Norris et al., 1999; Zhou et al., 2022), indoor air quality (Chipps et al., 2017; Kanchongkittiphon et al., 2015; Link, 2014; Michaels, 2017), weather (Link, 2014; Mireku et al., 2010; Schinasi et al., 2020), adherence to treatment regimens (Fu & Tsai, 2014; Kaplan et al., 2019; Sonney et al., 2016; Wood et al., 2018), allergens (Chipps et al., 2017; Kanchongkittiphon et al., 2015; Link, 2014), and upper respiratory infection (Bloomberg, 2010; Chipps et al., 2017; Fu & Tsai, 2014; Link, 2014; Ong et al., 2009).

Psychological stress and anxiety have been linked to asthma exacerbation in certain asthma patients via several neurophysiological pathways that result in type 2 T-helper (Th2)-type lung inflammation (Das et al., 2022; Miyasaka et al., 2018). Although this is particularly true within stress-induced asthma or the "neuropsychiatry phenotype," psychological stress and anxiety are strongly associated with asthma exacerbation generally (Chipps et al., 2017; Das et al., 2022; Miyasaka et al., 2018; Wood et al., 2018). There is some speculation that this stress-trigger pathway is one of the key contributors to asthma prevalence among those with low socioeconomic status (Miyasaka et al., 2018).

The presence of air pollutants, including particulate matter (PM) with diameters less than 10 micrometers (PM_{10}) and less than 2.5 micrometers ($PM_{2.5}$), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), and ozone (O_3) are associated with asthma exacerbation (Norris et al., 1999; Zhou et al., 2022). More recent studies using sophisticated analytic techniques identified the relationship between air quality and asthma exacerbation after allowing for a lagging effect anywhere from one to six days after exposure (Norris et al., 1999; Zhou et al., 2022). A lagging effect is the delay between the exposure to a trigger and the symptom intensity that motivates intervention. For example, a child may be exposed to tobacco smoke and, left unchecked and untreated, would develop symptoms of an exacerbation one to six days

later. Accounting for the lagging effect is important because subtle changes to the airway build upon each other and, although detectable by medical devices up to a week before an exacerbation, may not be noticed by the child or family. Air pollutants are typically found in the highest concentrations around low socioeconomic areas. This may be one key contributing factor to the increased rates of asthma among low-income and other marginalized individuals.

Indoor air quality, which is affected by many factors, including humidity, pet allergens, pest allergens, tobacco smoke, mold, and dust mites, is associated with asthma exacerbations (Kanchongkittiphon et al., 2015; Michaels, 2017). This broad category comprises more than the triggers themselves; a critical piece of information is that people spend up to 75% of their time indoors, causing prolonged exposure to these triggering agents (Kanchongkittiphon et al., 2015). For some, the generation and accumulation of triggers are within the locus of control of the occupants, particularly families who live in single-family homes. In addition, individuals who live in multi-family residences can suffer from their neighbors' second-hand tobacco smoke, inability or unwillingness to control pests like rodents and cockroaches, and/or gratuitous use of perfumes. Uncontrolled moisture or humidity, however, is a critical indoor factor for asthma exacerbation (Kanchongkittiphon et al., 2015; Michaels, 2017). Indoor humidity depends partly on the climate, the occupant, and the property owner. The presence of humidity may cause fungal / mold growth and even lead to infestations of pests or other bacteria if left unmitigated (Michaels, 2017). Indoor air quality may also be a driver in the increased prevalence of asthma among individuals of low socioeconomic status, as they are more likely to live in multi-family structures. These individuals with low socioeconomic status are not only subject to the actions of other residents but also have fewer resources and/or agency to mitigate the triggers (i.e., dependence on a landlord to mitigate mold or other moisture damage).

Weather, notably rain, temperature, and humidity, have an associated impact on asthma exacerbations (Mireku et al., 2010; Schinasi et al., 2020). Mierku et al., in 2008, conducted a single-site retrospective study out of Children's Hospital of Michigan in Detroit and found that there were statistically significant relationships between humidity and temperature on both asthma exacerbations and emergency department admission using a lagged (0 to 3 day) analysis and after controlling for air pollutants and airborne environmental allergens (mold spores and pollen) (Mireku et al., 2010). The Mireku et al. study also measured intra-day fluctuations in barometric pressure and found that it was not correlated with asthma exacerbation or emergency department visits related to asthma (Mireku et al., 2010). In 2020, Schinasi et al. conducted a case-crossover study using more than 13,000 medical records from the Children's Hospital of Philadelphia from 2011 to 2016 (Schinasi et al., 2020). Cases were identified as any treatment for asthma exacerbations, and control days were determined by the same day of the week of the treatment in the same month and year. Then, they compared lagged (0 to 5 days) precipitation and temperature between the case day and control days while controlling for confounding variables like air pollution, pollen, and mold spores (Schinasi et al., 2020). The Schinasi study found an increased risk of childhood asthma exacerbation following heavy precipitation (Schinasi et al., 2020).

Allergens such as pollen, pet dander, dust mites, and mold spores are linked to asthma exacerbations (Chipps et al., 2017; Kanchongkittiphon et al., 2015). The 2015 review by Kanchongkittiphon et al. updated the 2000 Institute of Medicine review and summary of scientific literature and findings surrounding indoor air quality and asthma exacerbation. Pet allergens like cat and dog dander have been linked to asthma exacerbation, and studies have shown that cat and dog dander are even present in buildings that do not currently have a cat or

dog in residence (Kanchongkittiphon et al., 2015; Rogers et al., 2024). Pests such as cockroaches and rodents also have a causal link to asthma exacerbations; cockroaches, in particular, are more likely to be found in low socioeconomic housing areas and are speculated to account for some of the socioeconomic differences in asthma exacerbation rates (Kanchongkittiphon et al., 2015).

Viral upper respiratory infections like the rhinovirus, influenza, respiratory syncytial virus, and coronavirus are common triggers of asthma exacerbations, with rhinovirus identified as one of the key contributors to pediatric asthma exacerbation (Bloomberg, 2010; Fu & Tsai, 2014; Ong et al., 2009). Seasonal viral upper respiratory tract infections are thought to cause the seasonal pattern of pediatric asthma exacerbations that follows cold and flu patterns, sometimes called the "September epidemic" (Bloomberg, 2010; Fu & Tsai, 2014).

Typical Asthma Treatments

An asthma action plan is the first line of defense for patients with asthma. It includes information on their known triggers, strategies to avoid them, and specific instructions on when and how to take their prescribed asthma medication(s) (AAFA, 2021; NIH, 2020; NIH, 2021). There are a few different types of medications for asthma, but the two most common are daily controller medications and quick relief medications. Controller medications are typically taken daily and help reduce the chronic inflammation or mucus that causes airway obstruction (AAFA, 2021; NIH, 2020). These medications are usually slow-acting and long-lasting, and adherence is often poor, especially if no obvious symptoms have been present (AAFA, 2021; Colland et al., 2004). Quick relief medications act fast and are taken immediately for asthma symptoms (AAFA, 2021; NIH, 2020). Other types of medications are a combination of quick-relief and control

medications and medications that target a specific type of cell or protein involved in airway swelling (AAFA, 2021).

Adherence to Treatment Regimen

Nonadherence to an asthma treatment regimen is predictive of asthma exacerbation (Fu & Tsai, 2014; Kaplan et al., 2019; Sonney et al., 2016; Wood et al., 2018). It has been established that the prescribed use of controller medications, asthma action plans, and rescue inhalers decreases the severity and duration of symptoms and may even prevent exacerbation (Sonney & Insel, 2019; Sonney & Insel, 2016). Despite this, only 20% to 50% of pediatric asthma patients adhere to their asthma treatment regimen (Sonney & Insel, 2019; Sonney et al., 2016). As few as 57% of adolescents filling their first prescription pick up the second refill of their controller medication (Wood et al., 2018). Nonadherence can be intentional or nonintentional. Intentional nonadherence includes health beliefs contrary to adherence; for example, they do not agree with preventative treatment in the absence of symptoms (Dhruve & Jackson, 2022; Sonney et al., 2016). Nonintentional nonadherence includes inability to pay for medication, improper administration technique, and forgetfulness (Dhruve & Jackson, 2022). Regardless of intention, both have a negative impact on asthma outcomes (Kaplan et al., 2019).

Parent-Child Shared Asthma Management

The caregiver impacts the child's adherence because pediatric asthma management is best thought of as parent-child shared management (Sonney et al., 2016). The distribution of responsibility for adhering to the treatment regimen between the parent and the child varies based on many factors. Generally, you could expect a younger child to have less responsibility,

and as they mature, an older child would have more responsibility for their own care (Sonney & Insel, 2016).

Parental Stress and Child Exacerbation

If the parent is stressed, it has been shown to lead to increased child asthma exacerbations via two separate pathways (Wood et al., 2018). First, since child adherence is a function of parent-child shared management, if the parent is not functioning normally due to stress, that results in decreased child adherence, which results in increased asthma exacerbations (Wood et al., 2018). Second, it has been shown that parental stress increases negative parenting, which increases child stress and also results in increased asthma exacerbations (Wood et al., 2018). To further compound the situation, increased child exacerbations and the resulting healthcare facility visits have been shown to increase parent stress, which creates a vicious cycle (Wood et al., 2018).

Geography and Asthma Exacerbations

Geography plays a role in asthma prevalence, incidence, and severity of exacerbations. One study linked 'hot spot' neighborhoods that contributed to increased rates of hospitalizations and increased intensive care unit (ICU) length of stay for children with asthma (Grunwell et al., 2022). The study conducted a geospatial analysis of pediatric asthma exacerbations. It noted that the two neighborhoods with the highest ICU admission rates for children with asthma were located next to a military airfield (Grunwell et al., 2022). Airfields and military bases are known producers of air pollutants, and the housing areas near them are predominantly of low socioeconomic status, both of which could contribute to this effect. However, the study found

that these geographical ‘hot spots’ also cut across racial and socioeconomic trends, neighborhoods with high poverty and low asthma admissions, and, likewise, neighborhoods with low poverty and high asthma-related hospital admissions (Grunwell et al., 2022). This suggests that the spatial clustering of asthma exacerbations was likely of a physical nature (like air quality) and not a social effect (like socioeconomic status).

Linking back to the known triggers for asthma exacerbation, several are phenomena caused by physical objects bound or distributed spatially, such as allergens, indoor air quality, air pollution, and weather. Each space, house, city, or military base has a different quantity, arrangement, and/or frequency of these triggers. Therefore, when people move from place to place, their exposure to triggers will change.

Children with Asthma Who Live in U.S. Military Areas

While little research has been published specifically about the health status of children with asthma living on or in the proximity of military bases, there have been studies that link several of the prevailing causes of asthma exacerbations to military areas. Military bases have a history of contaminated water, soil, and air, as well as outbreaks of black mold in on-base housing (Rogers et al., 2024; Tornay, 2023). U.S. Representatives Rogers, Waltz, Banks, and Bacon of the House Armed Services Committee reported in February 2024, “… mold, brown tap water, extreme temperatures, bedbugs, rodents, and cockroaches. These are just some of the conditions that our servicemembers have been subjected to in their barracks.” (Rogers et al., 2024). These conditions extend beyond the barracks to on-base family housing as well. In 2023, Kaylee Tornay, an investigative journalist, reported on the military housing at Joint Base Lewis-McChord, just south of Tacoma, Washington. These military families experienced black mold,

rodents, and questionable water quality, and due to the high cost of living off-base, many junior-ranked families have no choice but to live on the base (Tornay, 2023).

Several studies have also shown links between military base proximity and air quality (Alvarez et al., 2022; Marcello Campagna, 2016; Shtob et al., 2023). In 2022, Alvarez, Shtob, and Theis discovered that census tracts closest to military bases had higher cancer risk due to air toxins and that this disproportionally affected people of color (Alvarez et al., 2022). A 2016 study linked ultrafine airborne particles to the proximity of a military airport (Marcello Campagna, 2016). Although the concentrations were heavily impacted by seasonality, the net effect of military flight operations was correlated with flight line measurements; however, the same correlation was not represented in the residential measurements (Marcello Campagna, 2016). These sources link established asthma exacerbation triggers like mold, pests, and air pollution to U.S. military areas and also show that low rank (low socioeconomic status) and people of color were disproportionately exposed.

Geographic Relocation and Asthma Exacerbation

As geography plays a role in the severity and incidence of asthma exacerbations from spatial-dependent triggers, geographic relocation has been shown to affect non-spatial triggers like stress, upper-respiratory infection, and, to a certain extent, adherence. A 2014 study of all 179,486 military children aged 6 through 17 years who moved with their family in 2008 were at increased risk of utilizing mental health services in 2009, as high as a 20% increase in the risk of a psychiatric hospitalization (Millegan et al., 2014). A 2018 RAND study stated that military family moves are correlated with increased spousal stress and child stress disruptions (Tong et al., 2018). As stated previously, not only does the child's stress lead to an increased risk of

asthma exacerbations, but caregiver stress has also been demonstrated to have a negative impact on their child's adherence to their treatment regimen, which in turn leads to an increased risk of asthma exacerbations (Fu & Tsai, 2014; Kaplan et al., 2019; Sonney et al., 2016; Wood et al., 2018).

Travel has been associated with an increased risk of viral upper respiratory tract infections (Lovey et al., 2023). A 2023 systematic review and meta-analysis of travel-related respiratory symptoms and infections in travelers by Lovey et al. found that, on average, 21% of travelers in the Americas experienced an upper respiratory infection (Lovey et al., 2023). The 102 studies included in the meta-analysis for respiratory infections showed a 10% worldwide prevalence of confirmed respiratory infections among travelers (Lovey et al., 2023). The same study also noted that in the 22 years of data included in the analysis, 94% of the upper respiratory infections were caused by viruses. As previously stated, viral upper respiratory infections are a known trigger for asthma exacerbation (Lovey et al., 2023). Since a geographic relocation requires stressful travel to a new location, children with asthma could be expected to have an increase in asthma exacerbations from travel-related URI, stress, and nonadherence.

Significance

There have been numerous studies that causally link or strongly associate various triggers to asthma exacerbation (Bloomberg, 2010; Chipps et al., 2017; Das et al., 2022; Fu & Tsai, 2014; Kanchongkittiphon et al., 2015; Link, 2014; Michaels, 2017; Mireku et al., 2010; Miyasaka et al., 2018; Norris et al., 1999; Schinasi et al., 2020; Wood et al., 2018; Zhou et al., 2022). Many of these triggers are spatial phenomena and have been documented in and around U.S. military bases (Alvarez et al., 2022; Grunwell et al., 2022; Marcello Campagna, 2016; Rogers et al.,

2024; Shtob et al., 2023; Tornay, 2023). The remainder of the triggers, while not bound to locations, are affected as a result of moving between locations (Lovey et al., 2023; Millegan et al., 2014; Tong et al., 2018; Wood et al., 2018). No studies to date have been identified that address the net effect of family moves on the incidence of asthma exacerbation. While the assembled evidence strongly suggests that a geographic relocation will likely increase the incidence of pediatric asthma exacerbation, the following proposed studies will shed more light on this complex relationship.

Conceptual Framework

Ecological Theory

Urie Bronfenbrenner's Ecological Theory describes the interplay between the individual and a set of four interacting concentric environments, which depicts the overlapping and interactive nature of environmental spheres of influence on the individual and their psychological growth. This theory provides an exciting foundation and lens to examine the phenomenon of children with asthma experiencing a family geographic relocation.

Ecological Transition

A central concept, the *ecological transition* is the mechanism by which Ecological Theory affects or imparts human psychological development (Bronfenbrenner, 1979). Bronfenbrenner sates, "an ecological transition occurs whenever a person's position in the ecological environment is altered as a result of a change in role, setting, or both (Bronfenbrenner,

1979)." A geographic relocation fits within this description, but an in-depth examination of this concept and its components is required.

Purpose and Specific Aims

Asthma is a leading chronic respiratory condition affecting over 4 million children in the United States, and about 40% of those children are expected to have an acute asthma exacerbation each year (CDC, 2023). Many factors contribute to or precipitate an asthma exacerbation (stress, change in weather patterns, exposure to allergens, pollution, lack of adherence to treatment regimen, etc.) (Bloomberg, 2010; Chipps et al., 2017; Das et al., 2022; Fu & Tsai, 2014; Kanchongkittiphon et al., 2015; Link, 2014; Michaels, 2017; Mireku et al., 2010; Miyasaka et al., 2018; Norris et al., 1999; Schinasi et al., 2020; Sonney & Insel, 2019; Wood et al., 2018; Zhou et al., 2022). A geographic relocation is an event that can simultaneously expose children with asthma to all of these triggers. The needs of the branch of military service drive the timing and destination of a military family relocation or PCS. It is not currently known to what extent, if any, PCSs have an impact on pediatric asthma exacerbations or if there are specific locations where military families who have children with asthma should not be PCS'd. There is a critical need for this information, which will drive policy and clinical practice changes within the Military Health System to protect and support this vulnerable population.

My long-term goal is to improve the care and health outcomes of military-dependent children with asthma. My overall objective in this study is to determine if a PCS increases acute asthma exacerbation and identify the incidence by location of acute asthma exacerbation for the study population. My central hypothesis is that the incidence of acute asthma exacerbations is different in this population when compared to the general population and that a PCS increases

the likelihood of an acute asthma exacerbation when controlling for local and personal incidence rates. My rationale for this research is that the military is a uniquely itinerant population where all beneficiaries have unlimited access to healthcare, which can benefit from this information to improve the care of these patients. The following papers and their aims were written to address this purpose.

Introduction of Papers

Paper 1 – Conducts a concept analysis of Bronfenbrenner's 'Ecological Transition', incorporating physical and psychosocial effects that account for health outcomes like asthma exacerbation in children who experience a geographic relocation.

Aim: *analyze* the concept of 'Ecological transition' from the ecological theory using Walker and Avant's approach to concept analysis.

Paper 2 – Examines if parent veteran status has an impact on the likelihood of a facility-treated pediatric asthma exacerbation occurring in the past year from the interview date by using a series of multilevel binomial regression models to analyze secondary cross-sectional interview data from the Asthma Call-Back Survey (a follow-on interview of the Behavioral Risk Factor Surveillance Survey).

Aim 2 will *determine* if veteran status affects facility-treated asthma exacerbations while controlling for state, age, gender, air quality, household income, and other predictors.

- The hypothesis was that the likelihood of facility-treated asthma exacerbation in the last year in the children of veterans will not be the same as in the children of non-veterans after accounting for differences in age, gender, location, income, and air quality.

Paper 3 – Examines the effect of U.S. Military geographic relocation on the likelihood of facility-treated pediatric asthma exacerbation each month of the year following the move using a series of multilevel binomial regression models by analyzing secondary longitudinal Military health insurance data.

Aim 3.1 *describes* the incidence rate of facility-treated asthma exacerbation within the pediatric military population by Military Housing Area (MHA).

- The hypothesis was that the distribution of exacerbation incidence of the military pediatric population will not be uniform across all MHA locations and that some locations will have incidences significantly higher or lower than the average.

Aim 3.2 *determines* if PCS exposure changes the likelihood of pediatric asthma exacerbation while accounting for age, gender, AQI, and other predictors.

- The hypothesis was that a PCS will significantly increase the likelihood of acute asthma exacerbation beyond what would be predicted by using local (geographic) and individual predictors of exacerbation.

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Chapter 2: Using ecological transitions to understand geographic relocations in children with asthma: A concept analysis

Abstract

Theoretical principles: Ecological transition is a concept within Bronfenbrenner's ecological system theory of human development, where individuals and their environments interact to produce change. The ecological transition concept accounts for aspects of the individual and the broadening layers of the environmental interaction (microsystem, mesosystem, exosystem, macrosystem, and chronosystem) in a holistic approach that allows for seemingly indirect factors to be incorporated in the development process.

Phenomena addressed: Pediatric asthma is a leading chronic disease in America; however, it is best thought of as a syndrome of airway symptoms with various etiological origins. As a result, there are numerous combinations of "triggers" that can precipitate an exacerbation in individuals who have asthma. Categorically, these triggers can range from psychosocial, such as stress and anxiety, to physical, such as pollen and pet dander. Family geographic relocations are events that can expose a child with asthma to many of these triggers simultaneously.

Research linkages: This concept analysis of ecological transition examines the environmental elements, both psychosocial and physical, of geographic relocations for children with asthma.

Keywords: asthma; environment; concept analysis; asthma triggers; conceptual model; ecological transition; Bronfenbrenner

All that you touch, you change. All that you change changes you. The only lasting truth is change.

–Octavia E. Butler, Parable of the Sower

Introduction

Pediatric asthma is one of the most prevalent chronic childhood diseases in the United States, affecting more than 4.68 million children in 2021 (CDC, 2023). In 2020, 42.7% of children with asthma experienced an asthma exacerbation in the previous year (CDC, 2023). Even though asthma has a high incidence of exacerbation, it remains difficult to define clear and consistent geographic and demographic risks of asthma and asthma exacerbations (Grunwell et al., 2022). While asthma phenotypes vary, what is common is a collection of airway symptoms, chiefly 1) inflammation of the airways, 2) the accumulation of mucus that obstructs the airways, and 3) airway hyperresponsiveness or tightening of the muscles that surround the airways (AAFA, 2021; Link, 2014; NIH, 2020). Recent research into asthma phenotypes sheds light on the heterogeneous nature of asthma symptoms, treatment effectiveness, and prognosis (Kaplan et al., 2019). Importantly, asthma triggers vary widely, ranging from psychosocial to physiological, and as such, treatment regimens must be tailored to each patient.

There have been numerous studies that causally link or strongly associate various triggers (stress, change in weather patterns, exposure to allergens, pollution, lack of adherence to treatment regimen, etc.) to asthma exacerbation (Bloomberg, 2010; Chipps et al., 2017; Das et al., 2022; Fu & Tsai, 2014; Kanchongkittiphon et al., 2015; Link, 2014; Michaels, 2017; Mireku et al., 2010; Miyasaka et al., 2018; Norris et al., 1999; Schinasi et al., 2020; Wood et al., 2018; Zhou et al., 2022). Many of these triggers are spatial phenomena that are tied to physical locations, such as pollution, weather patterns, dust mites, and pollen (Alvarez et al., 2022; Grunwell et al., 2022; Marcello Campagna, 2016; Rogers et al., 2024; Shtob et al., 2023; Tornay, 2023). Another group of triggers, while not bound to locations, may occur as a result of moving between locations, like the stress associated with moving, disruptions in care and support

networks affecting medication adherence, or even upper respiratory infections (Lovey et al., 2023; Millegan et al., 2014; Tong et al., 2018; Wood et al., 2018). A geographic relocation is an event that can simultaneously expose children with asthma to many of these triggers. No studies to date have been identified that address the net effect of geographic relocations on the incidence of asthma exacerbation. While the assembled evidence strongly suggests that a geographic relocation will likely increase the incidence of pediatric asthma exacerbation, the following concept analysis seeks to better understand ecological transition in the context of pediatric asthma.

Methods

The Walker and Avant approach was used to conduct an in-depth concept analysis (Walker & Avant, 2019), which consists of eight iterative steps: 1) select a concept; 2) determine the aims or purposes of the analysis; 3) identify all the uses of the concept that you can discover; 4) determine the defining attributes; 5) identify a model case; 6) identify borderline, related, contrary, invented, and illegitimate cases; 7) identify antecedents and consequences; and 8) define empirical referents (Walker & Avant, 2019). The Walker and Avant approach to concept analysis was chosen because it offers clear, concise steps and a logical framework to conduct the analysis.

The first and second steps are selecting a concept to analyze and determining whether or how it can provide a theoretical foundation for the geographic relocation phenomenon (Walker & Avant, 2019). Bronfenbrenner's ecological systems theory explains how expanding environmental systems interact with an individual, and the ecological transition is the central concept that imparts that change (Bronfenbrenner, 1979). Understanding the components and

uses of an ecological transition will aid in defining and understanding geographic relocations in children with asthma.

While ecological transition is defined within the ecological systems theory, it is still important to validate it by identifying all uses of the concept in step three (Bronfenbrenner, 1979; Walker & Avant, 2019). To achieve this, a literature review was conducted using the following search phrases: “ecological transition” AND nursing; “ecological transition” AND Bronfenbrenner; “ecological transition” on the CINAHL, Academic Search Complete, and EBSCOhost catalogs. Ultimately, the search was broadened to the phrase “ecological transition” from the same search databases and the online dictionaries, Merriam-Webster Dictionary, and the Oxford English Dictionary.

The broad reading of the articles included in step three informed the establishment and verification of the defining characteristics that make up the concept in step four of the analysis (Walker & Avant, 2019). These defining characteristics are the attributes present across multiple uses of the concept (Walker & Avant, 2019). Steps five and six are critical to the concept analysis process because they allow for vignette testing of ideal and edge cases, ultimately informing and supporting inclusion and exclusion criteria selection for future studies (Walker & Avant, 2019). A model case was constructed in step five that describes a geographic relocation of a child with asthma that meets the definition of an ecological transition. Borderline and contrary cases in step six were constructed to delineate cases that nearly yet fail to meet the definition, and one that clearly does not meet the definition of an ecological transition.

Step seven involves identifying an ecological transition’s antecedents and consequences (Walker & Avant, 2019). These are the conditions that need to be in place for an ecological transition to occur, and the results following an ecological transition (Walker & Avant, 2019).

Finally, in step eight, we identify the empirical referents or the objective and measurable variables that verify that an ecological transition has occurred (Walker & Avant, 2019).

Results

Concept and aims of analysis

Identifying a theory that covers geographic relocation's context, antecedents, and outcomes is critical to orient and frame its hypothesized impact on pediatric asthma exacerbation. Urie Bronfenbrenner first described the ecological theory in his 1979 book "The Ecology of Human Development: Experiments by Nature and Design" as an interplay between the individual (at the center) and a set of four interacting concentric environments (see Figure 1) (Bronfenbrenner, 1979). The first of these environments is the *microsystem*, which encompasses the individual and consists of the immediate environment or setting and the people they interact with (Bronfenbrenner, 1979). Examples at this level include the child's home and their parents, siblings, or other immediate cohabitants. There may also be several microsystem settings, including school, daycare, work, or church, and the people associated with those settings with whom the individual interacts (Bronfenbrenner, 1979). The next level is the *mesosystem*, which includes the microsystem and is best thought of as interactions between settings or interactions between people between settings where the individual is involved or participates (Bronfenbrenner, 1979). This might be the individual's parent and teacher interacting between the individual's home and school settings. The third level from the individual is the *exosystem*, which encompasses the mesosystem (Bronfenbrenner, 1979). This level is the interactions

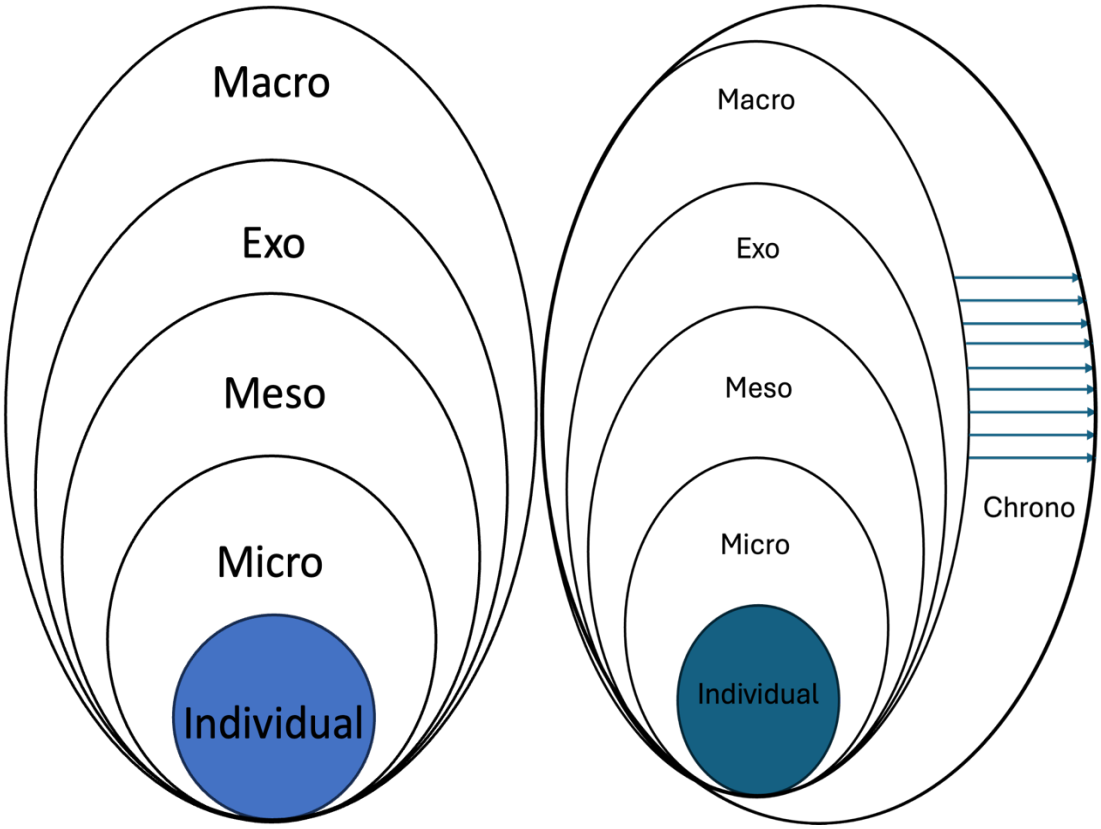
between persons and settings where the individual does not directly participate but affects or is affected by those interactions (Bronfenbrenner, 1979).

An example might be the individual's parent interacting with their boss at work. As the individual does not participate in the parent's work setting, interactions between the parent and the boss have implications for the developing individual. The *macrosystem* is the fourth and last level away from the individual (Bronfenbrenner, 1979). This system is the consistent attributes between the micro-, meso-, and exosystems, such as culture, values, norms, language, religion, beliefs, etc. (Bronfenbrenner, 1979). This could be, for example, Army policies that dictate how often soldiers must relocate. In the case of military family relocations, a policy like this has a consistent permeating effect all the way down to the individual. This design nicely depicts the overlapping and interactive nature of environmental spheres of influence on the individual and their psychological growth.

While Bronfenbrenner's ecological theory, as described in 1979, has been broadly cited, he progressively amended and developed it into the latest iteration of the bioecological model (Bronfenbrenner & Morris, 2007). This evolution enhances the original theory with new concepts, particularly the concept of *proximal processes*, which, coupled with the incorporation of time, drives a significant shift toward the quality and timing of critical relationships in the context of psychological development (Bronfenbrenner, 2000). Despite decades of refinement and evolution, the original model, which consisted of the individual at the center surrounded by four concentric environments, has remained intact, now with the addition of a time component or chronosystem (see Figure 2) (Bronfenbrenner & Morris, 2007).

Figure 1 Figure 2

Ecological Model *Bioecological Model*



The *ecological transition* concept was nested firmly within the original 1979 writing on ecological theory (Bronfenbrenner, 1979). Although not depicted in the model (see Figs. 1 and 2), ecological transition is the mechanism by which ecological theory affects or imparts human development (Bronfenbrenner, 1979). Bronfenbrenner defined "an ecological transition occurs whenever a person's position in the ecological environment is altered as a result of a change in role, setting, or both (Bronfenbrenner, 1979)." Bronfenbrenner's ecological model outlines how the concentric and broadening layers of the social and physical environment and their interaction with the individual drive children's psychological growth and development. This parallels known psychosocial and physical triggers for asthma exacerbation in children. While the ecological transition in the original psychological development context is well established, the use of ecological transition in the context of pediatric asthma is unexplored and requires further

analysis and specification. This concept analysis aims to describe Bronfenbrenner's ecological transition in the context of the social and physical environmental effects on children with asthma, particularly when they experience a geographic relocation.

Identify all uses of the concept

Identifying all uses of the concept is intended to inform and validate the selection of defining attributes in the next step (Walker & Avant, 2019). The initial literature review yielded a combined total of four articles, all of which were excluded because the only use of "ecological transition" was in the name of the department where one or more of the authors were affiliated. The same search terms were used in EBSCOhost, which resulted in a total of eight articles, of which seven were excluded for the same reason**.**

Neither the Merriam-Webster Dictionary nor the Oxford English Dictionary had an entry for "ecological transition," so the components of the phrase were defined. According to Merriam-Webster, ecology is defined as "of or relating to the environments of living things or to the relationships between living things and their environments," and very similarly, Oxford defines "of, relating to, or involving the interrelationships between living organisms and their environment" (Merriam-Webster, n.d.–a; Oxford, 2025). Where transition was defined "a change or shift from one state, subject, place, etc. to another" by Webster and "to make or undergo a transition from one place, state, or system (*to* or *into* another); to change over or switch" by Oxford (Merriam-Webster, n.d.–b; Oxford, 2023). Synthesizing these definitions produces the following textual definition for ecological transition: a change or shift of a living organism from one state or place in their environment, OR their interrelationship with their environment. This aligns well with Bronfenbrenner's original definition.

Although the "ecological transition" concept is strongly associated with developmental psychology, it is not unique to that field. It is used in environmental sustainability contexts as well as the biological discussion of ecosystems (ecology). The environmental sustainability uses bear little relation to Bronfenbrenner's ecological transition beyond the name (Rotondo et al., 2022). In this context, "[t]he ecological transition is the process of technological innovation to achieve change in our society, considering compliance with the criteria for environmental sustainability. (Rotondo et al., 2022)" However, its use in ecology does have some overlapping components (Levin, 2004). Within this domain, it describes how species enter a new environment that they are not well suited or adapted to, and over the course of time (in this case, generations), they adapt to their new environment (Levin, 2004). This parallels Bronfenbrenner's ecological transition, except it refers to multiple members of a species instead of an individual, and the change occurs over generations instead of multiple changes within a lifetime.

Within the human-centric domains, ecological transition is traditionally associated with developmental psychology owing to Bronfenbrenner's field of expertise (Bronfenbrenner, 1979). Here, the concept has been used extensively to describe school transitions for both children and adults (Bagby et al., 2015; Burrell, 2008; Seidman & French, 2004), as well as sexual identity transitions (Hollander & Haber, 1992). Seidman's work highlights some intriguing nuances surrounding ecological transition, particularly whether or not the change was expected or due course or normative and nonnormative, respectively (Seidman & French, 2004). His position is that while they both present an individual with a challenging developmental opportunity, a normative ecological transition occurs at a known time, usually by a group or cohort, making studying and intervening on them feasible (Seidman & French, 2004).

The developmental psychology use of ecological transition, while the basis for the analysis, is not wholly adequate to address the aims of this manuscript. The issue arises from the perspective that the environmental effects are primarily limited to the subject's perceptions or experiences of or within a social environment or the social context of a physical environment (Bronfenbrenner, 1979; Hollander & Haber, 1992; Seidman & French, 2004). While this approach is applicable to the psychosocial triggers for asthma exacerbation, there is also a need for the physical environment to directly interact with an individual's physiology, regardless of the individual's perception of the environment, as is observed in the physical triggers' (like mold, pollution, and pet dander) effect on asthma exacerbation.

Determine the defining attributes

Defining attributes are the characteristics that identify and differentiate one concept from other adjacent or similar concepts (Walker & Avant, 2019). An ecological transition occurs whenever a person experiences a change in their setting and or role (Bronfenbrenner, 1979). These "… transitions are a joint function of biological changes and altered environmental circumstances (Bronfenbrenner, 1979)." This change can occur at any environment level, from the microsystem to the macrosystem. One example is a family geographic relocation. A geographic relocation affects most, if not all, environmental levels. At the micro and meso levels, the family membership may or may not remain intact. Stress, strain, and anxiety surrounding the relocation will likely change the quality and nature of familial relationships, in addition to the change to the home, school, and work settings. With a change in the work and school settings, the exosystem will also change. The macrosystem would likely only change if it were a significant move or if moving to another country.

Exemplar cases

Exemplar cases help illustrate what is and is not the concept being addressed (Walker & Avant, 2019). In each of these cases, several instances of children with asthma who experienced a family geographic relocation and an asthma exacerbation are described. The case will be presented, followed by a brief explanation of which aspects do or do not fit the ecological transition concept.

Model Case

Frank, an 8-year-old boy with asthma, flies across the country with his mom, Clair. Moving from rural Arizona (dry, hot, large-scale agricultural exposure) to urban Georgia (hot, humid, busy roads and airports). On the plane, Frank sat in the middle seat next to another passenger, who was coughing and sneezing the whole flight. During the flight, the plane encountered turbulence, which caused Frank to become anxious. He started wheezing, used his inhaler to relieve his symptoms, and placed the inhaler in the seat pocket in front of him. Frank forgot the inhaler in the seat pocket when getting off the plane. When he realized hours later, Clair got mad at him as that was their last inhaler, and it was brand new to last them until they could get a new doctor in Georgia. Clair was unusually stressed after a recent job loss and chose to move home with her parents. They arrived at Frank's grandparents' house and were greeted by two golden retrievers at the door. He had never spent much time around dogs. As he petted them and they licked his face, his eyes started itching, and he began to sneeze. Clair gave him some Benadryl, and that helped his symptoms.

Shortly after arriving, his grandparents and Clair were arguing over Clair's employment challenges. Frank continued taking the Benadryl because of the dogs, but he started to notice that

his throat felt scratchy. By the morning of the third day, he had a fever and a worsening cough. As his symptoms progressed, he started having difficulty breathing and started wheezing. Without his inhaler, his mom was worried and called 911. The ambulance came and took him to the emergency room, where he was treated for an asthma exacerbation, dehydration, and influenza A. A case manager was able to help them get another inhaler.

In this case, Frank experiences an ecological transition with impacts at numerous system levels related to a significant geographic relocation. Frank and Clair represent the microsystem, Clair and her parents represent the mesosystem, and Clair's loss of employment represents the exosystem. Several factors during the ecological transition may have contributed to Frank's asthma exacerbation. Frank was exposed to an illness on the flight (individual level), which is common, as 21% of air travelers in the U.S. experienced an upper respiratory infection (Lovey et al., 2023). Viral upper respiratory infections like rhinovirus, influenza, respiratory syncytial virus, and coronavirus are common triggers of asthma exacerbations (Bloomberg, 2010; Fu & Tsai, 2014; Ong et al., 2009). The turbulence during the flight (microsystem) caused Frank to become anxious and require his inhaler. Also impacting the microsystem are psychological stress and anxiety experienced by Frank and Clair, which are strongly associated with asthma exacerbation (Chipps et al., 2017; Das et al., 2022; Miyasaka et al., 2018; Wood et al., 2018). Parental stress increases child stress, which is another known trigger for asthma exacerbations (Wood et al., 2018). Additionally, adherence to asthma treatment is dependent upon parent-child shared management (Sonney et al., 2016). Nonadherence to an asthma treatment regimen is predictive of asthma exacerbation (Fu & Tsai, 2014; Kaplan et al., 2019; Sonney et al., 2016; Wood et al., 2018). Within the mesosystem, Frank and Clair move in with the grandparents, experiencing a change in humidity, and the recent argument further exacerbates their stress.

Within this model case, ecological transition catalyzed multiple social-environmental and physical-environmental triggers for asthma exacerbation.

Borderline Case

Lydia, a 12-year-old girl with asthma, lives in an apartment building with her parents and brother. One Saturday morning, the apartment above theirs had a plumbing leak, and the water soaked through the ceiling and down the walls. Fortunately, the apartment across the hall had just become available, and the family was able to move all their belongings to the new apartment on the same day without any significant loss of their possessions. The new apartment was the same size and layout as the old one, but the former tenants had two cats. Lydia noticed that after spending some time in the new apartment, her eyes got watery and itchy, and she started to sneeze. After about an hour of walking back and forth between the two apartments, carrying her things, Lydia became short of breath and started wheezing. Fortunately, she had her inhaler and used it for relief.

Lydia experienced a geographic relocation by moving apartments within the same building. This change was at the microsystem level and had a minor impact on her asthma due to the pet dander and the physical exertion. However, the significance of this case does not rise to the level of an ecological transition. Neither the children nor the parents changed school or work, and the family interactions at the micro- and mesosystem were not greatly impacted. This is a borderline case because it approaches meeting the definition of an ecological transition but falls short due to the insignificance of the environmental change.

Contrary Case

Juan is a 15-year-old boy with asthma. His grandmother is turning 70, and his whole family is going to her house to celebrate her birthday. Juan sees his Grandma only once or twice a year because she lives about 400 miles away, and driving there takes about eight hours. When his family visits Grandma's house, they usually drive up early Friday and return home on Sunday. When Juan arrives at Grandma's house, he cuts the grass in the backyard where the party will be. Then, he helps with dusting and vacuuming before the rest of the guests arrive. The grass and the dust irritate Juan's lungs, and when he gets his inhaler, he realizes he only brought an empty one. He tells his parents. They have him sit inside the quiet, clean car to relax and breathe in slowly through his nose and out through his mouth. After some time, his symptoms subside, and he is able to rejoin the party, but he takes it easy.

Juan and his family traveled to another geographic location and stayed overnight; however, this was a temporary trip or vacation and would not constitute a relocation. He also experiences a mild asthma exacerbation from exposure to dust from vacuuming and cutting the grass. This exacerbation was treated without his inhaler. This is a contrary case because it does not meet the requirements for an ecological transition, as there is no significant deviation from his setting.

Identify antecedents

An antecedent is a condition that must be in place before the concept can occur (Walker & Avant, 2019). The primary antecedent to an ecological transition is a significant alteration in the environmental circumstances (Bronfenbrenner, 1979). When the positional change in the environment occurs, it must not be trivial, such as walking from one room to the next or role-

switching from the hider to the seeker in a game of hide-and-seek. Ecological transitions are significant life events. A parent presented with their infant for the first time, finding a job, marrying, moving, getting divorced, being diagnosed with a chronic condition, and going to the hospital are some examples of the magnitude of change required to cross the threshold of an ecological transition (Bronfenbrenner, 1979). These represent abrupt shifts in an individual's life and can be considered crises or turning points (Seidman & French, 2004). Within the context of a geographic relocation, this would preclude traveling on a vacation, for example, or moving from one apartment to another across the hall.

Identify consequences

A consequence is a result following the occurrence of the concept (Walker & Avant, 2019). The consequence of environmental transition is mutual accommodation between the individual and their environment (Bronfenbrenner, 1979, p. 27). That is, the individual must make an adjustment to the environment, themselves, or both. The individual changes could be developmental behavior or attitudinal changes, or the changes may be biological or both developmental and biological. The environmental changes may be a setting modification or a change in the relationships within various ecological levels. There is no inherent value or direction in which the consequence must take. The mutual accommodation may be constructive or destructive, positive or negative, adaptive or maladaptive, or effective or ineffective in nature. During an ecological transition, in other words, a crisis or turning point, all actions, even inaction, have a lasting outcome, a consequence.

These consequences also apply within the context of a child with asthma experiencing a geographic relocation. First and foremost, the hypothesized biological change would be an

asthma exacerbation. Other biological changes may or may not occur as well. A positive, constructive developmental change might be the child gaining more independence in their shared asthma management due to parental stress, or the child could revert and become more dependent on their parent due to the child's stress and uncertainty. The environmental changes may be physical or social; either way, a geographic relocation will change both at a minimum to the meso-level.

Conceptual Model

Figure 3

Conceptual Model of Ecological Transition

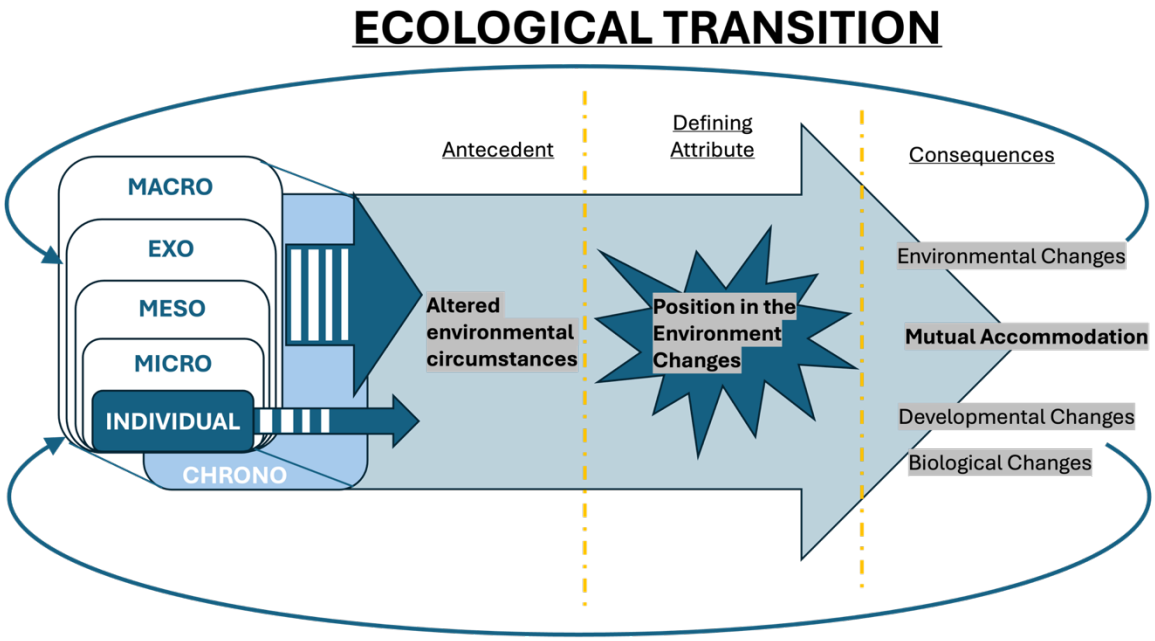


Figure 3 is a conceptual model of ecological transition, its antecedent, defining attribute, and consequences. The left side depicts the concentric layers of environmental interaction and the individual at the center as described in the ecological systems theory, with the chronosystem

that accounts for the temporal nature of change. The model reflects the dynamic, iterative nature of ecological transitions where the output feeds back to set the conditions for the next transition.

Define empirical referents

An empirical referent is an objective measure to determine that the concept has occurred (Walker & Avant, 2019). Considering the previously established antecedent and defining attribute, when there is a significant change to an individual's position (role, setting, or both) in the environment, these life events are easy to identify. This concept analysis aims to clarify the primary phenomenon of interest: when a child with asthma experiences a geographic relocation. These events are readily self-evident as well as obvious to an outside observer. However, in the secondary research, where interaction with a subject is impossible, these ecological transitions may be difficult to identify. In this case, it is prudent to identify a relevant environmental indicator, such as the subject's address or zip code, that can be observed over time to infer a geographic relocation.

Discussion

We recognize that this concept analysis departs from the traditional contextual definition of the environment as conceived and used by developmental psychology and sociology, where a significant emphasis is placed on the subject's perception of the physical as well as the psychosocial and relational aspects of the environment. However, with our application of an ecological transition to asthma as a disease process, in addition to the original approach, the physical environment becomes significant regardless of the subject's perception.

This is evident as the environment can affect the subject without the subject's awareness. For example, ragweed pollen may be high in the air and trigger physiological changes in the airway. This physiological response occurs whether or not the subject is consciously aware of the environmental trigger.

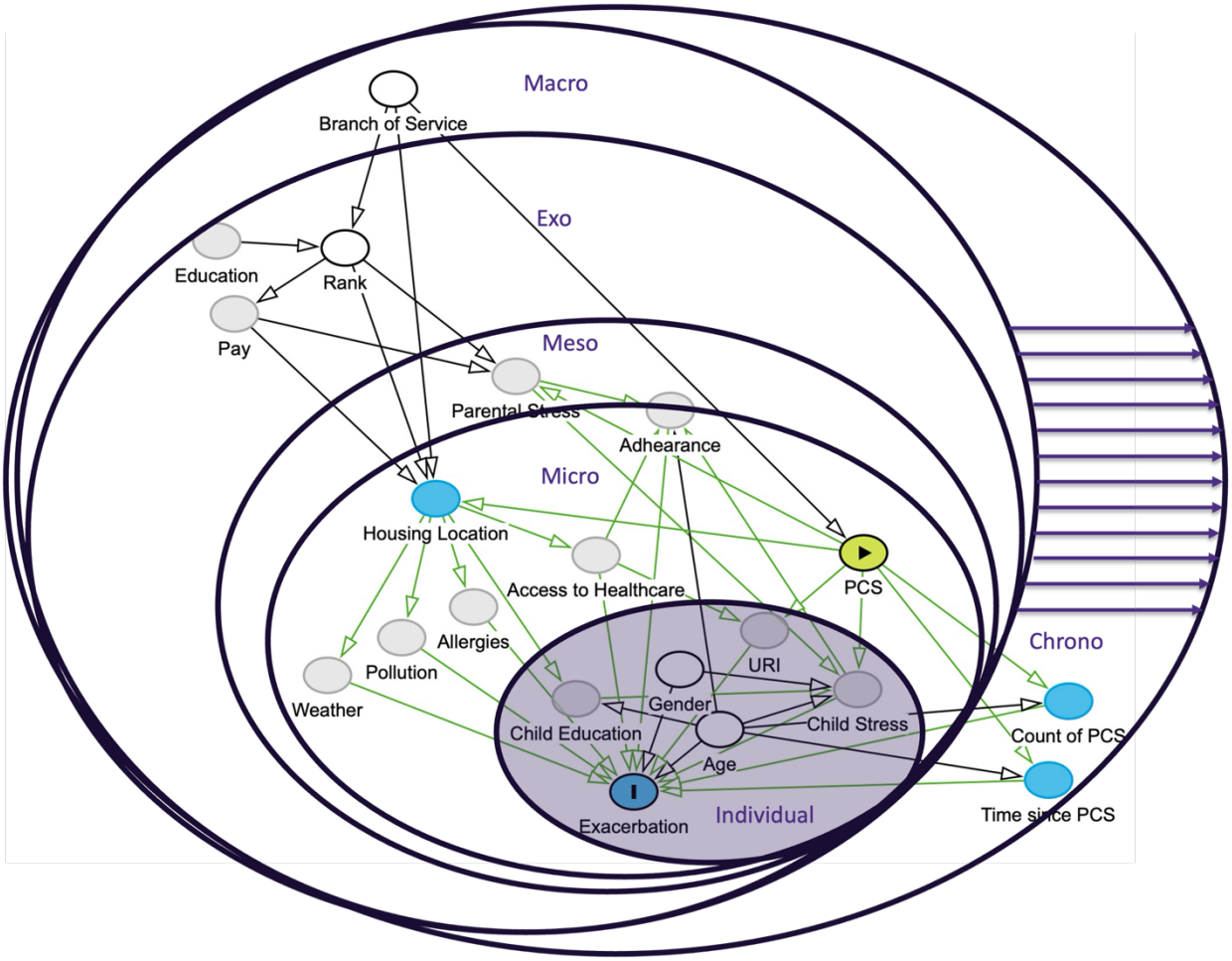
This analysis also assumes that every deviation of the social and or physical environment does not necessarily mean an ecological transition has occurred. Notably, using this conceptual lens to view family geographical relocations clarifies which relocations should be counted. This, along with the temporal aspects where a) iteration, the outputs of this model feed back to set the conditions for the next ecological transition, and b) acclimating, the individual (either actively or passively) adapts over time to the change in environmental circumstances. These considerations need to be accounted for when studying the effects of a geographic relocation on pediatric asthma exacerbation through the lens of an ecological transition.

Military Families are a potential population for studying the effect of geographic relocations on pediatric asthma exacerbations. This group is especially vulnerable to these ecological transitions as they experience a geographic relocation, referred to as a PCS (Permanent Change of Station) in the military vernacular, every two to four years (Clever & Segal, 2013; Kroke, 2022). Interestingly, they also benefit from unlimited, no-cost health insurance (Bond & Schwab, 2019).

The following graphic represents the variables associated with this phenomenon and how they align with ecological systems theory and an ecological transition.

Figure 4

Factors of Pediatric Asthma Exacerbation Related to Geographic Relocation



This model is a Directed Acyclic Graph (DAG) listing the factors of pediatric asthma exacerbation related to a geographic relocation and their relationship to one another, with the ecological systems theory environmental spheres superimposed. This clustered graph oversimplifies most of these relationships and does not address sign or magnitude. It does, however, allow us to take a step back, and while acknowledging that any one or more of these sixteen causal pathways (following green arrows) from geographic relocation (listed here as PCS or Permanent Change of Station which is the Military context of a family geographic relocation) to exacerbation may or may not be activated in any given subject, there are consistent, measurable variables that can be used to study this phenomenon. The color of the bubble indicates how each variable is treated: gray indicates this is a latent or insensible variable, white

indicates this is a measured variable that has been controlled for, blue indicates this is a measured variable, the blue I indicates the outcome variable (exacerbation) and the green right-pointing triangle is the exposure variable (PCS or geographic relocation).

Conclusion

Ecological transition conceptually reflects the physical and social environmental changes children with asthma experience following a geographic relocation, impacting most, if not all, of their ecological spheres. Applying this conceptual analysis to this phenomenon facilitates identifying and selecting relevant variables. It drives the selection criteria for which events constitute a geographic relocation within the ecological transition conceptual framework. The incorporation of the physical environmental effects of ecological transition facilitates environmental allergens, air quality, and weather to be considered alongside the social environmental effects. This work will serve as a theoretical basis for future research into pediatric asthma exacerbations following family geographic relocations.

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Chapter 3: The effect of parent veteran status on facility-treated pediatric asthma exacerbation: A multilevel regression analysis of the Asthma Call-back Survey

Abstract

Pediatric asthma is a significant and prevalent chronic condition. Studies have linked several known triggers for asthma exacerbation to military bases. Children with asthma of veteran parents may have greater exposure to known triggers by their proximity to military bases, while also potentially benefiting from Veterans Affairs programs supporting veterans. This study (n= 10,401 children) used a series of multilevel binomial regression models, which indicate that children with asthma of veteran parents are as likely to experience a facility-treated asthma exacerbation as children of non-veteran parents (OR= 0.96, p= .452), alleviating concerns that this sub-population requires any different or specialized support.

Keywords: pediatric asthma; asthma exacerbation; veteran parent; multilevel regression

Introduction

Pediatric asthma is one of the most prevalent chronic childhood diseases in the U.S., affecting more than 4.68 million children in 2021 (Centers for Disease Control and Prevention (CDC, 2023). Between 2010 and 2020, around two in five children with asthma experienced at least one exacerbation in the previous twelve months (CDC, 2023). There have been numerous studies that causally link or strongly associate various triggers (stress, change in weather patterns, exposure to allergens, pollution, lack of adherence to treatment regimen, etc.) to asthma exacerbation (Bloomberg, 2010; Chipps et al., 2017; Das et al., 2022; Fu & Tsai, 2014; Kanchongkittiphon et al., 2015; Link, 2014; Michaels, 2017; Mireku et al., 2010; Miyasaka et

al., 2018; Norris et al., 1999; Schinasi et al., 2020; Wood et al., 2018; Zhou et al., 2022). While little research has been published specifically about the health status of children with asthma living on or in the proximity of military bases, there have been studies that link several of the prevailing causes of asthma exacerbations to military areas. Military bases have a history of contaminated water, soil, and air, as well as outbreaks of black mold in on-base housing (Rogers et al., 2024; Tornay, 2023). U.S. Representatives Rogers, Waltz, Banks, and Bacon of the House Armed Services Committee reported in February 2024, "… mold, brown tap water, extreme temperatures, bedbugs, rodents, and cockroaches. These are just some of the conditions that our servicemembers have been subjected to in their barracks." (Rogers et al., 2024). These conditions extend beyond the barracks to on-base family housing as well. In 2023, a report revealed that families in military housing at Joint Base Lewis-McChord, just south of Tacoma, Washington, experienced black mold, rodents, and questionable water quality (Tornay, 2023). Despite this, the high cost of living off-base necessitates many junior-ranked families to live on the base.

Several studies have also shown links between military base proximity and air quality (Alvarez et al., 2022; Marcello Campagna, 2016; Shtob et al., 2023). In 2022, census tracts closest to military bases were found to have a higher risk of cancer due to air toxins, and this disproportionally affected people of color (Alvarez et al., 2022). A 2016 study linked ultrafine airborne particles to the proximity of a military airport (Marcello Campagna, 2016). These sources link established asthma exacerbation triggers like mold, pests, and air pollution to U.S. military areas and also show that low rank (low socioeconomic status) and people of color were disproportionately exposed.

Veterans and their families have increased exposure to asthma triggers related to their proximity to military bases during and possibly after their service; however, veterans also have

access to robust Veterans Affairs (VA) programs designed to support them and their families beyond the support non-veteran families receive. It is unknown whether parental veteran status affects their child's incidence of asthma exacerbation. The present study contributes to the literature addressing the question: Does parental veteran status affect the likelihood of their children experiencing a facility-treated asthma exacerbation in the last year when compared to children of non-veteran parents?

Methods

This is a secondary cross-sectional study using two joined publicly available government datasets. This study was pre-registered using the Open Science Framework at https://doi.org/10.17605/OSF.IO/T9PGX, which indicated the hypothesis, data sources, variables selected, and final regression model to be used. Only minor changes to variable coding occurred since pre-registration. Publicly accessible data sets were obtained, cleaned, and joined. Using G*Power to conduct a post hoc power analysis, our sample size of 10,401 children was powered to detect a moderate effect size OR of 1.3 ($\alpha = 0.05$, two-tailed) at 0.998 (Faul et al., 2009; Faul et al., 2007).

Data Sets

Child Asthma Call-back Study

The CDC's Behavioral Risk Factor Surveillance System (BRFSS) Asthma Call-back Survey (ACBS) annual data files contain cross-sectional interview data from January 2010 through January 2020. The BRFSS is an ongoing yearly survey that randomly calls adults residing within the U.S. and territories to assess behavioral risk factors and chronic disease status (CDC, 2022). The ACBS is a separate but linked survey that, a few weeks later, calls back BRFSS respondents who indicated that they have asthma (CDC, 2024). The child survey asks

questions about asthma status, symptoms, triggers, and treatment; an adult parent or caregiver reports results (CDC, 2024). The present study included ACBS data for children between four and eighteen.

Air Quality Data

The continuous air quality data is publicly available from the Environmental Protection Agency (EPA) and are collected at outdoor monitors across the United States (EPA, 2023). Air Quality Index (AQI) is chiefly driven by ground-level ozone and particulate pollution (EPA, 2023). AQI is a scale of air quality and approximate health risk. Starting at zero, the air is clean and healthy, while 301 is considered hazardous (EPA, 2023). The data are provided in pre-generated annual data files available in various levels of aggregation, from hourly readings from each monitor to the yearly average for each county. The data elements have consistent naming conventions and are included in each year's data file. AQI data from 2009 (the year before the study period, to permit a 12-month rolling average) through 2020 were obtained and aggregated to average daily values at the county level.

Measures

Dependent Variable

Facility-treated exacerbation in the last year (EXAC) –

For this study, a facility-treated asthma exacerbation is defined as having been reported to have received care for worsening asthma symptoms or an attack at any of the following locations in the last year: primary care, urgent care, emergency room, or hospital admission. The ACBS asks several questions related to the location of treatment for asthma exacerbations in the previous year:

Q5.8 During the past 12 months, has [child's name] had to visit an emergency room or urgent care center because of [his/her] asthma?

Q5.9 During the past 12 months, how many times did [he/she] visit an emergency room or urgent care center because of [his/her] asthma?

Q5.10 During the past 12 months, how many times did [child's name] see a doctor or other health professional for urgent treatment of worsening asthma symptoms or for an asthma episode or attack?

Q5.11 During the past 12 months, that is since [one year ago today], has [child's name] had to stay overnight in a hospital because of [his/her] asthma? Do not include an overnight stay in the emergency room.

Q5.12 During the past 12 months, how many different times did [he/she] stay in any hospital overnight or longer because of [his/her] asthma?

These five questions refer to specific locations of treatment for an asthma exacerbation; however, to determine if any facility-treated exacerbation occurred in the last year, a new binary variable (EXAC) was created that scored a (1) if any of the five questions were responded to the positive and a (0) if all responded to the negative. In 37 instances (0.36% of the total), unavailable data (NAs) made determining if an exacerbation occurred impossible. These instances were returned as NA for this variable.

Independent Variables

Age in Months of the Child (AGE) –

This is the child's age in whole months on the asthma call-back interview day. Only children between 48 and 216 months (four and eighteen years old) were included in this analysis. Age cut-offs were selected because the diagnostic criteria of asthma in children under four are

challenging and may overlap with other respiratory conditions. This study defines the pediatric population as being under the age of eighteen. However, responses collected in the 216th month were included as their responses reflect the previous twelve pediatric months. This variable was Z-scored for the analysis.

Female Status (FEM) –

The data collected is the sex of the child as reported by the adult survey respondent at the time of the call-back interview. In childhood, males have a higher prevalence of asthma than females (Chowdhury et al., 2021; Shah & Newcomb, 2018). However, according to the latest CDC data, males are less likely to experience an asthma exacerbation despite the higher incidence (CDC, 2023). This finding was also represented in the descriptive statistics of this study; therefore, males were chosen as the reference category since they are less likely to experience an exacerbation than females. This variable was effect coded for analysis.

Type of Health Insurance (TYP1-TYP4, TYPnone, TYPdk, TYPref) –

This seven-level effect coded categorical variable indicates what type of health insurance the adult respondent reports that they have: 1(Reference Value) = Parent's Employer; 2= Medicaid/Medicare; 3 = Children's Health Insurance Program (CHIP) [or state variant]; and 4= Other. Responses to the effect of "I have no health insurance", "I don't know what type of health insurance I have", and "I refuse to answer this health insurance question" were captured and, after the pre-registration, have been included in the analysis as additional categories instead of coding them as NA. The type or source of health insurance is expected to indicate socioeconomic status. As such, parents who have employer-provided health insurance are expected to be more resourced than the rest of the respondents and were selected as the reference value.

Gap in Health Insurance (GAP) –

This binary variable indicates whether the adult respondent reports that they, at any time in the last 12 months, had a gap in their health insurance coverage (1) or not (0). This variable automatically includes as a (1) anyone who currently does not have health insurance. GAP was considered a proxy measure of SES.

Income Level (INC1-INC8, INCdk, INCref) –

This is an 8-level ordinal variable that indicates annual household income from all sources where 1= less than $10,000; 2= between $10,000 and $15,000; 3= between $15,000 and $20,000; 4= between $20,000 and $25,000; 5= between $25,000 and $35,000; 6= between $35,000 and $50,000; 7= between $50,000 and $75,000; and finally 8 (reference value) = more than $75,000. Responses to the effect of "I don't know my annual income" and "I refuse to answer this income question" were captured and, after the pre-registration, have been included in the analysis as additional categories in an effort to reduce missing data resulting from coding them as NA.

12-Month Rolling Average Daily Air Quality Index (AQI) –

The AQI is a score that indicates the relative air quality sampled by air quality monitoring stations throughout the United States. These stations monitor for many substances that can impact the air quality and, when operable, provide constant values. This variable reflected the daily average AQI for all operating monitoring stations in each county in the United States. These were aggregated to the month and state, and a 12-month rolling average was obtained to reflect last year's average AQI for each state for any given month of the study. AQI values are interpreted as follows: 0-50 – Good; 51-100 – Moderate; 101-150 - Unhealthy for Sensitive Groups; 151-200 – Unhealthy; 201-300 Very Unhealthy; 301+ Hazardous (EPA, 2023).

12-Month Rolling Average Monthly Max Air Quality Index (AQImax) –

This L2 (State Level) variable is identical to the AQI, except it preserves the highest daily AQI in the state for each month. These highs were then averaged over a 12-month rolling basis to reflect last year's average Monthly Max AQI for each state for any given month of the study. AQI values are interpreted as follows: 0-50 – Good; 51-100 – Moderate; 101-150 - Unhealthy for Sensitive Groups; 151-200 – Unhealthy; 201-300 Very Unhealthy; 301+ Hazardous. This variable will be transformed by taking its inverse to produce a more normal distribution for regression.

Veteran Status (VET) – IV of Interest

In this context, a veteran is traditionally a person who is no longer in the military. In the present study, this binary variable indicates whether the adult respondent reports being a Military veteran (1) or not (0). The responses were not cross-checked or validated.

State of Residence (STATE) – L2 Units

The BRFSS data only provides consistent location data at the State level across the ten years of the data. Many factors that drive or contribute to asthma exacerbations can and do occur within meters of the individual. Some aspects, such as climate or types of pollen, are much more widely distributed. While not ideal, this is the most granular level available in the BRFSS data. Twenty-six states were included in the analysis.

Survey Weight (WT) –

The BRFSS data provides a final survey weight that accounts for several factors, including sampling, response rate, and demographic characteristics. These weights are established after each year's data collection and are specific to that survey. A scaled weight for

this analysis was calculated, accounting for the number of survey states and respondents included in each state.

Data Analysis Plan

Multilevel regression analyses were used to test the research questions using the *R* lme4 package (Bates et al., 2015). The multilevel analysis approach offers two advantages over other modeling choices. First, the use of random, rather than fixed, effects for clustering variables allows for the decomposition of lower-level effects into separate variance components between and within states. Second, it enables the predictor effects to be tested with (a) correct degrees of freedom and (b) at their appropriate levels. As is standard practice (Luo et al., 2021), intercept-only models were specified before formal analyses began to confirm the appropriate multilevel structure by assessing the degree of non-independence in exacerbations due to clustering. Specifically, a series of models were specified with children nested within states.

For this analysis, missing data will be coded as NA and ignored. The descriptive statistics reveal that only 54 total subjects (0.5% of the total) had any missing data across only two variables. Only 37 individuals (0.4% of the total) were missing data from the dependent variable (DV), facility-treated asthma exacerbation. Gap in insurance had 18 subjects with missing data (0.2% of the total). When computing a generalized linear mixed-effects model using the lmer4 package, it conducts a row-wise deletion when it encounters any missing values in any variables.

For ease of model results interpretation, for all analyses, binary and categorical predictors (female status, gap in insurance, income categories, and insurance type categories) were effect-coded, and continuous predictors (age and both AQI variables) were standardized as *z*-scores. Model results were compared using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and chi-square likelihood ratio tests (LRT). The final model was as

follows:

$$\text{Logit(Facility Treated Exacerbtions)}_{ij}$$
$$= \gamma_{00} + \gamma_{10}(Z\ Age)_{ij} + \gamma_{20}(Female\ Status\ Eff)_{ij}$$
$$+ \gamma_{30}(Insurance\ Gap\ Eff)_{ij} + \gamma_{40}(Income\ 1\ Eff)_{ij}$$
$$+ \gamma_{50}(Income\ 2\ Eff)_{ij} + \gamma_{60}(Income\ 3\ Eff)_{ij}$$
$$+ \gamma_{70}(Income\ 4\ Eff)_{ij} + \gamma_{80}(Income\ 5\ Eff)_{ij}$$
$$+ \gamma_{90}(Income\ 6\ Eff)_{ij} + \gamma_{100}(Income\ 7\ Eff)_{ij}$$
$$+ \gamma_{110}(Income\ DontKnow/Refused\ Eff)_{ij}$$
$$+ \gamma_{120}(Insurance\ Medicare\ Medicaid\ Eff)_{ij}$$
$$+ \gamma_{130}(Insurance\ CHIP\ Eff)_{ij} + \gamma_{140}(Insurance\ Other\ Eff)_{ij}$$
$$+ \gamma_{150}(Insurance\ None\ Eff)_{ij}$$
$$+ \gamma_{160}(Insurance\ DontKnow/Refused\ Eff)_{ij}$$
$$+ \gamma_{170}(Z\ Age * Female\ Status\ Eff)_{ij} + \gamma_{01}(Z\ AQI)_{ij}$$
$$+ \gamma_{02}(Z\ inverse\ AQImax)_{ij} + \gamma_{180}(Veteran\ Status\ Eff)_{ij} + U_{0j}$$
$$+ \varepsilon_{ij}$$

In the model above, the log-odds of the i^{th} cross-sectional interview of children with asthma within the j^{th} state is equal to the sum of the conditional mean (γ_{00}), the unique effects of age, female status, insurance gap, income, type of insurance, the interaction between age and female status, daily average AQI, and average month maximum AQI ($\gamma_{10} - \gamma_{02}$), and the residual error due to states (U_{0j}).

An alpha of .05, 2-tailed, was used for all statistical tests. To assess the practical significance of the results, odds ratios were computed by exponentiating each logistic regression coefficient

(i.e., $e^{coefficient}$). The 95% confidence intervals for the odds ratios were obtained by exponentiating the coefficient plus or minus 1.96 times the standard error (i.e., $e^{coefficient \pm (1.96 * SE)}$). The model Nakagawa & Schielzeth's R^2 will be obtained using the 'MuMIn' package (Bartoń, 2025; Nakagawa & Schielzeth, 2013). Last, data visualization of model-predicted odds ratios was implemented using the 'ggplot2' package (Wickham, 2016).

Results

Descriptive Statistics

Counts and percentages among all binary and categorical variables are provided in Table 1. The overall sample size was 10,401 children. The outcome variable, facility-treated asthma exacerbation, shows that 7,908 (76%) children did not experience one in the last year, while 2,456 (23.6%) did, and the responses of 37 (0.4%) children made it impossible to determine if they did or did not. Also, 4,200 (40%) of the children were female, and only 626 (6%) children had a veteran parent. Finally, the correlations between the continuous variables show that average daily AQI correlated with average monthly maximum AQI, which is expected since the AQI max is a subset of the AQI data.

Model Results

Model 1 consisted of all the demographic variables: age, female status, gap in insurance, income level, type of insurance, and the interaction between age and female status. As can be seen in the first set of columns in Table 2, Age, Female status, Gap in Insurance, Income below $10k, Income between $10k and $15k, Income between $35 and $50k, Medicare/Medicaid, Children's Health Insurance Plan (CHIP), and No Health Insurance demographic predictors were

significant. That is, for each standard deviation the child's age increases, they are 0.36 logits less likely (0.7 OR) to experience a facility-treated asthma exacerbation. Females are 0.22 logits more likely (1.25 OR) than Males, and a child having a gap in health insurance is 0.26 logits more likely (1.3 OR) than one having uninterrupted health insurance to have a facility-treated asthma exacerbation. Those children whose household earnings were less than $10k per year were 0.24 logits less likely (0.78 OR), between $10k-$15k a year were 0.53 logits more likely (1.70 OR), and those earning between $35k-$50k were 0.21 less likely (0.81 OR) to experience a facility-treated asthma exacerbation. Children covered by Medicare/Medicaid were 0.20 logits more likely (1.22 OR), CHIP, they were 0.41 logits more likely (1.50 OR), and children who had no health insurance coverage were 0.70 logits less likely (0.50 OR) to experience a facility-treated asthma exacerbation. The approximate variance explained with this set of predictors was 5.33%, which is 3.85% more than the null model.

Model 2 consisted of Model 1 variables with the addition of the air quality variables. All of the significant predictors from Model 1 were still significant, with no appreciable change in their likelihood of having a facility-treated asthma exacerbation. Additionally, AQImax was also significant. As the inverse of the average monthly maximum AQI for the year increased by one standard deviation (this means lower real AQI maximums), the likelihood of having a facility-treated asthma exacerbation decreased by 0.13 logits (0.87 OR). The approximate variance explained by this set of predictors was 5.84%, which is 0.5% more than Model 1. The LRT comparing this model to the previous indicated it was significantly different (7.55, $p = .023$). However, there was discordance in model-data fit measures. The AIC decreased by 3.6 points and the BIC value increased by 10.9 points, indicating that including the L2 predictors significantly improved the model's explanatory power but decreased model efficiency.

Finally, Model 3 consisted of Model 2 variables with the addition of the variable of interest, Veteran Status. In the last set of columns of Table 2, we see that the approximate variance explained with this set of predictors was 5.85%, which is 0.01% from the previous model. The LRT comparing this model to the previous indicated it was not significantly different (0.61, p = .434), AIC increased 1.4 points and the BIC value increased again by 8.7 points, indicating that the model with the Veteran Status predictor did not improve model-data fit over the previous model.

Model 3 Coefficients. In examining the coefficients for the final model, Age, Female status, Gap in Insurance, Income below $10k, Income between $10k and $15k, Income between $35 and $50k, Medicare/Medicaid, Children's Health Insurance Plan (CHIP), and No Health Insurance L1 demographic predictors, and the L2 predictor Average Monthly Maximum AQI were significant. This indicates that as children increase one standard deviation in age, they are 0.36 logits less likely (0.7 OR) to have a facility-treated asthma exacerbation, and females are 0.22 logits more likely (1.25 OR) to have a facility-treated asthma exacerbation compared to males. From an insurance perspective, children whose parents had a gap in their health insurance coverage in the last year are 0.26 logits more likely (1.30 OR) to have a facility-treated asthma exacerbation when compared to those who did not; children who are covered by Medicare/Medicaid are 0.19 logits more likely (1.21 OR) and children who are covered under CHIP are 0.40 logits more likely (1.50 OR) than the mean likelihood. Children not covered by insurance are 0.70 logits less likely (0.50 OR) to have a facility-treated asthma exacerbation. From an income perspective, children whose parents earned less than $10k per year are 0.25 logits less likely (0.78 OR), and children whose parents earn between $10k and $15k per year are 0.54 more likely (1.71 OR). Children whose parents earn between $35-$50k per year are 0.20

logits less likely (0.82 OR) to have a facility-treated asthma exacerbation when compared to the mean. Finally, a one standard deviation increase in the inverse average monthly maximum AQI for the year (again, lower real AQI maximums) results in 0.13 logits less likely (0.88 OR) to have a facility-treated asthma exacerbation.

Following the non-significant Model 3 result for Veteran Status, an exploratory model was specified that investigated whether veteran status interacted with any of the other eighteen variables. The exploratory model was the same as Model 3, except without the age*sex interaction and the addition of the eighteen interaction terms. Only three predictors were significant in this exploratory model: Age, Income 2, and CHIP, indicating no significant two-way interactions with veteran status. The AIC and BIC both increased 8.3 points and 131.5 points, respectively, from Model 3, yielding no improvement in model fit or efficiency. The LRT was not significantly different (25.68, p=.081), indicating that veteran status had no conditional effects.

Discussion

This study examined whether parental veteran status affected the likelihood of their children experiencing a facility-treated asthma exacerbation in the last year when compared to children of non-veteran parents. Study findings were consistent with several established factors related to pediatric asthma exacerbation. First, in children, females are more likely to experience an asthma exacerbation (CDC, 2023). Although this finding is supported through the CDC's Asthma Data Visualizations, literature does not appear to address sex-linked disparities in pediatric asthma exacerbations and only addresses differences in prevalence of asthma in children (Chowdhury et al., 2021; Naeem & Silveyra, 2019; Shah & Newcomb, 2018; Zhang et al., 2022). Second, socioeconomic factors like household income, type of insurance, and gap

status of insurance play a significant role in pediatric asthma outcomes, such as exacerbation (Chowdhury et al., 2021; Hill et al., 2011).

The final model results show veteran status has an OR of 0.96 with a $p = .452$. Additionally, the LRT between the second and third models and the analysis of AICs and BICs indicate that the addition of veteran status as a predictor does not enhance model-data fit or increase the explanatory power. Despite the hypothesis that parental veteran status would have a significant effect, this well-powered analysis fails to reject the null hypothesis that children with asthma of veteran parents are as likely to experience a facility-treated asthma exacerbation as children of non-veteran parents.

Although this study failed to reject the null hypothesis, significant findings, particularly of those with the lowest income level and those having no insurance, are striking as they experience facility-treated asthma exacerbations a fifth and a half, respectively, than the mean likelihood. This absence of a facility-treated asthma exacerbation is not necessarily an indication of health and may actually result from the child's family not having had the means (time, money, or accessibility) to receive care. This appears to be evident in the final regression results where children whose family makes less than $10 thousand were 22% less likely (0.78 OR) to have a facility-treated asthma exacerbation than the mean likelihood; while children whose family makes $10-$15 thousand were 71% more likely (1.71 OR) to have a facility-treated asthma exacerbation than the mean. It is more likely that the $10-$15k group crosses a resource threshold to actually receive healthcare rather than representing a doubling likelihood of exposure-driven exacerbation.

An additional finding of note is the significant result from the average monthly maximum AQI (OR= 0.88, p= .039) while daily average AQI was not significant (OR= 0.98, p= .731). The

result suggests that this technique of preserving monthly maximums to get an idea of chronic extreme exposures, even when aggregated over the space of an entire state over the course of an entire year, provides more useful explanatory power over the likelihood that a child would have a facility-treated exacerbation than merely averaging the daily values.

There were several key limitations to this study. First, the data collection method relied on recalled reports of the child's asthma symptoms, treatment, and exposures by an adult who answered the phone. For instance, 536 (~5%) respondents reported that the child had no asthma exacerbations in the last year; however, they went on to report that the child had been treated in the healthcare facility for an asthma exacerbation. This points to validity issues related to recall bias. Second, the aforementioned facility-treated asthma exacerbation outcome alone fails to capture the whole picture and is inherently biased towards those with the means to receive health care. Lastly, the veteran status of the respondent may not necessarily indicate that the child had much or any exposure to triggers on or near military bases. These veterans could have served for only a few years before the child was born, and thus may not offer any contrasting exposure than that of children of non-veteran parents.

Conclusion

Findings from this study indicate that children of veterans with asthma do not require special or additional support. Future studies should delve into the factors that drive the disparity in the likelihood of being treated at a healthcare facility for asthma exacerbations, particularly among and between those at the lowest and second-lowest income levels, as well as those with no health insurance. Additionally, future studies should examine the benefits of measuring chronic extreme air quality exposure vs acute or average exposure for asthma severity and outcomes like exacerbation.

Table 1. Sample Demographics (n = 10,401)

DV	Binary	0 = No		1 = Yes		NA	
		n	%	n	%	n	%
	Exacerbation	7908	76.03%	2456	23.61%	37	0.36%

L1 IVs	Binary	0 = No		1 = Yes		NA		Exacerbations (when Status = 0)		Exacerbations (when Status = 1)	
		n	%	n	%	n	%	n	%	n	%
	Veteran Status	9775	93.98%	626	6.02%	0	0.00%	2319	23.72%	137	21.88%
	Female Status	6201	59.62%	4200	40.38%	0	0.00%	1401	22.59%	1055	25.12%
	Gap In Insurance	9454	91.05%	929	8.93%	18	0.17%	2230	23.59%	223	24.00%

	Continous	Mean	SD	MIN	MAX	NA
	Age (in months)	149.14	45.68	48	216	0

				Exacerbations		
	Categrical	n	%	n	%	
	Income					
	<$10k	487	4.94%	150	30.80%	
	$10k-$15k	420	4.26%	150	35.71%	
	$15k-$20k	599	6.08%	198	33.06%	
	$20k-$25k	757	7.68%	234	30.91%	
	$25k-$35k	785	7.96%	202	25.73%	
	$35k-$50k	1137	11.53%	273	24.01%	
	$50k-$75k	1526	15.48%	328	21.49%	
	>$75k	*4147*	*42.07%*	*797*	*19.22%*	*Reference*
	Dont know/Refused	543	5.51%	124	22.84%	
	Insurance Type					
	Parents Employer	*6367*	*61.22%*	*1310*	*20.57%*	*Reference*
	Medicare/Medicaid	2255	21.68%	733	32.51%	
	CHIP	498	4.79%	141	28.31%	
	Other	780	7.50%	176	22.56%	
	No Insurance	422	4.06%	77	18.25%	
	Dont know/Refused	79	0.76%	21	26.58%	

L2 IVs	Continous	Mean	SD	MIN	MAX	NA
	Air Quality Index (AQI)	43.48	6.68	20.77	62.57	0
	Avg Mornthly Max AQI	147.15	218.49	58.00	2573.69	0

Correlation		1.	2.	3.
	L1 Continious IV			
	1. Age	--		
	L2 Continious IVs			
	2. AQI	-0.02	--	
	3. AQImax	-0.01	0.37	--

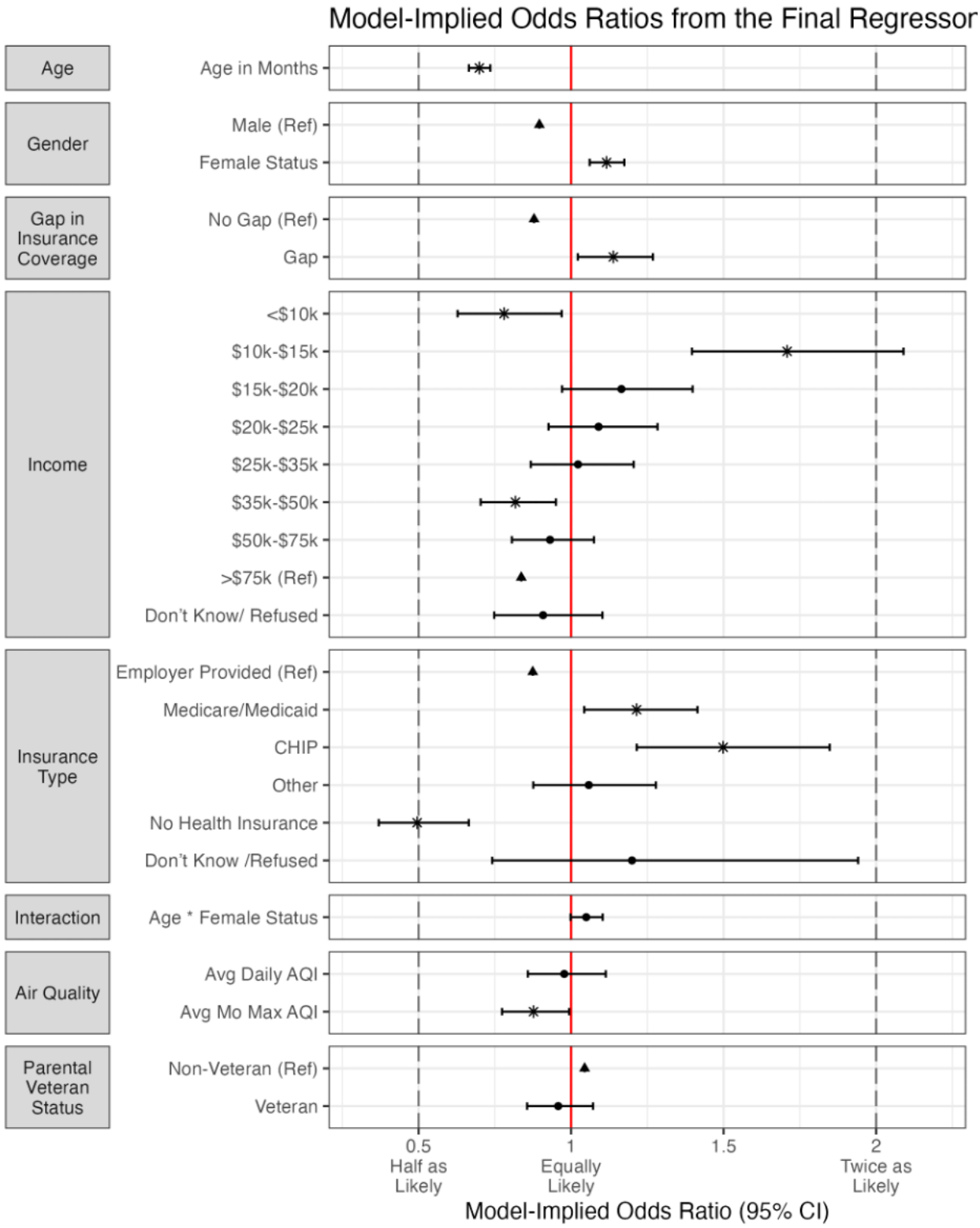
Note. *N* = 10,401 Children (L1) within 26 States (L2). Avg = Average, CHIP = Children's Health Insurance Program, DV = Dependent Variable, IV= Independent Variable, L1= Level 1, L2= Level 2, NA= Not Available/Missing, SD= Standard Devition

Table 2. Results from Regression Models Testing Predictors of Pediatric Facility-Treated Asthma Exacerbations

	Model 1: L1 Demographic Effects							Model 2: + L2 Air Quality							Model 3: + Veteran Status						
						95% CI							95% CI								95% CI
Fixed Effects	*Coeff*	*(SE)*	*Z*	*p*	*OR*	*LB*	*UB*	*Coeff*	*(SE)*	*Z*	*p*	*OR*	*LB*	*UB*	*Coeff*	*(SE)*	*Z*	*p*	*OR*	*LB*	*UB*
(Intercept)	**-1.03**	**(0.08)**	**-12.33**	**<.001**				**-1.04**	**(0.09)**	**-11.79**	**<.001**				**-1.07**	**(0.10)**	**-10.55**	**<.001**			
Age in Months	**-0.36**	**(0.03)**	**-14.05**	**<.001**	**0.70**	**0.66**	**0.73**	**-0.36**	**(0.03)**	**-13.98**	**<.001**	**0.70**	**0.66**	**0.73**	**-0.36**	**(0.03)**	**-13.98**	**<.001**	**0.70**	**0.66**	**0.74**
Female Status	**0.11**	**(0.03)**	**4.29**	**<.001**	**1.12**	**1.06**	**1.18**	**0.11**	**(0.03)**	**4.20**	**<.001**	**1.12**	**1.06**	**1.17**	**0.11**	**(0.03)**	**4.23**	**<.001**	**1.12**	**1.06**	**1.17**
Gap in Insurance	**0.13**	**(0.05)**	**2.36**	**.018**	**1.14**	**1.02**	**1.27**	**0.13**	**(0.06)**	**2.36**	**.018**	**1.14**	**1.02**	**1.27**	**0.13**	**(0.06)**	**2.36**	**.019**	**1.14**	**1.02**	**1.27**
Income <$10k	**-0.24**	**(0.11)**	**-2.20**	**.027**	**0.78**	**0.63**	**0.97**	**-0.25**	**(0.11)**	**-2.22**	**.026**	**0.78**	**0.63**	**0.97**	**-0.25**	**(0.11)**	**-2.24**	**.025**	**0.78**	**0.63**	**0.97**
Income $10k-$15k	**0.53**	**(0.10)**	**5.16**	**<.001**	**1.70**	**1.39**	**2.08**	**0.54**	**(0.10)**	**5.22**	**<.001**	**1.71**	**1.40**	**2.09**	**0.54**	**(0.10)**	**5.21**	**<.001**	**1.71**	**1.40**	**2.09**
Income $15k-$20k	0.16	(0.09)	1.72	.085	1.17	0.98	1.41	0.16	(0.09)	1.72	.086	1.17	0.98	1.41	0.15	(0.09)	1.64	.102	1.16	0.97	1.40
Income $20k-$25k	0.08	(0.08)	1.01	.315	1.09	0.92	1.28	0.09	(0.08)	1.07	.284	1.09	0.93	1.29	0.09	(0.08)	1.04	.300	1.09	0.93	1.28
Income $25k-$35k	0.02	(0.08)	0.30	.768	1.02	0.87	1.21	0.02	(0.08)	0.22	.827	1.02	0.86	1.20	0.02	(0.08)	0.27	.790	1.02	0.87	1.21
Income $35k-$50k	**-0.21**	**(0.08)**	**-2.70**	**.007**	**0.81**	**0.70**	**0.94**	**-0.21**	**(0.08)**	**-2.68**	**.007**	**0.81**	**0.70**	**0.95**	**-0.20**	**(0.08)**	**-2.63**	**.009**	**0.82**	**0.70**	**0.95**
Income $50k-$75k	-0.08	(0.07)	-1.05	.293	0.93	0.80	1.07	-0.08	(0.07)	-1.03	.303	0.93	0.80	1.07	-0.07	(0.07)	-0.98	.329	0.93	0.81	1.08
Don't Know/Refused Income	-0.09	(0.10)	-0.93	.353	0.91	0.75	1.11	-0.10	(0.10)	-0.97	.333	0.91	0.75	1.10	-0.10	(0.10)	-0.97	.330	0.91	0.75	1.10
Medicare/Medicaid	**0.20**	**(0.08)**	**2.55**	**.011**	**1.22**	**1.05**	**1.42**	**0.20**	**(0.08)**	**2.53**	**.011**	**1.22**	**1.05**	**1.42**	**0.19**	**(0.08)**	**2.50**	**.012**	**1.21**	**1.04**	**1.41**
CHIP	**0.41**	**(0.11)**	**3.82**	**<.001**	**1.50**	**1.22**	**1.85**	**0.41**	**(0.11)**	**3.79**	**<.001**	**1.50**	**1.22**	**1.85**	**0.40**	**(0.11)**	**3.78**	**<.001**	**1.50**	**1.22**	**1.85**
Other Health Insurance	0.04	(0.10)	0.47	.642	1.05	0.87	1.26	0.06	(0.10)	0.60	.550	1.06	0.88	1.28	0.06	(0.10)	0.59	.559	1.06	0.88	1.28
No Health Insurance	**-0.70**	**(0.15)**	**-4.65**	**<.001**	**0.50**	**0.37**	**0.67**	**-0.70**	**(0.15)**	**-4.67**	**<.001**	**0.50**	**0.37**	**0.67**	**-0.70**	**(0.15)**	**-4.69**	**<.001**	**0.50**	**0.37**	**0.66**
Don't Know/Refused Insurance	0.18	(0.25)	0.72	.474	1.19	0.74	1.93	0.17	(0.25)	0.69	.491	1.18	0.73	1.92	0.18	(0.25)	0.74	.459	1.20	0.74	1.94
Age * Female Status	0.05	(0.03)	1.82	.069	1.05	1.00	1.10	0.05	(0.03)	1.86	.063	1.05	1.00	1.10	0.05	(0.03)	1.89	.058	1.05	1.00	1.10
Avg Daily AQI								-0.03	(0.07)	-0.38	.703	0.97	0.86	1.11	-0.02	(0.07)	-0.34	.731	0.98	0.86	1.11
Inv(Avg Mo Max AQI)								**-0.13**	**(0.06)**	**-2.10**	**.035**	**0.87**	**0.77**	**0.99**	**-0.13**	**(0.06)**	**-2.06**	**.039**	**0.88**	**0.77**	**0.99**
Veteran Status															-0.04	(0.06)	-0.75	.452	0.96	0.86	1.07
Random Effects	*Var*							*Var*							*Var*						
Intercept (L2)	0.06							0.08							0.08						
Model Fit	*Value*							*Value*	*p*						*Value*	*p*					
Pseudo Total R^2	0.05							0.06							0.06						
AIC	9670.20							9666.60							9668.00						
BIC	9807.80							9818.70							9827.40						
Deviance (-2LL)	9632.20							9624.60							9624.00						
Residual *df*	10328							10326							10325						
LRT Chi-square test	--							**7.55**	**.023**						0.61	.434					

Note. N = 10,401 Children (L1) within 26 States (L2). All values in log-odds units (logits). AQI = Air Quality Index, Avg = Average, CHIP = Children's Health Insurance Program, Inv= Inverse (1/x or x^-1), Mo = Month; all categorical predictors effect-coded and continuous predictors standardized. Models estimated using full maximum likelihood by *R* lme4. Observed *p*-values reported; values in boldface indicate significance at the .05 level.

Table 3. Model-Implied Odds Ratios of the Final Regression Model



Note. n= 10,401; 'Ref' = Refence Value and is marked with a '▲';
Significant values ($p < .05$) are marked with an asterisk; Not-significant values ($p > .05$) are marked '●'.

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Appendix: R Code

```
+++++++++++++++ Start File +++++++++++++++
#Disseration Paper 2 AQI Data Prep ----
# Pre-Analysis Preparatory Tasks ----

## Prep the cyberspace----
options(scipen=999) ## forces full display of results, all digits
setwd("~/[REDACTED]/AQI Data/Raw")
### clean up the environment/remove old objects ----
rm(list=ls())
gc()

## Load Packages----
library(haven) ### Import SAS files
library(misty)  ### manipulating data
library(dplyr)  ### manipulating data (note: dplyr can overlap with other packages)
### if masking occurs, use: dplyr::function() to use dplyr functions
library(car)    ### manipulating data
### if masking occurs, use: car::function() to use car functions
library(ggplot2) ### plotting
library(psych)  ### descriptives
library(tidyverse) ### data manipulation
library(tidyselect) ### data manipulation
library(maps) ### contains state.fips data file
library(mice) ### for missing data

## Load the data----
AQI2009 <- read.csv("daily_aqi_by_county_2009.csv")
AQI2010 <- read.csv("daily_aqi_by_county_2010.csv")
AQI2011 <- read.csv("daily_aqi_by_county_2011.csv")
AQI2012 <- read.csv("daily_aqi_by_county_2012.csv")
AQI2013 <- read.csv("daily_aqi_by_county_2013.csv")
AQI2014 <- read.csv("daily_aqi_by_county_2014.csv")
AQI2015 <- read.csv("daily_aqi_by_county_2015.csv")
AQI2016 <- read.csv("daily_aqi_by_county_2016.csv")
AQI2017 <- read.csv("daily_aqi_by_county_2017.csv")
AQI2018 <- read.csv("daily_aqi_by_county_2018.csv")
AQI2019 <- read.csv("daily_aqi_by_county_2019.csv")
AQI2020 <- read.csv("daily_aqi_by_county_2020.csv")

##Bind data
AQIbound <-
bind_rows(AQI2009,AQI2010,AQI2011,AQI2012,AQI2013,AQI2014,AQI2015,AQI2016,AQI2017,AQI2018,AQI2019
,AQI2020)
rm(AQI2009,AQI2010,AQI2011,AQI2012,AQI2013,AQI2014,AQI2015,AQI2016,AQI2017,AQI2018,AQI2019,AQI202
0)

##Add Date and Period variables
AQIbound$mo <- substring(AQIbound$Date,6,7)
AQIbound$yr <- substring(AQIbound$Date,1,4)
AQIbound$PER <- ((as.numeric(AQIbound$yr)-2010)*12)+as.numeric(AQIbound$mo)

##Aggregate to Month and State
AQIbound <- AQIbound %>% group_by(State.Code,State.Name,PER) %>% summarise(X = mean(AQI), Max =
max(AQI))


#split states off and add moving average values for Mean and Max AQI
# 6  9 12 13 15 18 20 21 23 24 26 27 28 30 31 34 35 36 39 40 42 48 49 50 53 72

## CA, 6
CA <- AQIbound[AQIbound$State.Code == 6,]
CA$Xma <- stats::filter(CA$X, rep(1,13)/13, sides = 1)
CA$Maxma <- stats::filter(CA$Max, rep(1,13)/13, sides = 1)

## CT, 9
CT <- AQIbound[AQIbound$State.Code == 9,]
CT$Xma <- stats::filter(CT$X, rep(1,13)/13, sides = 1)
CT$Maxma <- stats::filter(CT$Max, rep(1,13)/13, sides = 1)
```

```
## FL, 12
FL <- AQIbound[AQIbound$State.Code == 12,]
FL$Xma <- stats::filter(FL$X, rep(1,13)/13, sides = 1)
FL$Maxma <- stats::filter(FL$Max, rep(1,13)/13, sides = 1)

## GA, 13
GA <- AQIbound[AQIbound$State.Code == 13,]
GA$Xma <- stats::filter(GA$X, rep(1,13)/13, sides = 1)
GA$Maxma <- stats::filter(GA$Max, rep(1,13)/13, sides = 1)

## HI, 15
HI <- AQIbound[AQIbound$State.Code == 15,]
HI$Xma <- stats::filter(HI$X, rep(1,13)/13, sides = 1)
HI$Maxma <- stats::filter(HI$Max, rep(1,13)/13, sides = 1)

## IN, 18
IN <- AQIbound[AQIbound$State.Code == 18,]
IN$Xma <- stats::filter(IN$X, rep(1,13)/13, sides = 1)
IN$Maxma <- stats::filter(IN$Max, rep(1,13)/13, sides = 1)

## KS, 20
KS <- AQIbound[AQIbound$State.Code == 20,]
KS$Xma <- stats::filter(KS$X, rep(1,13)/13, sides = 1)
KS$Maxma <- stats::filter(KS$Max, rep(1,13)/13, sides = 1)

## KY, 21
KY <- AQIbound[AQIbound$State.Code == 21,]
KY$Xma <- stats::filter(KY$X, rep(1,13)/13, sides = 1)
KY$Maxma <- stats::filter(KY$Max, rep(1,13)/13, sides = 1)

## ME, 23
ME <- AQIbound[AQIbound$State.Code == 23,]
ME$Xma <- stats::filter(ME$X, rep(1,13)/13, sides = 1)
ME$Maxma <- stats::filter(ME$Max, rep(1,13)/13, sides = 1)

## MD, 24
MD <- AQIbound[AQIbound$State.Code == 24,]
MD$Xma <- stats::filter(MD$X, rep(1,13)/13, sides = 1)
MD$Maxma <- stats::filter(MD$Max, rep(1,13)/13, sides = 1)

## MI, 26
MI <- AQIbound[AQIbound$State.Code == 26,]
MI$Xma <- stats::filter(MI$X, rep(1,13)/13, sides = 1)
MI$Maxma <- stats::filter(MI$Max, rep(1,13)/13, sides = 1)

## MN, 27
MN <- AQIbound[AQIbound$State.Code == 27,]
MN$Xma <- stats::filter(MN$X, rep(1,13)/13, sides = 1)
MN$Maxma <- stats::filter(MN$Max, rep(1,13)/13, sides = 1)

## MS, 28
MS <- AQIbound[AQIbound$State.Code == 28,]
MS$Xma <- stats::filter(MS$X, rep(1,13)/13, sides = 1)
MS$Maxma <- stats::filter(MS$Max, rep(1,13)/13, sides = 1)

## MT, 30
MT <- AQIbound[AQIbound$State.Code == 30,]
MT$Xma <- stats::filter(MT$X, rep(1,13)/13, sides = 1)
MT$Maxma <- stats::filter(MT$Max, rep(1,13)/13, sides = 1)

## NE, 31
NE <- AQIbound[AQIbound$State.Code == 31,]
NE$Xma <- stats::filter(NE$X, rep(1,13)/13, sides = 1)
NE$Maxma <- stats::filter(NE$Max, rep(1,13)/13, sides = 1)

## NJ, 34
NJ <- AQIbound[AQIbound$State.Code == 34,]
NJ$Xma <- stats::filter(NJ$X, rep(1,13)/13, sides = 1)
NJ$Maxma <- stats::filter(NJ$Max, rep(1,13)/13, sides = 1)
```

```
## NM, 35
NM <- AQIbound[AQIbound$State.Code == 35,]
NM$Xma <- stats::filter(NM$X, rep(1,13)/13, sides = 1)
NM$Maxma <- stats::filter(NM$Max, rep(1,13)/13, sides = 1)

## NY, 36
NY <- AQIbound[AQIbound$State.Code == 36,]
NY$Xma <- stats::filter(NY$X, rep(1,13)/13, sides = 1)
NY$Maxma <- stats::filter(NY$Max, rep(1,13)/13, sides = 1)

## OH, 39
OH <- AQIbound[AQIbound$State.Code == 39,]
OH$Xma <- stats::filter(OH$X, rep(1,13)/13, sides = 1)
OH$Maxma <- stats::filter(OH$Max, rep(1,13)/13, sides = 1)

## OK, 40
OK <- AQIbound[AQIbound$State.Code == 40,]
OK$Xma <- stats::filter(OK$X, rep(1,13)/13, sides = 1)
OK$Maxma <- stats::filter(OK$Max, rep(1,13)/13, sides = 1)

## PA, 42
PA <- AQIbound[AQIbound$State.Code == 42,]
PA$Xma <- stats::filter(PA$X, rep(1,13)/13, sides = 1)
PA$Maxma <- stats::filter(PA$Max, rep(1,13)/13, sides = 1)

## TX, 48
TX <- AQIbound[AQIbound$State.Code == 48,]
TX$Xma <- stats::filter(TX$X, rep(1,13)/13, sides = 1)
TX$Maxma <- stats::filter(TX$Max, rep(1,13)/13, sides = 1)

## UT, 49
UT <- AQIbound[AQIbound$State.Code == 49,]
UT$Xma <- stats::filter(UT$X, rep(1,13)/13, sides = 1)
UT$Maxma <- stats::filter(UT$Max, rep(1,13)/13, sides = 1)

## VT, 50
VT <- AQIbound[AQIbound$State.Code == 50,]
VT$Xma <- stats::filter(VT$X, rep(1,13)/13, sides = 1)
VT$Maxma <- stats::filter(VT$Max, rep(1,13)/13, sides = 1)

## WA, 53
WA <- AQIbound[AQIbound$State.Code == 53,]
WA$Xma <- stats::filter(WA$X, rep(1,13)/13, sides = 1)
WA$Maxma <- stats::filter(WA$Max, rep(1,13)/13, sides = 1)

## PR, 72 (!!!Missing PER 94,95,96 -> rolling averages for thru 108 are not accurate!!!)
PR <- AQIbound[AQIbound$State.Code == 72,]
PR$Xma <- stats::filter(PR$X, rep(1,13)/13, sides = 1)
PR$Maxma <- stats::filter(PR$Max, rep(1,13)/13, sides = 1)

#Reassemble data
AQIlookup <-
bind_rows(CA,CT,FL,GA,HI,IN,KS,KY,MD,ME,MI,MN,MS,MT,NE,NJ,NM,NY,OH,OK,PA,PR,TX,UT,VT,WA)
rm(CA,CT,FL,GA,HI,IN,KS,KY,MD,ME,MI,MN,MS,MT,NE,NJ,NM,NY,OH,OK,PA,PR,TX,UT,VT,WA,AQIbound)

#Save the Lookup file
save(AQIlookup, file = "~/[REDACTED]/AQIlookup.RData")

++++++++++++++++ End File ++++++++++++++++


++++++++++++++++ Start File ++++++++++++++++

#Disseration Paper 2 BRFSS Data Prep ----
# Pre-Analysis Preparatory Tasks ----

## Prep the cyberspace----
options(scipen=999) ## forces full display of results, all digits
setwd("~/[REDACTED]/BRFSS Data/Raw")
### clean up the environment/remove old objects ----
rm(list=ls())
```

```
gc()

## Load Packages----
library(readxl)#import Excel files
library(haven) ### Import SAS files
library(effects)
library(moments)
library(robustlmm)
library(lme4)   ### multilevel modeling software
library(Matrix) ### needed for lme4
library(lmerTest) ### to get df and t/p values for lme4 output
library(misty)  ### manipulating data
library(dplyr)  ### manipulating data (note: dplyr can overlap with other packages)
### if masking occurs, use: dplyr::function() to use dplyr functions
library(car)    ### manipulating data
### if masking occurs, use: car::function() to use car functions
library(ggplot2) ### plotting
library(psych)  ### descriptives
library(r2mlm)  ### R2 values for linear 2L models
library(viridis) ### for complex color plots
library(ggthemes) ### for complex color plots
library(Hmisc)
library(tidyverse) ### data manipulation
library(tidyselect) ### data manipulation
library(maps) ### contains state.fips data file
library(mice) ### for missing data
library(stats)
library(survey)
library(MuMIn) ### for R2 values for Binomal Multi-Level models using r.squaredGLMM()

## Load the data----
ACBS2010 <- read_sas("acbs_2010_child_public.sas7bdat")
ACBS2011 <- read_sas("acbs_2011_child_public.sas7bdat")
ACBS2012 <- read_sas("acbs_2012_child_public_llcp.sas7bdat")
ACBS2013 <- read_sas("acbs_2013_child_public_llcp.sas7bdat")
ACBS2014 <- read_sas("ACBS_2014_CHILD_PUBLIC_LLCP.sas7bdat")
ACBS2015 <- read_sas("ACBS_2015_CHILD_PUBLIC_LLCP.SAS7bdat")
ACBS2016 <- read_sas("acbs_2016_child_public_llcp.sas7bdat")
ACBS2017 <- read_sas("ACBS_2017_CHILD_PUBLIC_LLCP.sas7bdat")
ACBS2018 <- read_sas("acbs_2018_child_public_llcp.sas7bdat")
ACBS2019 <- read_sas("acbs_2019_child_public_llcp.sas7bdat")
ACBS2020 <- read_sas("acbs_2020_child_public_llcp.sas7bdat")
ACBS1517 <- read_sas("acbs_2015_2017_child_public_llcp.sas7bdat")
data("state.fips")
load("~/[REDACTED]/AQIlookup.RData")

## Subset the data----
ACBS2010 <- ACBS2010 %>% select(`_STATE`, IDATE, IYEAR_F, IMONTH_F, CAGEG_F4, CHILDAGE,
`_CIMPAGE`, `_CUR_ASTH_C`, INS1, INS_TYP, INS2, EPIS_12M, NER_TIME, ER_VISIT, ER_TIMES, URG_TIME,
HOSP_VST, HOSPTIME, CPOST, CWEIGHT_IN, `_CSEXG_`, CHILDWT_F, MNTHDIFF, VETERAN2, INCOME2, `_PSU`,
`_STSTR`, NRECSTR, NRECSEL)

ACBS2011 <- ACBS2011 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CAGEG_F4,CHILDAGE,`_CIMPAGE`,`_CUR_ASTH_C`,INS1,INS_TYP,IN
S2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CPOST,CWEIGHT_IN,CSEXG,CLANDWT_F,MNTHDIFF,V
ETERAN3,INCOME2,
                                )
ACBS2012 <- ACBS2012 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CAGEG_F4,CHILDAGE,`_CIMPAGE`,`_CUR_ASTH_C`,INS1,INS_TYP,IN
S2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CPOST,CWEIGHT_IN,CSEXG,CLLCPWT_F,MNTHDIFF,V
ETERAN3,INCOME2,
                                )
ACBS2013 <- ACBS2013 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CAGEG_F4,CHILDAGE,`_CIMPAGE`,`_CUR_ASTH_C`,INS1,INS_TYP,IN
S2,EPIS_12M,
```

```
NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CPOST,CWEIGHT_IN,CSEXG,CLLCPWT_F,MNTHDIFF,V
ETERAN3,INCOME2,
                                  )
ACBS2014 <- ACBS2014 %>%
select(`_state`,IDATE,IYEAR_F,IMONTH_F,CAGEG_F4,CHILDAGE,`_CIMPAGE`,`_CUR_ASTH_C`,INS1,INS_TYP,IN
S2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CPOST,CWEIGHT_IN,CSEXG,CLLCPWT_F,MNTHDIFF,V
ETERAN3,INCOME2,
                                  )
ACBS2015 <- ACBS2015 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,`_IMPCSE
X`,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CWEIGHT_IN,CLLCPWT_F,MNTHDIFF,VETERAN3,INCO
ME2,
                                  )
ACBS2016 <- ACBS2016 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,RCSGENDR
,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CWEIGHT_IN,CLLCPWT_F,`_PSU`,VETERAN3,INCOME
2,
                                  )
ACBS2017 <- ACBS2017 %>%
select(`_state`,IDATE,IYEAR_F,IMONTH_F,CAGEG_F4,`_CIMPAGE`,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_1
2M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CPOST,CWEIGHT_IN,CSEXG,CLLCPWT_F,MNTHDIFF,V
ETERAN3,INCOME2,
                                  )
ACBS2018 <- ACBS2018 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CPOST,CWEIGHT_IN,SEX,CSEXG,CLLCPWT_F,MNTHDI
FF,VETERAN3,INCOME2,
                                  )
ACBS2019 <- ACBS2019 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CPOST,CWEIGHT_IN,SEX,CSEXG,CLLCPWT_F,MNTHDI
FF,VETERAN3,INCOME2,
                                  )
ACBS2020 <- ACBS2020 %>%
select(`_state`,IDATE,IYEAR_F,IMONTH_F,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,`_IMPCAG
E`,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CWEIGHT_IN,SEX,`_IMPCSEX`,CLLCPWT_F,MNTHDIF
F,VETERAN3,INCOME2,
                                  )

ACBS1517 <- ACBS1517 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,`_IMPCSE
X`,MNTHDIFF,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,`_LLCPWT`,`_CLLCPWT_M_YEARS`,CWEIGHT_IN,`_P
SU`,VETERAN3,INCOME2)

#Standarding variable names across years
ACBS2010$CSEXG <- ACBS2010$`_CSEXG_`
#in 2010 Veteran question is different than 2011-2020; recodes 2010 responses and renames to
align with 2011-2020 data files
ACBS2010$VETERAN3 <- as.numeric(car::recode(ACBS2010$VETERAN2," 1:4 = 1; 5 = 2; 7:9 = NA"))
ACBS2014$"_STATE" <- ACBS2014$`_state`
ACBS2017$"_STATE" <- ACBS2017$`_state`
ACBS2020$"_STATE" <- ACBS2020$`_state`
ACBS2020$CSEXG <- ACBS2020$`_IMPCSEX`
ACBS2016$CSEXG <- ACBS2016$RCSGENDR
ACBS2015$CSEXG <- ACBS2015$`_IMPCSEX`
ACBS2010$CLLCPWT_F <- ACBS2010$CHILDWT_F
```

```
ACBS2011$CLLCPWT_F <- ACBS2011$CLANDWT_F
ACBS2020$IYEAR_F <- as.character(ACBS2020$IYEAR_F)
ACBS2020$IMONTH_F <- as.character(ACBS2020$IMONTH_F)
ACBS2016$MNTHDIFF <- as.numeric(NA)
ACBS1517$CSEXG <- ACBS1517$`_IMPCSEX`

#Merging to get missing 2016 MNTHDIFF (Age) data
temp2016 <- ACBS2016 %>%
select(`_STATE`,IDATE,CAGEG_F4,CSEXG,ER_VISIT,HOSP_VST,NER_TIME,EPIS_12M)
temp1517 <- ACBS1517 %>%
select(`_STATE`,IDATE,CAGEG_F4,CSEXG,ER_VISIT,HOSP_VST,NER_TIME,EPIS_12M,MNTHDIFF)
temp2016 <- temp2016 %>% left_join(temp1517, by =
c("_STATE","IDATE","CAGEG_F4","CSEXG","ER_VISIT","HOSP_VST","NER_TIME","EPIS_12M"), multiple =
"any")
ACBS2016$MNTHDIFF <- temp2016$MNTHDIFF

#Selecting standard varible names across all years
ACBS2010 <- ACBS2010 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CSEXG,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CLLCPWT_F,MNTHDIFF,VETERAN3,INCOME2,
                                )
ACBS2011 <- ACBS2011 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CSEXG,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CLLCPWT_F,MNTHDIFF,VETERAN3,INCOME2,
                                )
ACBS2012 <- ACBS2012 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CSEXG,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CLLCPWT_F,MNTHDIFF,VETERAN3,INCOME2,
                                )
ACBS2013 <- ACBS2013 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CSEXG,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CLLCPWT_F,MNTHDIFF,VETERAN3,INCOME2,
                                )
ACBS2014 <- ACBS2014 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CSEXG,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CLLCPWT_F,MNTHDIFF,VETERAN3,INCOME2,
                                )
ACBS2015 <- ACBS2015 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CSEXG,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CLLCPWT_F,MNTHDIFF,VETERAN3,INCOME2,
                                )
ACBS2016 <- ACBS2016 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CSEXG,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CLLCPWT_F,MNTHDIFF,VETERAN3,INCOME2,
                                )
ACBS2017 <- ACBS2017 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CSEXG,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CLLCPWT_F,MNTHDIFF,VETERAN3,INCOME2,
                                )
ACBS2018 <- ACBS2018 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CSEXG,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CLLCPWT_F,MNTHDIFF,VETERAN3,INCOME2,
                                )
ACBS2019 <- ACBS2019 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CSEXG,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CLLCPWT_F,MNTHDIFF,VETERAN3,INCOME2,
                                )
ACBS2020 <- ACBS2020 %>%
select(`_STATE`,IDATE,IYEAR_F,IMONTH_F,CSEXG,CAGEG_F4,`_CUR_ASTH_C`,INS1,INS_TYP,INS2,EPIS_12M,

NER_TIME,ER_VISIT,ER_TIMES,URG_TIME,HOSP_VST,HOSPTIME,CLLCPWT_F,MNTHDIFF,VETERAN3,INCOME2,
```

```
                                )

#Combine all into one dataset
data <- bind_rows(ACBS2010,ACBS2011,ACBS2012,ACBS2013,ACBS2014,ACBS2015,ACBS2016,
                  ACBS2017,ACBS2018,ACBS2019,ACBS2020)
#Removing raw and temp data files
rm(ACBS2010,ACBS2011,ACBS2012,ACBS2013,ACBS2014,ACBS2015,ACBS2016,ACBS2017,ACBS2018,ACBS2019,ACBS
2020,temp1517,temp2016,ACBS1517)

# Convert State FIPs codes to Abv
x <- c(15,NA,NA,NA,"HI","hawaii")
z <- c(72,NA,NA,NA,"PR","puerto rico")
state.fips <- rbind(state.fips,x)
state.fips <- rbind(state.fips,z)
data <- mutate(data, ST = state.fips$abb[match(data$`_STATE`, state.fips$fips)])
rm(x,z,state.fips)

## Re-coding ----
data$`_CUR_ASTH_C` <- as.numeric(car::recode(data$`_CUR_ASTH_C`," 1 = 1; 2 = 0 ; 7 = NA"))
data$INS1 <- as.numeric(car::recode(data$INS1," 1 = 1; 2:9 = 0")) #codebook treats "dont know"
(7) or "refused" (9) as "no insurance" (2)
data$INS2 <- as.numeric(car::recode(data$INS2," 1 = 1; 2 = 0; 5 = 1 ; 7:9 = NA"))
data$NER_TIME <- as.numeric(car::recode(data$NER_TIME," 500:776 = 0 ; 777 = NA ; 778:998 = 0 ;
999 = NA"))
data$ER_VISIT <- as.numeric(car::recode(data$ER_VISIT," 1 = 1; 2:6 = 0 ; 7:9 = NA"))
data$ER_TIMES <- as.numeric(car::recode(data$ER_TIMES," 500:776 = 0 ; 777:999 = NA"))
data$URG_TIME <- as.numeric(car::recode(data$URG_TIME,"88 = 0; 500:776 = 0 ; 777 = NA ; 778:998 =
0 ; 999 = NA"))
data$HOSP_VST <- as.numeric(car::recode(data$HOSP_VST," 1 = 1; 2:6 = 0 ; 7:9 = NA"))
data$HOSPTIME <- as.numeric(car::recode(data$HOSPTIME," 400:776 = 0 ; 777 = NA ; 778:998 = 0 ;
999 = NA"))
data$EPIS_12M <- as.numeric(car::recode(data$EPIS_12M," 1 = 1; 2:6 = 0 ; 7:9 = NA"))
data$CSEXG <- as.numeric(car::recode(data$CSEXG," 1 = 1; 2 = 0"))
data$VETSTAT <- as.numeric(car::recode(data$VETERAN3," 1 = 1; 2:6 = 0 ; 7:9 = NA"))

#Create an interview period (PER) variable where Jan 2010 = 1 and Jan 2020 = 121
data$YR <- as.numeric(data$IYEAR_F)-2010
data$PER <- (data$YR * 12)+as.numeric(data$IMONTH_F)

#Create a variable that looks at last 12 months for a facility treated asthma exacerbation (EXAC)
#If responses indicate subject had asthma treated in ER, Urgent Care, or Hospital Admission then
EXAC=1
data <- mutate(data, EXAC = ifelse((ER_VISIT == 0 & (URG_TIME ==  0 | is.na(URG_TIME)) & HOSP_VST
== 0) , 0 ,
                                   ifelse(ER_VISIT >= 1 | URG_TIME >= 1 | HOSP_VST >= 1 , 1,
NA)))

#Creates variable that fixes the "WTF" issue where (n=538) EPIS_12M = 0 or NA AND EXAC = 1 !?!
#(report that child did NOT have ANY exacerbation in last 12 months but WAS treated for an
exacerbation in a facility)
# if EPIS_12M = 0 or NA AND EXAC = 1 THEN EPIS_12Me = 1
#(in this situation assumption that report of facility treated exacerbation is correct and sets
ANY exacerbation in last 12 months to TRUE)
data <- mutate(data, EPIS_12Me = ifelse((EPIS_12M == 0 | is.na(EPIS_12M)) & EXAC == 1 , 1,
EPIS_12M))

# Exclusions ----
data <- data[which(data$MNTHDIFF>47),] #excluding 1085 children younger than 4 years (12113 ->
11028)
data <- data[which(data$MNTHDIFF<217),]#excluding 10 children older than 18 years (11028 ->
11018)
data <- data[which(data$PER<122),]#excluding 611 children where data was collected after Jan 2020
(11018 -> 10407)
#data <- data[which(is.na(data$EXAC)==FALSE),]#excluding 37 children where DV is missing (10407 -
> 10370)

# Add ID
data$ID <- 1:nrow(data)

# Adding AQI data
tempData <- data %>%  select(ID,`_STATE`,PER)
```

```
tempData$State.Code <- data$`_STATE`
tempData$`_STATE` <- NULL
tempData <- dplyr::left_join(tempData,AQIlookup)
data$AQI <- tempData$X
data$AQImax <- tempData$Max
data$maAQI <- tempData$Xma
data$maAQImax <- tempData$Maxma
rm(tempData,AQIlookup)

#Save Prepped BRFSS Data
save(data, file = "~/[REDACTED]/BRFSSdata.RData")

# Working dataset
H1 <- data %>% select(ID,PER,EXAC,ST)
H1$VET <- data$VETSTAT
H1$AGE <- data$MNTHDIFF
H1$SEX <- data$CSEXG
H1$STATE <- data$`_STATE`
H1$GAP <- data$INS2
H1$AQI <- data$maAQI
H1$invAQImax <- 1/data$maAQImax
H1$WT <- data$CLLCPWT_F


# Working Dataset Categorical Varaibles
## Type of insurance where (1) "Parents Employer" is the reference value
H1$INSmed_eff <- as.numeric(car::recode(data$INS_TYP,"1=-1;2=1;3:9=0")) #Medicare/Medicaid
H1$INSchip_eff <- as.numeric(car::recode(data$INS_TYP,"1=-1;2=0;3=1;4:9=0")) #CHIP
H1$INSoth_eff <- as.numeric(car::recode(data$INS_TYP,"1=-1;2:3=0;4=1;5:9=0")) #Other
H1$INSnone_eff <- as.numeric(car::recode(data$INS_TYP,"1=-1;2:4=0;5=1;7:9=0")) #No Insurance
H1$INSdk_eff <- as.numeric(car::recode(data$INS_TYP,"1=-1;2:5=0;7=1;9=0")) #Dont Know
H1$INSref_eff <- as.numeric(car::recode(data$INS_TYP,"1=-1;2:7=0;9=1")) #Refused to answer
H1$INSdkRef_eff <- as.numeric(car::recode(data$INS_TYP,"1=-1;2:5=0;7:9=1")) #Dont Know & Refused
to answer

H1$INSmed_dum <- as.numeric(car::recode(data$INS_TYP,"1=0;2=1;3:9=0")) #Medicare/Medicaid
H1$INSchip_dum <- as.numeric(car::recode(data$INS_TYP,"1:2=0;3=1;4:9=0")) #CHIP
H1$INSoth_dum <- as.numeric(car::recode(data$INS_TYP,"1:3=0;4=1;5:9=0")) #Other
H1$INSnone_dum <- as.numeric(car::recode(data$INS_TYP,"1:4=0;5=1;7:9=0")) #No Insurance
H1$INSdk_dum <- as.numeric(car::recode(data$INS_TYP,"1:5=0;7=1;9=0")) #Dont Know
H1$INSref_dum <- as.numeric(car::recode(data$INS_TYP,"1:7=0;9=1")) #Refused to answer

## Income level where (8) >$75k is the refrence value
H1$INC1_eff <- as.numeric(car::recode(data$INCOME2,"1=1;2:7=0;8=-1;9:99=0")) #<$10k
H1$INC2_eff <- as.numeric(car::recode(data$INCOME2,"1=0;2=1;3:7=0;8=-1;9:99=0")) #$10k-$15k
H1$INC3_eff <- as.numeric(car::recode(data$INCOME2,"1:2=0;3=1;4:7=0;8=-1;9:99=0")) #$15k-$20k
H1$INC4_eff <- as.numeric(car::recode(data$INCOME2,"1:3=0;4=1;5:7=0;8=-1;9:99=0")) #$20k-$25k
H1$INC5_eff <- as.numeric(car::recode(data$INCOME2,"1:4=0;5=1;6:7=0;8=-1;9:99=0")) #$25k-$35k
H1$INC6_eff <- as.numeric(car::recode(data$INCOME2,"1:5=0;6=1;7=0;8=-1;9:99=0")) #$35k-$50k
H1$INC7_eff <- as.numeric(car::recode(data$INCOME2,"1:6=0;7=1;8=-1;9:99=0")) #$50k-$75k
H1$INCdk_eff <- as.numeric(car::recode(data$INCOME2,"1:7=0;8=-1;77=1;99=0")) #Dont know income
H1$INCref_eff <- as.numeric(car::recode(data$INCOME2,"1:7=0;8=-1;77=0;99=1")) #Refused to answer
H1$INCdkRef_eff <- as.numeric(car::recode(data$INCOME2,"1:7=0;8=-1;9:99=1")) #Dont know & Refused
to answer

H1$INC1_dum <- as.numeric(car::recode(data$INCOME2,"1=1;2:99=0")) #<$10k
H1$INC2_dum <- as.numeric(car::recode(data$INCOME2,"1=0;2=1;3:99=0")) #$10k-$15k
H1$INC3_dum <- as.numeric(car::recode(data$INCOME2,"1:2=0;3=1;4:99=0")) #$15k-$20k
H1$INC4_dum <- as.numeric(car::recode(data$INCOME2,"1:3=0;4=1;5:99=0")) #$20k-$25k
H1$INC5_dum <- as.numeric(car::recode(data$INCOME2,"1:4=0;5=1;6:99=0")) #$25k-$35k
H1$INC6_dum <- as.numeric(car::recode(data$INCOME2,"1:5=0;6=1;7:99=0")) #$35k-$50k
H1$INC7_dum <- as.numeric(car::recode(data$INCOME2,"1:6=0;7=1;8:99=0")) #$50k-$75k
H1$INCdk_dum <- as.numeric(car::recode(data$INCOME2,"1:8=0;77=1;99=0")) #Dont know income
H1$INCref_dum <- as.numeric(car::recode(data$INCOME2,"1:77=0;99=1")) #Refused to answer

#Effect Code Binary Variables (references are chosen as the most privileged/benefited group)
H1$VET_eff <- as.numeric(car::recode(H1$VET,"0=-1;1=1")) #Non-veteran (ref) = -1
H1$FEM_eff <- as.numeric(car::recode(H1$SEX,"1=-1;0=1")) #Male (ref) = -1
H1$FEM_dum <- as.numeric(car::recode(H1$SEX,"1=0;0=1")) #Male (ref) = 0
H1$GAP_eff <- as.numeric(car::recode(H1$GAP,"0=-1;1=1")) #No insurance gap (ref) = -1
```

```
#Z score metrical scores
H1$zAGE <- as.numeric(scale(H1$AGE, scale = TRUE))
H1$zAQI <- as.numeric(scale(H1$AQI, scale = TRUE))
H1$zAQImax <- as.numeric(scale(H1$invAQImax, scale = TRUE))

#scale final survey weights relative to the sample size within States
#within each sampling unit, sum the weights
wts<-tapply(H1$WT,H1$ST,sum)
#make a data frame from this
wts<-data.frame(id=names(unlist(wts)), wt=unlist(wts))
#get the unique State ids'
t1<-as.data.frame(table(H1$ST))
#put all of this into a data set
wts2<-data.frame(ids=wts$id, sumwt=wts$wt, jn=t1$Freq)
#merge all of this back to the original data file
test<-merge(H1, wts2, by.x="ST", by.y="ids", all.x=T)
#In the new data set, multiply the original weight by the fraction of the
#State total population each person represents
H1$swts<-test$WT*(test$jn/test$sumwt)
rm(t1,test,wts,wts2)

H1 <- H1[which(is.na(H1$VET)==FALSE),] #removes 6 obs where VET is NA 10407 -> 10401
#H1 <- H1[which(is.na(H1$EXAC)==FALSE),]

# Intercept Only Model ----
M0 <- glmer(EXAC ~ 1 + (1|STATE), data=H1, weights = swts, family = binomial)
M0variances = as.data.frame(VarCorr(M0))
M0cluster_var = M0variances[1,'vcov']
resid_var = (pi^2)/3
M0ICC <- M0cluster_var/(M0cluster_var + resid_var) # ICC = 2.49%
r.squaredGLMM(M0) #R2= 0.01485414


# M1 using Demographic predictors
M1 <- glmer(EXAC ~ zAGE + FEM_eff + GAP_eff + INC1_eff + INC2_eff +
              INC3_eff + INC4_eff + INC5_eff + INC6_eff + INC7_eff +
              INCdkRef_eff + INSmed_eff + INSchip_eff +
              INSoth_eff + INSnone_eff + INSdkRef_eff +
              zAGE * FEM_eff +
            (1|STATE),
            data=H1, weights = swts, family = binomial)
summary(M1)

# approx R2
r.squaredGLMM(M1, null = M0) # R2 =  0.05333189

# M2 using Demographic predictors + AQI
M2 <- glmer(EXAC ~ zAGE + FEM_eff + GAP_eff + INC1_eff + INC2_eff +
              INC3_eff + INC4_eff + INC5_eff + INC6_eff + INC7_eff +
               INCdkRef_eff + INSmed_eff + INSchip_eff +
              INSoth_eff + INSnone_eff + INSdkRef_eff +
              zAGE * FEM_eff + zAQI + zAQImax +
              (1|STATE),
            data=H1, weights = swts, family = binomial)
summary(M2)
# approx R2
r.squaredGLMM(M2, null = M0) # R2 =  0.05841014


# M3 using Demographic predictors + AQI + IV of interest gap in Veteran Status (VET)
M3 <- glmer(EXAC ~ VET_eff + zAGE + FEM_eff + GAP_eff + INC1_eff + INC2_eff +
              INC3_eff + INC4_eff + INC5_eff + INC6_eff + INC7_eff +
               INCdkRef_eff + INSmed_eff + INSchip_eff +
              INSoth_eff + INSnone_eff + INSdkRef_eff +
              zAGE * FEM_eff + zAQI + zAQImax +
              (1|STATE),
            data=H1, weights = swts, family = binomial)
summary(M3)
# approx R2
r.squaredGLMM(M3, null = M0) # R2 =  0.05854572
```

```
anova(M1,M2) #p = 0.02299
anova(M2,M3) #p = 0.4341


#Odds Ratio Plot of

p1data <- read_xlsx("~/[REDACTED]/Paper 2 Tables.xlsx",sheet = 4)
p1data$order <- 1:nrow(p1data)
p1data[4:5,1] <- "Gap in\nInsurance\nCoverage"
p1data[15:20,1] <- "Insurance\nType"
p1data[24:25,1] <- "Parental\nVeteran\nStatus"
p1data <- p1data %>% mutate(Variable=factor(Variable,levels =
rev(Variable)),Category=factor(Category,levels = unique(p1data$Category)))


p1 <- ggplot(p1data)+
  geom_hline(yintercept = 1, color="red")+
  geom_hline(yintercept = c(0.5,2), linetype= "longdash", alpha=.5)+
  geom_errorbar(aes(x=Variable,y=OR,ymin = LB,ymax = UB),width=.2)+
  geom_point(aes(x=Variable,y=OR), shape = ifelse(is.na(p1data$p),17,ifelse(p1data$p<0.05,8,16)))
+
  scale_y_continuous(breaks = c(.5,1,1.5,2),limits = c(.3,2.2),labels = c("0.5\nHalf
as\nLikely","1\nEqually\nLikely","1.5","2\nTwice as\nLikely")) +
  coord_flip()+
  facet_grid(rows=vars(Category), scales = "free_y", space = "free",switch = "y") +
  theme_bw()+
  theme(strip.placement = "outside", strip.text.y.left = element_text(angle = 0)) +
  labs(y = "Model-Implied Odds Ratio (95% CI)", x = NULL, title = "Model-Implied Odds Ratios from
the Final Regresson Model", caption = "Note. n= 10,401; 'Ref' = Refence Value and is marked with
a '▲';\nSignificant values (p < .05) are marked with an asterisk; Not-significant values (p >
.05) are marked '●'.")

ggsave(filename="ppr2plt1.png",plot = p1,path = '~/[REDACTED]/',width = 6.5,height = 8.5,units =
"in")

## Exploratory Model (EM)

## testing Vet interactions


EM1 <- glmer(EXAC ~ VET_eff + zAGE + FEM_eff + GAP_eff + INC1_eff + INC2_eff +
               INC3_eff + INC4_eff + INC5_eff + INC6_eff + INC7_eff +
               INCdkRef_eff + INSmed_eff + INSchip_eff +
               INSoth_eff + INSnone_eff + INSdkRef_eff +
               VET_eff * INSdkRef_eff + zAQI + zAQImax +
               VET_eff * zAGE + VET_eff * FEM_eff +
               VET_eff * GAP_eff + VET_eff * INC1_eff +
               VET_eff * INC2_eff + VET_eff * INC3_eff +
               VET_eff * INC4_eff + VET_eff * INC5_eff +
               VET_eff * INC6_eff + VET_eff * INC7_eff +
               VET_eff * INCdkRef_eff +
               VET_eff * INSmed_eff + VET_eff * INSchip_eff +
               VET_eff * INSoth_eff + VET_eff * INSnone_eff +
                VET_eff * zAQI + VET_eff * zAQImax +

               (1|STATE),
             data=H1, weights = swts, family = binomial)
summary(EM1)

anova(M3,EM1)
+++++++++++++++ End File +++++++++++++++
```

Chapter 4: The effect of military family relocations on facility-treated pediatric asthma exacerbation: A multilevel regression analysis of military health insurance data

Abstract

Pediatric asthma is a significant and prevalent chronic condition. Studies have linked several known triggers for asthma exacerbation to military bases. Military families experience geographic relocations on average every 3 years. Geographic relocations expose children to many causes of asthma exacerbation simultaneously. This study (n= 1,055,742 months [level 1]; 15,981 children [level 2]) used a series of multilevel binomial regression models that identified a significant correlation between the month of and the first several months following a geographic relation and the increased likelihood of facility-treated asthma exacerbation. Month of PCS (OR= 2.10, p= <.001); 1 Month after PCS (OR= 1.26, p= <.001); 2 Months after PCS (OR= 1.13, p= <.001); 3 Months after PCS (OR= 1.06, p= .012); and 5 Months after PCS (OR= 1.05, p= .041). These findings were consistent with the conceptual and theoretical foundations of the research.

Keywords: pediatric asthma; asthma exacerbation; geographic relocation; military family; multilevel regression

Introduction

Asthma is a leading chronic respiratory condition affecting over 4 million children in the United States, and an estimated 40% of children with asthma experience an acute asthma exacerbation each year (CDC, 2023). Many factors contribute to or precipitate an asthma exacerbation (stress, change in weather patterns, exposure to allergens, pollution, lack of adherence to treatment regimen, etc.) (Bloomberg, 2010; Chipps et al., 2017; Das et al., 2022; Fu & Tsai, 2014; Kanchongkittiphon et al., 2015; Link, 2014; Michaels, 2017; Mireku et al., 2010; Miyasaka et al., 2018; Norris et al., 1999; Schinasi et al., 2020; Sonney & Insel, 2019; Wood et

al., 2018; Zhou et al., 2022). A geographic relocation is an event that can simultaneously expose children with asthma to many of these triggers. Military Families are especially vulnerable to geographic relocations as they experience a Permanent Change of Station (PCS) every two to four years (Clever & Segal, 2013; Kroke, 2022).

While little research has been published specifically about the health status of children with asthma living on or in the proximity of military bases, there have been studies that link several of the prevailing causes of asthma exacerbations to military areas. Military bases have a history of contaminated water, soil, and air, as well as outbreaks of black mold in on-base housing (Rogers et al., 2024; Tornay, 2023). U.S. Representatives Rogers, Waltz, Banks, and Bacon of the House Armed Services Committee reported in February 2024, "… mold, brown tap water, extreme temperatures, bedbugs, rodents, and cockroaches. These are just some of the conditions that our servicemembers have been subjected to in their barracks." (Rogers et al., 2024). These conditions extend beyond the barracks to on-base family housing as well. In 2023, a report revealed that families in military housing at Joint Base Lewis-McChord, just south of Tacoma, Washington, experienced black mold, rodents, and questionable water quality (Tornay, 2023). Despite these findings, the high cost of living off-base necessitates many military families living on base.

Several studies have also shown links between military base proximity and air quality (Alvarez et al., 2022; Marcello Campagna, 2016; Shtob et al., 2023). In 2022, census tracts closest to military bases were found to have a higher risk of cancer due to air toxins, and this disproportionally affected people of color (Alvarez et al., 2022). A 2016 study linked ultrafine airborne particles to the proximity of a military airport (Marcello Campagna, 2016). These sources link established asthma exacerbation triggers like mold, pests, and air pollution to U.S.

military areas and also show that low rank (low socioeconomic status) and people of color were disproportionately exposed.

As geography plays a role in the severity and incidence of asthma exacerbations from spatial-dependent triggers, geographic relocation has also been shown to affect non-spatial triggers like stress, upper-respiratory infection, and, to a certain extent, adherence. A 2014 study of all 179,486 military children aged 6 through 17 years who moved with their family in 2008 were at increased risk of utilizing mental health services in 2009, as high as a 20% increase in the risk of a psychiatric hospitalization (Millegan et al., 2014). A 2018 RAND study stated that military family moves are correlated with increased spousal stress and child stress disruptions (Tong et al., 2018). Not only does child stress lead to an increased risk of asthma exacerbations, but caregiver stress has also been demonstrated to have a negative impact on their child's adherence to their treatment regimen, which in turn leads to an increased risk of asthma exacerbation (Fu & Tsai, 2014; Kaplan et al., 2019; Sonney et al., 2016; Wood et al., 2018)

The assembled evidence strongly suggests that a geographic relocation will likely increase the incidence of pediatric asthma exacerbation. The present study contributes to the literature addressing the questions: 1) Are there locations where Military-dependent children with asthma experience facility-treated asthma exacerbation at a higher or lower rate than average? 2) Does a Military Family geographic relocation (PCS) make it more likely for their children with asthma to have a facility-treated asthma exacerbation?

Methods

This secondary longitudinal study used two joined government datasets, one restricted and one publicly available. Human subjects research approval was obtained from the University of Washington IRB Committee D (FWA #00006878) and the U.S. Army Office of Research and

Human Subject Protections (25-00001e MEDCoE). Research use of the personally identifiable information and protected health data is authorized and governed by a data sharing agreement for a limited data set with the Defense Health Agency Privacy and Civil Liberties Office (25-3356). Only aggregated, unidentifiable results will be disseminated. This study was pre-registered using the Open Science Framework at https://doi.org/10.17605/OSF.IO/8KS2X, which indicated the hypothesis, data sources, variables selected, and final regression model to be used. Only minor changes to variable coding occurred since pre-registration. The restricted Military health insurance data and the publicly accessible air quality data were obtained, cleaned, and joined.

Data Sets

Military Health System Insurance Data

The Military Health System (MHS) Data Repository (MDR) is comprised of all billed healthcare encounters of military beneficiaries. Data is collected automatically through billing processes with reliable and persistent individual identifiers throughout the data. Data elements have consistent naming conventions and are consistently included and available across all years of data. The initial data export of all children with an asthma diagnosis in the MHS from January 2010 to December 2019 yielded 35,312,616 months of level one (L1) data for 979,307 unique children with asthma at level two (L2). Exclusions were applied to produce the final samples for analysis (see Fig. 1). Aim 1 used 24,504,224 months (L1) of data for 706,333 unique children with asthma (L2) to establish local monthly rates of facility-treated asthma exacerbations. Aim 2 used 1,055,742 months (L1) of data for 15,981 unique children with asthma (L2) to evaluate the association between PCS and the likelihood of facility-treated asthma exacerbation.

Air Quality Data

The continuous air quality data is publicly available from the Environmental Protection Agency (EPA) and are collected at outdoor monitors across the United States (EPA, 2023). The Air Quality Index (AQI) is a scale of air quality and levels of health concern. The AQI value is driven by the highest single concentration of five main pollutants: ground-level ozone, particulate matter, carbon monoxide, sulfur dioxide, and nitrogen dioxide (EPA, 2023). An AQI of zero indicates the air is clean and healthy, while 301 is considered hazardous (EPA, 2023). AQI is chiefly driven by ground-level ozone and particulate pollution (EPA, 2023). The data are available in pre-generated annual data files available at various levels of aggregation, from hourly readings from each monitor to the yearly average for each county. The data elements have consistent naming conventions and are included in each year's data file. Average daily values from 2010 through 2019 were obtained at the Core-Based Statistical Area (CBSA) level. These values were aggregated to produce the average daily value for each month for each CBSA. The maximum single-day value was also preserved for each month for each CBSA.

Measures

Dependent Variables (DV)

Facility-treated exacerbation (EXAC) –

This study defines a facility-treated asthma exacerbation as any asthma exacerbation treated in a health care facility (including but not limited to primary care clinic, urgent care clinic, emergency department, or a hospital admission) that produces a billable insurance claim. This is a calculated binary variable for each month, indicating whether any treatment code or diagnosis code for treating an acute asthma exacerbation is identified (1) or not (0). Due to the nature of billing and the escalation of care, a child can start at urgent care with an exacerbation,

transfer to an emergency department, and be admitted to the hospital. Each location could generate a bill; even though there was only one exacerbation episode, there could be many separate insurance bills. It is also possible that a child could seek medical care on multiple separate occasions for the same exacerbations. Therefore, any exacerbation coding in a given month will be treated as one exacerbation.

Independent Variables (IV)

Period (per) –

This is the sequential month of the study period. Period 1 is January 2010, and Period 120 is December 2019. This variable is essential for joining air quality data.

Age in Months of the Child (AGE) –

This variable is calculated each month from the child's date of birth and is the child's age in whole months. Only children between 48 and 216 months (four and eighteen years old) were included in this analysis. Age cut-offs were selected because the diagnostic criteria of asthma in children under four are challenging and may overlap with other respiratory conditions. This study defines the pediatric population as being under the age of eighteen.

Female Status (FEM) –

This element is the child's sex as indicated by records for each month of data. Initially, this is the sex recorded at birth and is preserved each month of the record; if there is a change to this variable, the changes are not propagated retrospectively. For the purposes of this study, the first recorded sex will be used for all analyses. In childhood, males have a higher prevalence of asthma than females (Chowdhury et al., 2021; Shah & Newcomb, 2018). However, according to the latest CDC data, males are less likely to experience an asthma exacerbation despite the higher

incidence (CDC, 2023). Therefore, males were chosen as the reference category since they are less likely to experience an exacerbation than females.

Branch of Service –

This six-level categorical variable indicates which branch of service the child's parent belongs to: Army, Navy, Air Force, Marine Corps, Coast Guard, and Public Health Service. The descriptive statistics show that the Air Force has the lowest facility-treated asthma exacerbation incidence rate (0.061 per person-months) of the four main branches (Army, Navy, Air Force, and Marines). For this study, the Air Force was chosen as the reference category.

Rank Enlisted Status –

This binary variable indicates whether the child's parent is either enlisted (1) or an Officer (0). This variable was calculated from a categorical Rank Group which had six levels: Cadet, Enlisted Junior, Enlisted Senior, Warrant Officer, Officer Junior, and Officer Senior. Enlisted Junior and Enlisted Senior were combined into the Enlisted category; all others (Cadet, Warrant Officer, Officer Junior, and Officer Senior) were combined into the Officer category. Rank is a measure of Socioeconomic Status, where officers have more education, income, and autonomy than enlisted. As a result, Officers were selected as the reference category.

Months Following PCS (pm00-pm12) – IV of Interest

This is the distance in time from an observed PCS. It is expected that exacerbations are more likely to occur closer to the previous PCS rather than farther due to the subject 'adapting' to their environment over time. In order to allow for non-linear effects of time following a PCS, each month following a PCS from 0 (the month of the move) to 12 (the year after the move) was treated as a categorical variable and effect coded, where any other month was coded as -1. This aids in the interpretation of the results. Coding of this variable has changed since pre-registration

from a single variable that counted months since last PCS, which forced the time effect to be linear and ultimately did not align with the theoretical framework guiding the study.

Cumulative PCSs (cumPCS) – IV of Interest

This is a running count of captured PCSs within the study period. It is hypothesized that the number of PCSs will affect the incidence of asthma exacerbations. Some literature suggests that over iterations of PCSs, the subjects build resilience that would decrease exacerbations. In contrast, others suggest that repeated shocks and stress accumulate an allostatic load that would increase exacerbations (Hix et al., 1998; Kroke, 2022; Tong et al., 2018). While the direction of the effect is uncertain, there is an expectation of some effect on subsequent PCSs.

Monthly Average of Daily Air Quality Index (AQI) –

The AQI is a score that indicates the relative air quality sampled by air quality monitoring stations throughout the United States. These stations monitor for many substances that can impact the air quality and, when operable, provide constant values. This variable reflects the daily average AQI for all operating monitoring stations in each CBSA in the United States each month. Each subject's zip code was aligned monthly to a CBSA to obtain AQI values. An NA was returned when a subject's zip code did not align with a CBSA. AQI values are interpreted as follows: 0-50 – Good; 51-100 – Moderate; 101-150 - Unhealthy for Sensitive Groups; 151-200 – Unhealthy; 201-300 Very Unhealthy; 301+ Hazardous. This variable was transformed by taking its square root to produce a more normal distribution for regression.

Monthly Max of Daily Air Quality Index (AQImax) –

This variable is identical to the AQI, except it preserves each month's highest daily AQI in the CBSA. Each subject's zip code was aligned monthly to a CBSA to obtain AQImax values. An NA was returned when a subject's zip code did not align with a CBSA. AQI values are

interpreted as follows: 0-50 – Good; 51-100 – Moderate; 101-150 - Unhealthy for Sensitive Groups; 151-200 – Unhealthy; 201-300 Very Unhealthy; 301+ Hazardous. This variable was transformed by taking its square root to produce a more normal distribution for regression.

Local Incidence of Facility-Treated Asthma Exacerbation (LOC) –

This is a calculated variable that is the result of Aim 1. The local incident rate of facility-treated asthma exacerbation was calculated monthly for each Military Housing Area (MHA). It is crucial to account for changes in local asthma rates before and after a PCS to identify if there is a change beyond what is expected from the change in these rates alone. The assumption is that this local incident rate would account for latent spatial traits affecting asthma exacerbations that are otherwise insensible to this study.

Data Analysis Plan

To achieve the goals of aim 1, a descriptive analysis of the Military Insurance data examined the incidence rate of facility-treated asthma exacerbations grouped by Military Housing Areas (MHA) for each month of the study. This was achieved by grouping all the data into each MHA each period and calculating the incident rate of the facility-treated asthma exacerbations by dividing the total of all exacerbations in each MHA each month by the total number of children with asthma who were present in that MHA that month (person-months). These local incident rates were then compared in aggregate and over time to identify patterns, trends, and outliers. These Military incident rates were also compared to the U.S. average incident rates of facility-treated asthma exacerbation with data from the Centers for Disease Control and Prevention (CDC)'s Asthma Call-Back Survey (ACBS). ACBS data is cross-sectional, and because each interviewee was specifically asked about the last twelve months (or one person-year), ACBS percentages were converted into incident rates for comparison.

Multilevel regression analyses were used to test aim 2 using the *R* lme4 package (Bates et al., 2015). The multilevel analysis approach offers two advantages over other modeling choices. First, the use of random, rather than fixed, effects for clustering variables allows for the decomposition of lower-level effects into separate variance components between and within States. Second, it enables the predictor effects to be tested with (a) correct degrees of freedom and (b) at their appropriate levels. As is standard practice (Luo et al., 2021), intercept-only models were specified before formal analyses began in order to confirm the appropriate multilevel structure by assessing the degree of non-independence in exacerbations due to clustering. Specifically, a series of models were specified with months nested within children.

For this analysis, months with missing and erroneous location data had to be dropped (see Figure 1). The only demographic variable in the raw data file for months that contained no exacerbation was age, which was calculated each month from the date of birth. All other demographic data (gender, branch of service, and rank) in non-exacerbation months were carried forward and backward from months (containing exacerbations) with known values. After demographic imputation, the descriptive statistics reveal that only 26 months (0% of the total) from 1 child had missing rank data, and 9,393 months (0.89% of the total) from 164 children were missing branch data. However, the Air Quality data (AQI and AQImax) were missing the same 101,709 months of data (9.63% of the total) from 3,669 children. AQI data was joined to this dataset by taking the child's zip code for a given month and matching that zip code to a CBSA by using a crosswalk file downloaded from huduser.gov. The air quality data is reported at the CBSA level. The AQI missingness occurs due to either a zip code not aligning to a CBSA or a CBSA having no reported AQI for that month. This data is Missing Not At Random (MNAR) because this missingness is dependent on several unobserved characteristics of the

location the child is residing, including but not limited to population density and a history of consecutive low AQI. As such, this data will not be imputed and will remain NA. When computing a generalized linear mixed-effects model using the lmer4 package, it conducts a row-wise deletion when it encounters any missing values in any variables.

For ease of model results interpretation, for all analyses, binary and categorical predictors (female status, gap in insurance, income categories, and insurance type categories) were effect-coded, and continuous predictors (age and both AQI variables) were standardized as *z*-scores. Model results were compared using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and chi-square likelihood ratio tests (LRT). The final model was as follows:

$$\text{Logit(Facility Treated Exacerbtions)}_{ij}$$

$$= \gamma_{00} + \gamma_{10}(Period)_{ij} + \gamma_{20}(Z\ Age)_{ij} + \gamma_{30}(Z\sqrt{AQI})_{ij}$$
$$+ \gamma_{40}(Z\sqrt{AQImax})_{ij} + \gamma_{50}(Z\ Local\ Exacerbation\ Rate)_{ij}$$
$$+ \gamma_{60}(Post\ Move\ 00\ Eff)_{ij} + \gamma_{70}(Post\ Move\ 01\ Eff)_{ij}$$
$$+ \gamma_{80}(Post\ Move\ 02\ Eff)_{ij} + \gamma_{90}(Post\ Move\ 03\ Eff)_{ij}$$
$$+ \gamma_{100}(Post\ Move\ 04\ Eff)_{ij} + \gamma_{110}(Post\ Move\ 05\ Eff)_{ij}$$
$$+ \gamma_{120}(Post\ Move\ 06\ Eff)_{ij} + \gamma_{130}(Post\ Move\ 07\ Eff)_{ij}$$
$$+ \gamma_{140}(Post\ Move\ 08\ Eff)_{ij} + \gamma_{150}(Post\ Move\ 09\ Eff)_{ij}$$
$$+ \gamma_{160}(Post\ Move\ 10\ Eff)_{ij} + \gamma_{170}(Post\ Move\ 11\ Eff)_{ij}$$
$$+ \gamma_{180}(Post\ Move\ 12\ Eff)_{ij} + \gamma_{01}(Cumlative\ PCS\ Exposure)_{ij}$$
$$+ \gamma_{02}(Female\ Status\ Eff)_{ij} + \gamma_{03}(Branch\ Army\ Eff)_{ij}$$
$$+ \gamma_{04}(Branch\ Navy\ Eff)_{ij} + \gamma_{05}(Branch\ Marines\ Eff)_{ij}$$
$$+ \gamma_{06}(Branch\ Coast\ Guard\ Eff)_{ij} + \gamma_{07}(Branch\ PHS\ Eff)_{ij}$$
$$+ \gamma_{08}(Rank\ Enlisted\ Status\ Eff)_{ij}$$
$$+ \gamma_{11}(Z\ Age * Female\ Status\ Eff)_{ij} + U_{0j} + \varepsilon_{ij}$$

In the model above, the log-odds of having a facility-treated asthma exacerbation in the i^{th} month within the j^{th} child with asthma is equal to the sum of the conditional mean (γ_{00}), the unique effects of the period number, age, daily average AQI, average month maximum AQI, the local rate of exacerbation, the time since the last PCS, the cumulative number of PCSs, female status, branch of service of parent, enlisted status of parent, and the interaction between age and female status ($\gamma_{10} - \gamma_{08}$), and the residual error due to the child (U_{0j}).

An alpha of .05, 2-tailed, was used for all statistical tests. To assess the practical significance of the results, odds ratios were computed by exponentiating each logistic regression coefficient (i.e., $e^{coefficient}$). The 95% confidence intervals for the odds ratios were obtained by exponentiating the coefficient plus or minus 1.96 times the standard error (i.e., $e^{coefficient \pm (1.96 * SE)}$). The model Nakagawa & Schielzeth's R^2 will be obtained using the 'MuMIn' package (Bartoń, 2025; Nakagawa & Schielzeth, 2013). Last, data visualization of model-predicted odds ratios was implemented using the 'ggplot2' package (Wickham, 2016); interaction term predicted values extracted with the 'effects' package (Fox & Hong, 2009; Fox & Weisberg, 2018).

Results

Descriptive Statistics

Counts and percentages among all binary and categorical variables are available in Table 1. The outcome variable, facility-treated asthma exacerbation, 985,864 (93.4%) of the observed months did not have one, while 69,878 (6.6%) did, and zero observed months were missing the facility-treated asthma exacerbation status. The Month of Move has the highest exacerbation rate, with 3,491 exacerbations in 20,831 observed months, an incident rate of 0.17 per person-month. Of note, the reference selections for all the categorical variables had the lowest exacerbation rate for their groupings. In the PCS group, months that were not the month of move or the twelve months following had 46,453 exacerbations for 809,012 observed months, an incident rate of 0.06 per person-month. In the branch of service group, the Air Force had the lowest of the four main branches: Army, Navy, Air Force, and Marines, with 13,514 exacerbations in 220,691 months, an incident rate of 0.06 per person-month. In the rank group,

officers had 14,907 exacerbations in 252,749 months, an incident rate of 0.06 per person-month. Finally, the correlations between the continuous variables show that average daily AQI correlated with average monthly maximum AQI, which is expected since the AQI max is a subset of the AQI data.

Aim 1 Results

Aim 1 used 24,504,224 months (L1) of data for 706,333 unique children with asthma (L2) to establish local monthly incident rates of facility-treated asthma exacerbations to be included in the regression models of Aim 2. The monthly incident rates were aggregated and converted to annual rates, and the top and bottom five locations were selected and placed into a table for comparison to each other and to the (ACBS) facility-treated asthma exacerbation rates (see Table 2). Asheville, NC, had the single highest facility-treated asthma exacerbation incident rate in 2016, with 0.9563 per person-year. While Fairbanks, AK had the single lowest incident rate in 2017, with 0.017 exacerbations per person-year.

Aim 2 Model Results

Model 1 consisted of all the predictors except the cumulative PCS and categorical time since PCS variables. The approximate variance explained (Nakagawa & Schielzeth's R^2) with this set of predictors was 0.04, which was 0.02 more than the null model. Model 2 included all the predictors from Model 1 with the addition of the cumulative PCS variable. The approximate variance explained with this set of predictors was 0.04, which is no change from Model 1. The LRT comparing this model to the previous indicated it was significantly different (451.2, $p = <.001$). The AIC and BIC decreased by 449.2 points and 437.5 points, respectively, indicating that model efficiency and the explanatory power of the model significantly improved. Finally, in Model 3, the last set of columns of Table 2 shows that the variance explained with this set of

predictors was 0.04, which is 0.002 more than the previous model. The LRT comparing this model to the previous indicated it was significantly different (3254.9, p = <.001), and the AIC and BIC values decreased again by 3229 and 3076.1 points, respectively, indicating that the model with the categorical time since PCS predictors did improve model-data fit over the previous model.

In Model 3 (see Table 3), period, age, local rate of exacerbation, Army, enlisted status, the interaction between age and female status, and all the categorical time since PCS, except for 4 months post and 6 months post move, were significant. Period (OR 1, p <.001) did not correlate with the likelihood of facility-treated asthma exacerbation. As children increase one standard deviation in age, they are 0.14 logits less likely (0.87 OR), and for each standard deviation increase in the local rate of facility-treated asthma exacerbation, children are 0.48 logits more likely (1.62 OR) to have a facility-treated asthma exacerbation. Children whose parents are in the Army are 0.16 logits more likely (1.17 OR) to experience an exacerbation than the mean likelihood. Children of enlisted parents are 0.03 logits (1.03 OR) more likely to have an exacerbation. The month of PCS had the largest likelihood of children having an asthma exacerbation at 0.74 logit increase (2.10 OR), from there it dropped to a 0.23 logit increase (1.26 OR); 0.13 logit increase (1.13 OR); and 0.06 logit increase (1.06 OR) at one, two, three months post move. Children in the fifth month post-move are 0.05 logits more likely (1.05 OR) to have an exacerbation. Months seven through twelve were all less likely to have an asthma exacerbation with logits 0.12 (0.88 OR), 0.10 (0.90 OR), 0.09 (0.91 OR), 0.15 (0.86 OR), 0.14 (0.87 OR), and 0.19 (0.82 OR), respectively.

Finally, an interaction between Age and Female status was examined. Separately, female status failed to reach a significant level, and an increase in age oveall was associated with a

lower likelihood of asthma exacerbation. To understand the nature of the interaction, I computed model-implied values for the following levels of each (-2 *SD* through +3 *SD*) age and (+1=Female, -1=Male). As shown in Figure 3, the interaction shows that, at -2 SD in Age, the likelihood of asthma exacerbation was lower for females (a difference of approximately -0.8% Odds) compared with males. By +3 SD in Age, the relationship flips, where the likelihood of asthma exacerbation was higher for females (a difference of approximately +0.5% likelihood) than males.

Discussion

This study examined whether a military family geographic relocation (PCS) was associated with increased likelihood of their children experiencing a facility-treated asthma exacerbation in the year following their move, compared to all other months for each child. Study findings were consistent with two established factors related to pediatric asthma exacerbation. First, as children age, overall, they are less likely to experience an asthma exacerbation (CDC, 2023; Chowdhury et al., 2021; Naeem & Silveyra, 2019; Shah & Newcomb, 2018; Zhang et al., 2022). Second, the interaction with Age and Female status indicates females are more likely to experience an asthma exacerbation as they age compared to males. Although this finding is supported through the CDC's Asthma Data Visualizations (CDC, 2023), literature does not appear to address sex-linked disparities in pediatric asthma exacerbations, and only address differences in prevalence of asthma in children (Chowdhury et al., 2021; Naeem & Silveyra, 2019; Shah & Newcomb, 2018; Zhang et al., 2022).

The final model results show that the Month of Move and the first five months after move have an OR >1 with four of those months significant ($p<.05$). Additionally, the LRT between the second and third models and the analysis of AICs and BICs indicate that the

addition categorical time since PCS predictors enhance model-data fit and increase the explanatory power. Supporting the hypothesis that a geographic relocation would significantly increase the likelihood that children with asthma would experience a facility-treated asthma exacerbation following the move.

With the present study, months six through twelve and cumulative PCSs ORs were <1. The six thorough twelve-month findings align with the theoretical underpinnings of this study, where children would acclimate to a new environment over time (Bronfenbrenner & Morris, 2007). Although not significant, the regression results of cumulative PCSs (0.99 OR) suggest that military children may develop resilience over subsequent moves and are less likely to experience an asthma exacerbation, which is supported by other research related to children who have experienced a PCS (Hix et al., 1998; Kroke, 2022; Tong et al., 2018).

There were several key limitations to this study. First, the data collection method required the child to be treated in a healthcare facility, which is inherently biased towards those with the means to receive health care. That means a lower likelihood of a facility-treated asthma exacerbation is not necessarily an indication of health and may actually result from the child's family not having had the means (time, money, or accessibility) to receive care. While all children in this study benefit from unlimited, no-cost health insurance, there are other factors that can affect a Military Family's ability to access health care. For example, if the serving parent is deployed or away from home for training, that leaves one parent or caregiver alone to manage the whole household, a task that becomes more difficult with each additional child (Clever & Segal, 2013). Second, the only demographic variable available in months that did not contain an exacerbation was age, which was calculated each month based on the child's date of birth. The remainder of the demographics (sex assigned at birth, parental branch of service, and rank) were

carried forward and backward from known values for each child. While sex and branch are unlikely to change and thus very safe for imputation, imputing rank, which tends to increase over time, is problematic, and interpretation of rank findings should be tempered as a result. Lastly, the method of linking location to children was through either the billing or treatment facility zip code. These zip codes were used to identify Military Housing Areas to determine local rates of asthma, Core-Based Statistical Areas to determine air quality, and to infer a PCS. It is possible for a child to live separately from the service member whose billing zip code is reported. Due to the administrative time to change the billing zip code, it is possible the update may not occur in the month of the move.

Conclusion

Findings from this study indicate that children with asthma who experience a geographic relocation are more likely to experience a facility-treated asthma exacerbation in the month of move and for the first five months following the move. This study will support administrative and policy changes within the military health system to better support families who have children with asthma before, during, and after PCS. Future studies should isolate the factors that drive this increase in the likelihood of being treated at a healthcare facility for asthma exacerbations and identify potential mitigation strategies. Additionally, future studies should examine the root of branch disparities and why some locations have a far greater likelihood of facility-treated asthma exacerbations.

Table 1. Sample Demographics (N = 1,055,742 months (L1) within 15,981 children (L2))

DV	Binary	0 = No		1 = Yes		NA	
		n	%	n	%	n	%
	Exacerbation	985,864	93.38%	69,878	6.62%	0	0.00%

L1 IVs	Continuous	Mean	SD	MIN	MAX	NA
	Period	65.59	31.38	1	120	0
	Age (in months)	112.13	41.16	48	216	0
	Air Quality Index (AQI)	55.67	17.54	4.04	315.65	101,709
	Avg Monthly Max AQI	96.20	57.41	8	2403	101,709

				Exacerbations		
	Categorical	n	%	n	IR	
	PCS					
	Not Post Move	*809,012*	*76.63%*	*46,453*	*0.06*	*Reference*
	Month of Move	20,831	1.97%	3,491	0.17	
	1 Month Post Move	20,573	1.95%	2,389	0.12	
	2 Months Post Move	19,901	1.89%	2,110	0.11	
	3 Months Post Move	19,673	1.86%	1,990	0.10	
	4 Months Post Move	19,436	1.84%	1,853	0.10	
	5 Months Post Move	19,168	1.82%	1,802	0.09	
	6 Months Post Move	18,949	1.79%	1,662	0.09	
	7 Months Post Move	18,752	1.78%	1,536	0.08	
	8 Months Post Move	18,496	1.75%	1,477	0.08	
	9 Months Post Move	18,239	1.73%	1,411	0.08	
	10 Months Post Move	17,963	1.70%	1,281	0.07	
	11 Months Post Move	17,557	1.66%	1,237	0.07	
	12 Months Post Move	17,192	1.63%	1,186	0.07	

L2 IVs	Count	Mean	SD	MIN	MAX	NA
	Cumulative PCS	0.86	0.83	0	13	0

								Exacerbations			
	Binary	0 = No		1 = Yes		NA		(when Status = 0)		(when Status = 1)	
		n	%	n	%	n	%	n	IR	n	IR
	Female Status	649,942	61.56%	405,800	38.44%	0	0.00%	43,403	0.07	26,475	0.07

				Exacerbations		
	Categorical	n	%	n	IR	
	Branch					
	Army	478,053	45.28%	33,521	0.07	
	Navy	213,996	20.27%	13,665	0.06	
	Air Force	220,691	20.90%	13,514	0.06	*Reference*
	Marines	102,988	9.76%	6,796	0.07	
	Coast Guard	30,157	2.86%	1,860	0.06	
	Public Health Service	464	0.04%	19	0.04	
	NA	9,393	0.89%	503	0.05	
	Rank					
	Enlisted	802,967	76.06%	54,969	0.07	
	Officer	252,749	23.94%	14,907	0.06	*Reference*
	NA	26	0.00%	2	0.08	

Correlation		1.	2.	3.	4.	5.
	L1 Continuous IV					
	1. Period	--				
	2. Age	0.34	--			
	3. AQI	-0.09	-0.01	--		
	4. AQImax	-0.08	-0.01	0.72	--	
	L2 IV					
	5. Cumulative PCS	0.49	0.23	-0.05	-0.04	--

Note. *N* = 1,055,742 months (L1) within 15,981 children with asthma (L2). IR is in person-months. Avg = Average, DV = Dependent Variable, IR= Incident Rate, IV= Independent Variable, L1= Level 1, L2= Level 2, NA= Not Available/Missing, PCS= Permanent Change of Station aka family geographic relocation, SD= Standard Deviation

Table 2. Top and Bottom Five Locations Annualized Rates of Facility-Treated Asthma Exacerbations

Annual Incident Rates of Facility-Treated Asthma Exacerbation

		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Top 5 Locations	DURHAM / CHAPEL HILL, NC	0.50	0.74	0.73	0.60	0.86	0.46	0.63	0.67	0.59	0.53
	ASHEVILLE, NC	0.27	0.32	0.30	0.66	0.35	0.83	0.96	0.81	0.62	0.49
	ANN ARBOR, MI	0.50	0.60	0.63	0.32	0.41	0.33	0.54	0.52	0.76	0.46
	NEW YORK CITY, NY	0.80	0.66	0.62	0.50	0.46	0.41	0.44	0.40	0.38	0.35
	FORT PIERCE, FL	0.59	0.68	0.89	0.61	0.38	0.39	0.46	0.29	0.40	0.32
	Dataset Avg Facility-Treated Exacerbation Rate	**0.32**	**0.31**	**0.36**	**0.30**	**0.28**	**0.24**	**0.28**	**0.27**	**0.27**	**0.29**
	ACBS Facility-Treated Exacerbation Rate	**0.24**	**0.25**	**0.24**	**0.23**	**0.24**	**0.23**	**0.24**	**0.22**	**0.22**	**0.23**
Bottom 5 Locations	WHIDBEY ISLAND, WA	0.14	0.17	0.19	0.19	0.17	0.19	0.21	0.18	0.21	0.18
	FORT HUACHUCA, AZ	0.11	0.09	0.17	0.19	0.14	0.19	0.21	0.19	0.27	0.18
	CHINA LAKE, CA	0.19	0.06	0.19	0.14	0.21	0.21	0.09	0.12	0.19	0.13
	ANCHORAGE, AK	0.03	0.04	0.05	0.06	0.07	0.07	0.10	0.08	0.08	0.09
	FAIRBANKS, AK	0.02	0.03	0.03	0.02	0.02	0.02	0.03	0.02	0.02	0.03

Note. N= 24,504,224 months (L1) within 706,333 children (L2). ACBS data N= 10,401 Children. Rates are in person-years. ACBS = Asthma Call Back Survey ; Avg = Average.

Table 3. Results from Regression Models

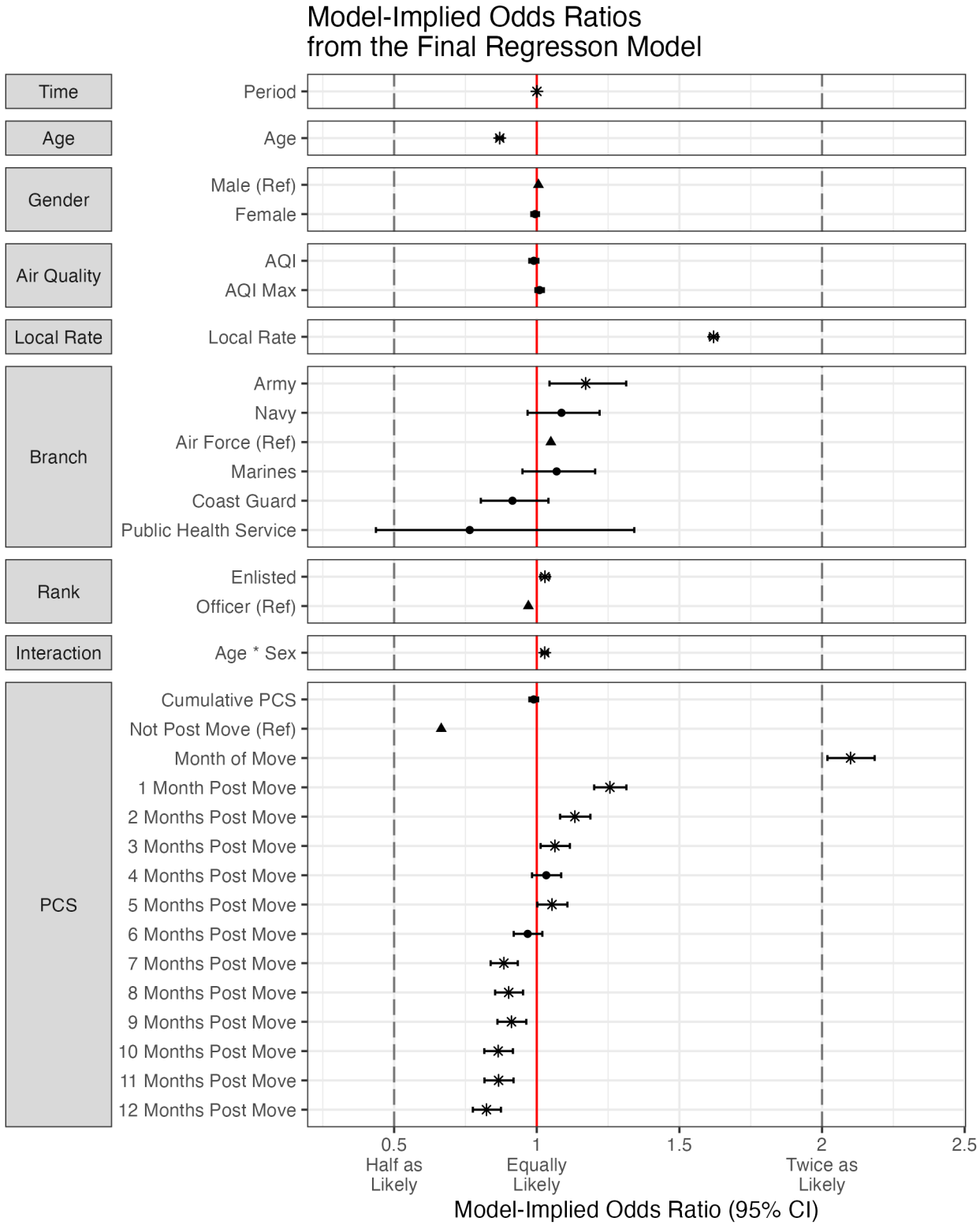
	Model 1					95% CI		Model 2: M1 + Cumulative PCS					95% CI		Model 3x: M2 + Categorical PCS Time					95% CI	
Fixed Effects	*Coeff*	*(SE)*	*Z*	*p*	*OR*	*LB*	*UB*	*Coeff*	*(SE)*	*Z*	*p*	*OR*	*LB*	*UB*	*Coeff*	*(SE)*	*Z*	*p*	*OR*	*LB*	*UB*
(Intercept)	**-3.04**	**(0.06)**	**-52.66**	**<.001**				**-3.03**	**(0.06)**	**-54.53**	**<.001**				**-2.74**	**(0.06)**	**-45.87**	**<.001**			
Period	**0.00**	**(0.00)**	**3.54**	**<.001**	**1.00**	**1.00**	**1.00**	**0.00**	**(0.00)**	**-6.42**	**<.001**	**1.00**	**1.00**	**1.00**	**0.00**	**(0.00)**	**2.54**	**.011**	**1.00**	**1.00**	**1.00**
Age in Months	**-0.15**	**(0.01)**	**-23.19**	**<.001**	**0.86**	**0.85**	**0.87**	**-0.17**	**(0.01)**	**-26.01**	**<.001**	**0.84**	**0.83**	**0.85**	**-0.14**	**(0.01)**	**-21.04**	**<.001**	**0.87**	**0.86**	**0.88**
Female Status	-0.01	(0.01)	-0.74	.458	0.99	0.98	1.01	0.00	(0.01)	-0.05	.962	1.00	0.99	1.01	-0.01	(0.01)	-0.86	.392	0.99	0.98	1.01
Avg Daily AQI	-0.01	(0.01)	-0.69	.488	0.99	0.98	1.01	-0.01	(0.01)	-0.77	.440	0.99	0.98	1.01	-0.01	(0.01)	-1.28	.201	0.99	0.97	1.01
Avg Mo Max AQI	0.01	(0.01)	1.08	.282	1.01	0.99	1.02	0.01	(0.01)	1.11	.268	1.01	0.99	1.02	0.01	(0.01)	1.34	.180	1.01	1.00	1.02
Local Rate of Exacerbat	**0.48**	**(0.00)**	**105.31**	**<.001**	**1.62**	**1.61**	**1.63**	**0.48**	**(0.00)**	**105.17**	**<.001**	**1.62**	**1.60**	**1.63**	**0.48**	**(0.00)**	**105.01**	**<.001**	**1.62**	**1.61**	**1.63**
Branch: Army	**0.18**	**(0.06)**	**3.12**	**.002**	**1.19**	**1.07**	**1.33**	**0.16**	**(0.05)**	**2.99**	**.003**	**1.18**	**1.06**	**1.31**	**0.16**	**(0.06)**	**2.71**	**.007**	**1.17**	**1.04**	**1.31**
Branch: Navy	0.08	(0.06)	1.47	.141	1.09	0.97	1.22	0.08	(0.06)	1.47	.143	1.08	0.97	1.21	0.08	(0.06)	1.41	.160	1.09	0.97	1.22
Branch: Marines	0.08	(0.06)	1.38	.167	1.09	0.97	1.22	0.07	(0.06)	1.18	.236	1.07	0.96	1.20	0.07	(0.06)	1.11	.267	1.07	0.95	1.20
Branch: Coast Guard	-0.09	(0.06)	-1.41	.158	0.91	0.80	1.04	-0.11	(0.06)	-1.71	.088	0.90	0.79	1.02	-0.09	(0.07)	-1.35	.176	0.91	0.80	1.04
Branch: PHS	-0.30	(0.28)	-1.09	.275	0.74	0.43	1.27	-0.26	(0.27)	-0.97	.333	0.77	0.46	1.30	-0.27	(0.29)	-0.93	.350	0.77	0.44	1.34
Rank: Enlisted Status	**0.03**	**(0.01)**	**3.75**	**<.001**	**1.03**	**1.01**	**1.05**	**0.03**	**(0.01)**	**3.64**	**<.001**	**1.03**	**1.01**	**1.04**	**0.03**	**(0.01)**	**3.86**	**<.001**	**1.03**	**1.01**	**1.05**
Age * Female Status	**0.03**	**(0.01)**	**5.49**	**<.001**	**1.03**	**1.02**	**1.04**	**0.03**	**(0.01)**	**5.76**	**<.001**	**1.03**	**1.02**	**1.04**	**0.03**	**(0.01)**	**5.02**	**<.001**	**1.03**	**1.02**	**1.04**
Cumulative PCSs								**0.15**	**(0.01)**	**21.47**	**<.001**	**1.16**	**1.14**	**1.18**	-0.01	(0.01)	-1.39	.164	0.99	0.97	1.00
Month of PCS															**0.74**	**(0.02)**	**36.92**	**<.001**	**2.10**	**2.02**	**2.18**
1 Mo After PCS															**0.23**	**(0.02)**	**9.96**	**<.001**	**1.26**	**1.20**	**1.31**
2 Mo After PCS															**0.13**	**(0.02)**	**5.25**	**<.001**	**1.13**	**1.08**	**1.19**
3 Mo After PCS															**0.06**	**(0.02)**	**2.51**	**.012**	**1.06**	**1.01**	**1.12**
4 Mo After PCS															0.03	(0.03)	1.30	.194	1.03	0.98	1.09
5 Mo After PCS															**0.05**	**(0.03)**	**2.04**	**.041**	**1.05**	**1.00**	**1.11**
6 Mo After PCS															-0.03	(0.03)	-1.23	.220	0.97	0.92	1.02
7 Mo After PCS															**-0.12**	**(0.03)**	**-4.47**	**<.001**	**0.88**	**0.84**	**0.93**
8 Mo After PCS															**-0.10**	**(0.03)**	**-3.74**	**<.001**	**0.90**	**0.85**	**0.95**
9 Mo After PCS															**-0.09**	**(0.03)**	**-3.28**	**.001**	**0.91**	**0.86**	**0.96**
10 Mo After PCS															**-0.15**	**(0.03)**	**-4.91**	**<.001**	**0.86**	**0.82**	**0.92**
11 Mo After PCS															**-0.14**	**(0.03)**	**-4.79**	**<.001**	**0.87**	**0.82**	**0.92**
12 Mo After PCS															**-0.19**	**(0.03)**	**-6.36**	**<.001**	**0.82**	**0.78**	**0.87**
Random Effects	*Var*							*Var*							*Var*						
Intercept (L2)	0.38							0.36							0.35						
Model Fit	*Value*							*Value*	*p*						*Value*	*p*					
Pseudo Total R^2	0.04							0.04							0.04						
AIC	437813.30							437364.10							434135.10						
BIC	437989.70							437552.20							434476.10						
Deviance (-2LL)	437783.30							437332.10							434077.10						
Residual *df*	944967							944966							944953						
LRT Chi-square test	--							451.22	**<.001**						3254.90	**<.001**					

Note. N = 1,055,742 Months (L1) within 15,981 Children (L2). All coefficient values in log-odds units (logits). AQI = Air Quality Index, Avg = Average, Jr = Junior, Mo = Month, PCS = Permeant Chage of Station (aka family geographic relocation), PHS = Public Health Service, Sr = Senior; categorical predictors effect-coded and continuous predictors standardized. Models estimated using full maximum likelihood by *R* lme4. Observed *p*-values reported; values in boldface indicate significance at the .05 level.

Figure 1. Results from Exclusion Criteria

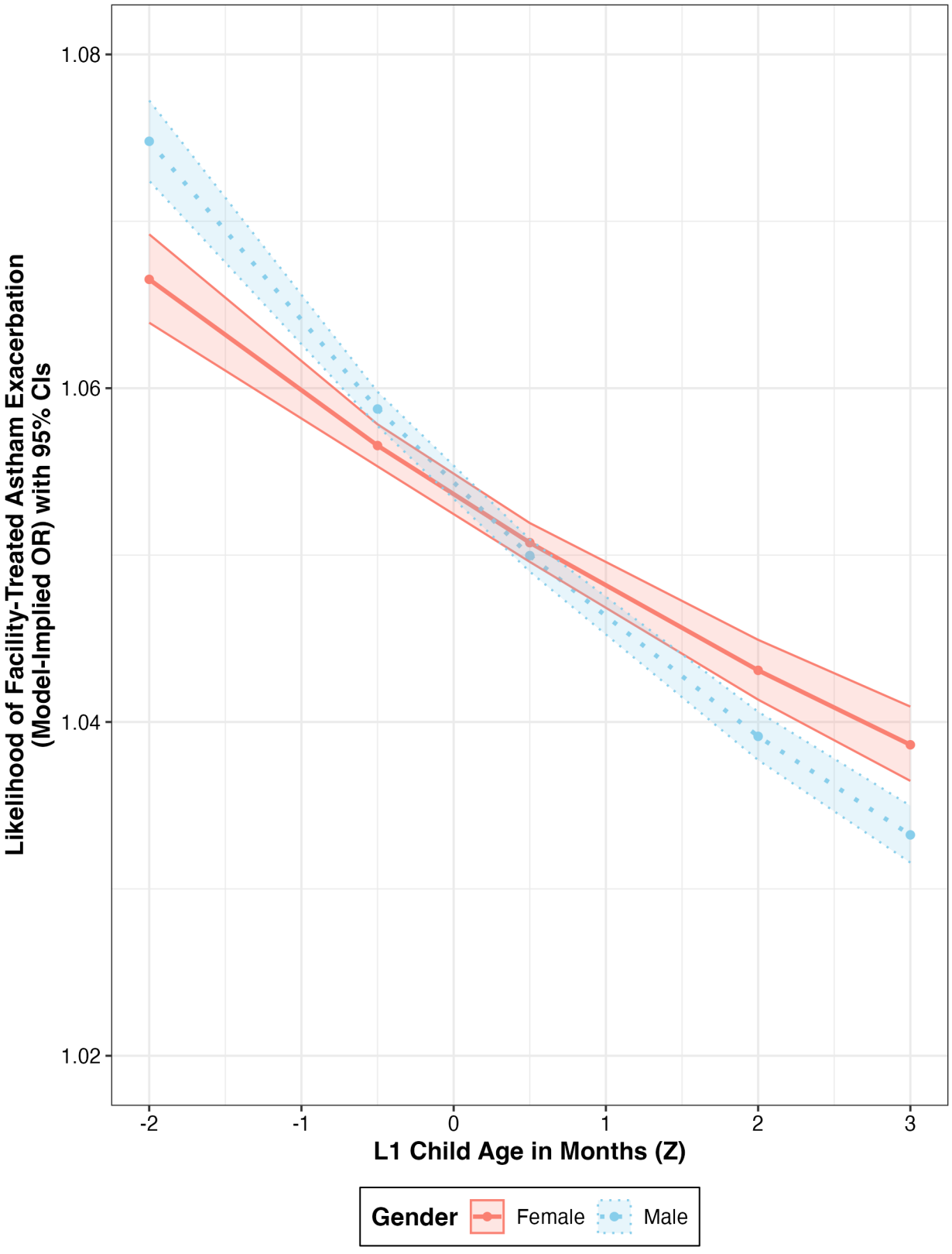
		L1 - Months			L2 - Children		
	Exclusion Criteria	**Start**	**Remove**	**End**	**Start**	**Remove**	**End**
Aim 1	less than 48monts old	**35,312,616**	8,330,701	26,981,915	**979,307**	226,514	752,793
	216 months or older	26,981,915	2,475,969	24,505,946	752,793	46,291	706,502
	event file billing zip code issue	24,505,946	169	24,505,777	706,502	-	706,502
	event file treatment zip code issue	24,505,777	167	24,505,610	706,502	4	706,498
	person file zip code issue	24,505,610	1,386	**24,504,224**	706,498	165	**706,333**
Aim 2	missing location data	**24,504,224**	64,492	24,439,732	**706,333**	4,722	701,611
	Cadets and AD teens	24,439,732	539	24,439,193	701,611	244	701,367
	missing consolidated Zip	24,439,193	71	24,439,122	701,367	14	701,353
	stationed/living in europe	24,439,122	294,244	24,144,878	701,353	13,313	688,040
	stationed/living in pacific, AK, or HI	24,144,878	634,265	23,510,613	688,040	24,329	663,711
	never had an facility treated exacerbation	23,510,613	10,203,825	13,306,788	663,711	397,229	266,482
	did not reside within a MHA	13,306,788	4,385	13,302,403	266,482	165	266,317
	duplicate event months	13,302,403	65,695	13,236,708	266,317	-	266,317
	had no relocations in data	13,236,708	11,427,305	1,809,403	266,317	236,318	29,999
	less than 24 monts of continuious data	1,809,403	93,030	1,716,373	29,999	4,674	25,325
	at least one local rate of "0" or "1"	1,716,373	306,586	1,409,787	25,325	4,209	21,116
	ever resided in a "County Cost Group"	1,409,787	354,045	**1,055,742**	21,116	5,135	**15,981**

Figure 2. Plot of Model-Implied Odds Ratios from Final Regression Model



Note. n= 1,055,742 months (L1) and 15,981 children (L2); 'Ref' = Refence Value and is marked with a '▲'; Significant values ($p < .05$) are marked with an asterisk; Not-significant values ($p > .05$) are marked '●'.

Figure 3. Graph of Interaction Between Age (in months) and Female Status



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Appendix: R Code

```
+++++++++++++++ Start File +++++++++++++++
#Disseration Paper 3 MHS Data Prep ----

# Pre-Analysis Preparatory Tasks ----


## Prep the cyberspace----

options(scipen=999) ## forces full display of results, all digits

setwd('/[REDACTED]/Working')

### clean up the environment/remove old objects ----

rm(list=ls())

gc()


## Load Packages----

library(readxl) #import Excel files

library(lubridate) #date handling

library(dplyr) #data wrangling

library(data.table) #better format for fast data indexing

library(zipcodeR) #Zip Code handleling and information lookup

library(parallel) #parallel/mulitcore processing


## Test Data and Pathfinding ----

#Create test data

#Person File variable names
c("x_edipn","startcy","startcm","endcy","endcm","d_zip_cd","patdob","age_first_month","length_mon
ths")

#Event File variable names
c("cy","cm","x_edipn","sex","branch","rank_final","dob","dc_pc","dispstat","PATZIP","tx_zip","enr
loc","dxpx","n_ip","n_op")

personTestRaw <- as.data.table(cbind.data.frame(c(rep(paste0(rep(1,10),collapse =
""),2),rep(paste0(rep(2,10),collapse = ""),2),rep(paste0(rep(3,10),collapse =
""),9),paste0(rep(4,10),collapse = "")),


c(2012,2014,2016,2017,2010,2012,2013,2013,2014,2015,2016,2018,2019,2009),

                                            c(8,8,11,11,6,7,10,11,2,5,12,2,12,10),


c(2012,2020,2017,2019,2010,2013,2013,2014,2015,2016,2017,2019,2020,2013),

                                            c(12,9,10,6,8,9,10,1,4,11,12,11,9,10),


as.character(c("50023","43571","96786","76522","36303","38654","35216","36301","73501","36303","7
3505","73505","76549","92069")),

                                            as.Date(c("2011-12-16","2011-12-16","2016-10-
28","2016-10-28","2009-08-03","2009-08-03","2009-08-03","2009-08-03","2009-08-03","2009-08-
03","2009-08-03","2009-08-03","2009-08-03","1999-10-19")),
```

```
                                          c(8,32,1,13,10,35,50,51,54,69,88,102,124,120),

                                          c(4,73,11,19,2,14,0,2,14,8,12,21,9,48)

                                          ))

names(personTestRaw) <-
c("x_edipn","startcy","startcm","endcy","endcm","d_zip_cd","patdob","age_first_month","length_mon
ths")

eventTestRaw <-
as.data.table(cbind.data.frame(c(2012,2012,2014,2014,2018,2014,2017,2010,2011,2012,2014),

                                             c(07,12,09,11,05,12,03,01,08,12,02),

                                             c(rep(paste0(rep(1,10),collapse =
""),4),rep(paste0(rep(2,10),collapse = ""),1),rep(paste0(rep(3,10),collapse =
""),2),rep(paste0(rep(4,10),collapse = ""),4)),

                                             c(rep("M",4),rep("F",7)),

                                             c(rep("F",4),rep("A",7)),


c("XX","OS","OS","OS","EJ","EJ","EJ","EJ","ES","ES","XX"),

                                             as.Date(c(rep("2011-12-16",4),"2016-10-28","2009-
08-03","2009-08-03",rep("1999-10-19",4))),

                                             c(rep("PC",4),rep("DC",3),rep("PC",4)),

                                             c(rep("",11)),


as.character(c("50023","50023","43571","43571","76522","73501","29206","92069","92069","92069","9
2069")),


as.character(c("50021","50021","43537","43537","76544","73503","29207","92025","92025","92014","9
2123")),


as.character(c("NONE","7919","7917","7917","0110","0098","0098","6919","6919","6919","NONE")),

                                             c("PX",rep("DX",4),"PX","PX",rep("DX",3),"PX"),

                                             c(rep(0,11)),

                                             c(1,1,3,4,1,1,1,2,1,3,1)))

names(eventTestRaw) <-
c("cy","cm","x_edipn","sex","branch","rank_final","dob","dc_pc","dispstat","PATZIP","tx_zip","enr
loc","dxpx","n_ip","n_op")



#Event File Pathfinding

eventTest <- eventTestRaw #duplicate raw file to preserve raw data

eventTest$per <- ((eventTest$cy-2010)*12)+eventTest$cm #create period (per) variable to track
events

eventTest$BDper <- ((year(eventTest$dob)-2010)*12)+month(eventTest$dob)

eventDataTable <- as.data.table(unique(eventTest$x_edipn)) # create a table that is all unique
IDs

names(eventDataTable) <- "x_edipn"

addCol <- as.data.table(rep("",nrow(eventDataTable)))

names(addCol) <- "z"
```

```
x <- 1

while(x <= 120){

  names(addCol) <- as.character(x)

  eventDataTable <- base::cbind(eventDataTable,addCol)

  x <- x+1

}

rm(addCol,x)

loopCount <- 1 #loop counting variable

ipR <- 1L #input row variable

ipC <- 2L #input column variable

opR <- 1L #output row variable

opC <- 2L #output column variable

current_percent <- 0

last_printed_percent <- -1


eventTest <- eventTest %>% dplyr::arrange(x_edipn,per) #arrange the working file to be ordered by
ID and Per

eventDataTable <- eventDataTable %>% dplyr::arrange(x_edipn) #arrange data table to be ordered by
ID

while(ipR<=nrow(eventTest)){

  while(eventTest$x_edipn[ipR]==eventDataTable$x_edipn[opR]){

    if(eventDataTable[[opC]][opR]!=""||is.na(eventDataTable[[opC]][opR])){

      set(eventDataTable,opR,as.integer(eventTest$per[ipR])+1L,1)

      ipR <- ipR+1L

      if(ipR>nrow(eventTest)){break}

      next

    }

    while(opC<=121){

      ifelse(eventTest$BDper[ipR]>(opC-1),set(eventDataTable,opR,opC,NA),

             ifelse(eventTest$per[ipR]==(opC-
1),set(eventDataTable,opR,opC,1),set(eventDataTable,opR,opC,0)))

      opC <- opC+1L

    }

    opC <- 2L

    ipR <- ipR+1L

    if(ipR>nrow(eventTest)){break}

  }

  opR <- opR+1L

  current_percent <- floor((opR / nrow(eventDataTable)) * 100)
```

```
  if (current_percent != last_printed_percent && current_percent <= 100) {

    cat(sprintf("[%s] Progress: %d%%\n", Sys.time(), current_percent))

    last_printed_percent <- current_percent

  }

}

#long form person test

personTest <- personTestRaw #duplicate raw file to preserve raw data

personTest$startPer <- ((personTest$startcy-2010)*12)+personTest$startcm #create start period
(startPer) variable

personTest$endPer <- ((personTest$endcy-2010)*12)+personTest$endcm #create end period (endPer)
variable

personTest$BDoffset <- ((year(personTest$patdob)-2010)*12)+month(personTest$patdob) #create a
Birthday offset (BDoffset) variable that adjusts the given period to figure the childs age in
months



personLong <- as.data.frame(rbind(rep("",5)))

names(personLong) <- c("x_edipn","per","age","zip","event")

loopCount <- 1 #loop counting variable

ipR <- 1 #input row variable

opR <- 1 #output row variable

opC <- 1 #output column variable

x <- 1 #Per counting variable

outputRow <- as.data.frame(rbind(rep("",5)))

names(outputRow) <- c("x_edipn","per","age","zip","event")

while (ipR<=nrow(personTest)) {

  loopCount <- 1

  x <- max(1,personTest$startPer[ipR])

  while(loopCount<=(min(120,personTest$endPer[ipR])-max(1,personTest$startPer[ipR]))+1){

    outputRow <- as.data.frame(rbind(c(personTest$x_edipn[ipR],x,x-
personTest$BDoffset[ipR],personTest$d_zip_cd[ipR],ifelse(is.null(eventDataTable[which(eventDataTa
ble$x_edipn==personTest$x_edipn[ipR]),x+1]),NA,as.numeric(eventDataTable[which(eventDataTable$x_e
dipn==personTest$x_edipn[ipR]),x+1]))))))

    names(outputRow) <- c("x_edipn","per","age","zip","event")

    personLong <- as.data.frame(rbind(personLong,outputRow))

    x <- x+1

    loopCount <- loopCount+1

    }

  ipR <- ipR+1

}



rm(eventDataTable,eventTest,eventTestRaw,personTest,personTestRaw)
```

```
# #load raw data
# eventRaw <- read_xlsx('/[REDACTED]/Asthma extract.xlsx',1)
# personRaw <- read_xlsx('/[REDACTED]/new_person_file.xlsx',1)
# temp1 <- read_xlsx('/[REDACTED]/new_person_file.xlsx',2)
# temp2 <- read_xlsx('/[REDACTED]/new_person_file.xlsx',3)
# personRaw <- rbind(personRaw,temp1,temp2)
# rm(temp1,temp2)

# # create working r data files
# eventFile <- eventRaw
# personFile <- personRaw
# save(eventFile,file='/[REDACTED]/eventFile.RData')
# save(personFile,file='/[REDACTED]/personFile.RData')
# rm(eventRaw,personRaw)

#load working data files ----
load("eventFile.RData")
load("personFile.RData")

## prep event file ----
eventFile <- as.data.table(eventFile)
eventFile$cy <- as.numeric(eventFile$cy)
eventFile$cm <- as.numeric(eventFile$cm)
eventFile$dob <- as.Date(eventFile$dob)

eventFile$per <- ((eventFile$cy-2010)*12)+eventFile$cm #create period (per) variable to track
events
eventFile$BDper <- ((lubridate::year(eventFile$dob)-2010)*12)+lubridate::month(eventFile$dob)

## Create Event Table ----
# eventTable <- as.data.table(unique(eventFile$x_edipn)) # create a table that is all unique IDs
# names(eventTable) <- "x_edipn"
# addCol <- as.data.table(rep("",nrow(eventTable)))
# names(addCol) <- "z"
# x <- min(eventFile$per)
# while(x <= max(eventFile$per)){
```

```
#   names(addCol) <- as.character(x)
#   eventTable <- base::cbind(eventTable,addCol)
#   x <- x+1
# }
# rm(addCol,x)
# loopCount <- 1 #loop counting variable
# ipR <- 1L #input row variable
# ipC <- 2L #input column variable
# opR <- 1L #output row variable
# opC <- 2L #output column variable
# current_percent <- 0
# last_printed_percent <- -1
#
# eventFile <- eventFile %>% dplyr::arrange(x_edipn,per) #arrange the working file to be ordered
by ID and Per
# eventTable <- eventTable %>% dplyr::arrange(x_edipn) #arrange data table to be ordered by ID
# while(ipR<=nrow(eventFile)){
#   while(eventFile$x_edipn[ipR]==eventTable$x_edipn[opR]){
#     if(eventTable[[opC]][opR]!=""||is.na(eventTable[[opC]][opR])){
#       set(eventTable,opR,as.integer(eventFile$per[ipR])+1L,1)
#       ipR <- ipR+1L
#       if(ipR>nrow(eventFile)){break}
#       next
#     }
#     while(opC<=121){
#
#       ifelse(eventFile$BDper[ipR]>(opC-1),set(eventTable,opR,opC,NA),
#              ifelse(eventFile$per[ipR]==(opC-
1),set(eventTable,opR,opC,1),set(eventTable,opR,opC,0)))
#       opC <- opC+1L
#     }
#     opC <- 2L
#     ipR <- ipR+1L
#     if(ipR>nrow(eventFile)){break}
#   }
#   opR <- opR+1L
#   current_percent <- floor((opR / nrow(eventTable)) * 100)
#   if (current_percent != last_printed_percent) {
#     cat(sprintf("[%s] Progress: %d%%\n", Sys.time(), current_percent))
```

```
#     last_printed_percent <- current_percent

#   }

# }

#

# save(eventTable,file='/[REDACTED]/eventTable.RData')


load("eventTable.RData")


## Expand person data to long form ----

personFile$patdob <- as.Date(personFile$patdob)


personFile$startPer <- ((personFile$startcy-2010)*12)+personFile$startcm #create start period
(startPer) variable

personFile$endPer <- ((personFile$endcy-2010)*12)+personFile$endcm #create end period (endPer)
variable

personFile$BDoffset <- ((year(personFile$patdob)-2010)*12)+month(personFile$patdob) #create a
Birthday offset (BDoffset) variable that adjusts the given period to figure the childs age in
months

eventFile$age <- eventFile$per-eventFile$BDper

#eventFile$local <-
ifelse(substr(eventFile$PATZIP,1,3)==substr(eventFile$tx_zip,1,3),1,ifelse(zip_distance(eventFile
$PATZIP,eventFile$tx_zip)$distance<50,1,0))




personLong <- eventFile %>% select(x_edipn,per,age,sex,branch,rank_final,PATZIP,tx_zip)

personLong$PFzip <- NA

personLong$event <- 1

names(personLong) <-
c("x_edipn","per","age","sex","branch","rank","EFzip","TXzip","PFzip","event")

personLong <- as.data.table(personLong)


loopCount <- 1 #loop counting variable

ipR <- 1L #input row variable

opR <- 1L #output row variable

opC <- 1L #output column variable

x <- 1 #Per counting variable

current_percent <- 0

last_printed_percent <- -1



ipR <- 1
```

```
m2 <- Sys.time()

while (ipR<=nrow(personFile)) {

 if (personFile$endPer[ipR]<1 || personFile$startPer[ipR]>120) {

   ipR <- ipR+1L

   next

 }

  reps <- (min(120,personFile$endPer[ipR])-max(1,personFile$startPer[ipR]))+1

  output <- data.table("x_edipn"=c(rep(personFile$x_edipn[ipR],reps)),


"per"=max(1,personFile$startPer[ipR]):(max(1,personFile$startPer[ipR])+reps-1),


"age"=(max(1,personFile$startPer[ipR]):(max(1,personFile$startPer[ipR])+reps-1))-
personFile$BDoffset[ipR],

                        "sex"=rep(NA,reps),

                        "branch"=rep(NA,reps),

                        "rank"=rep(NA,reps),

                        "EFzip"=rep(NA,reps),

                        "TXzip"=rep(NA,reps),

                        "PFzip"=rep(personFile$d_zip_cd[ipR],reps),


"event"=as.numeric(eventTable[which(eventTable$x_edipn==personFile$x_edipn[ipR]),(max(1,personFil
e$startPer[ipR])+1):(min(120,personFile$endPer[ipR])+1)]))

  output <- output[-which(output$event==1),]

  personLong <- as.data.table(rbind(personLong,output))


  ipR <- ipR+1L

  current_percent <- floor((ipR / nrow(personFile)) * 100)

  if (current_percent != last_printed_percent) {

    cat(sprintf("[%s] Progress: %d%%\n", Sys.time(), current_percent))

    last_printed_percent <- current_percent

  }

}

m2 <- Sys.time()-m2

m2




reps <- (min(120,personFile$endPer[ipR])-max(1,personFile$startPer[ipR]))+1

output <- data.table("x_edipn"=c(rep(personFile$x_edipn[ipR],reps)),

           "per"=max(1,personFile$startPer[ipR]):(max(1,personFile$startPer[ipR])+reps-1),

           "age"=(max(1,personFile$startPer[ipR]):(max(1,personFile$startPer[ipR])+reps-1))-
personFile$BDoffset[ipR],
```

```
            "sex"=rep(NA,reps),

            "branch"=rep(NA,reps),

            "rank"=rep(NA,reps),

            "EFzip"=rep(NA,reps),

            "TXzip"=rep(NA,reps),

            "PFzip"=rep(personFile$d_zip_cd[ipR],reps),


"event"=as.numeric(eventTable[which(eventTable$x_edipn==personFile$x_edipn[ipR]),(max(1,personFil
e$startPer[ipR])+1):(min(120,personFile$endPer[ipR])+1)]))

output <- output[-which(output$event==1),]




# Military Housing Area (MHA) prep

MHAzip <- read.table('/[REDACTED]/AQI Data/Raw/sorted_zipmha24.txt',header = FALSE,sep = "
",colClasses = "character")

names(MHAzip) <- c("Zip","MHA.Code")

MHAnames <- read.csv('/[REDACTED]/AQI Data/Raw/mhanames24.csv',header = FALSE,sep =
",",colClasses = "character")

names(MHAnames) <- c("MHA.Code","MHA.Name")

MHAzip <- left_join(MHAzip,MHAnames)

MHAzip$Zip <- as.character(MHAzip$Zip)

MHAzip$MHA.grp <-
ifelse(is.na(MHAzip$MHA.Name),NA,ifelse(substr(MHAzip$MHA.Name,1,6)=="UNKNOW",NA,ifelse(substr(MH
Azip$MHA.Name,1,6)=="COUNTY","X","MHA")))

rm(MHAnames)


eventFile$Zip <- eventFile$PATZIP

eventFile <- left_join(eventFile,MHAzip,by="Zip")




# AQI prep

AQI2010 <- read.csv('/[REDACTED]/AQI Data/Extra Data/daily_aqi_by_cbsa_2010.csv')

AQI2011 <- read.csv('/[REDACTED]/AQI Data/Extra Data/daily_aqi_by_cbsa_2011.csv')

AQI2012 <- read.csv('/[REDACTED]/AQI Data/Extra Data/daily_aqi_by_cbsa_2012.csv')

AQI2013 <- read.csv('/[REDACTED]/AQI Data/Extra Data/daily_aqi_by_cbsa_2013.csv')

AQI2014 <- read.csv('/[REDACTED]/AQI Data/Extra Data/daily_aqi_by_cbsa_2014.csv')

AQI2015 <- read.csv('/[REDACTED]/AQI Data/Extra Data/daily_aqi_by_cbsa_2015.csv')

AQI2016 <- read.csv('/[REDACTED]/AQI Data/Extra Data/daily_aqi_by_cbsa_2016.csv')

AQI2017 <- read.csv('/[REDACTED]/AQI Data/Extra Data/daily_aqi_by_cbsa_2017.csv')

AQI2018 <- read.csv('/[REDACTED]/AQI Data/Extra Data/daily_aqi_by_cbsa_2018.csv')
```

```
AQI2019 <- read.csv('/[REDACTED]/AQI Data/Extra Data/daily_aqi_by_cbsa_2019.csv')

AQIdata <- rbind(AQI2010,AQI2011,AQI2012,AQI2013,AQI2014,AQI2015,AQI2016,AQI2017,AQI2018,AQI2019)

rm(AQI2010,AQI2011,AQI2012,AQI2013,AQI2014,AQI2015,AQI2016,AQI2017,AQI2018,AQI2019)


AQIdata$CBSA.Code <- as.character(AQIdata$CBSA.Code)

AQIdata$Date <- as.Date(AQIdata$Date)

AQIdata$per <- ((lubridate::year(AQIdata$Date)-2010)*12)+lubridate::month(AQIdata$Date)

AQIdata$quarter <- ((lubridate::year(AQIdata$Date)-2010)*4)+lubridate::quarter(AQIdata$Date)

AQIdata <- as.data.table(AQIdata)

AQIdata <- AQIdata %>% group_by(CBSA.Code,per) %>% summarise("AQImax"=max(AQI),"AQI"=mean(AQI))



CW2010Q1 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2010Q1.xlsx', range =
cell_cols("A:B"))

CW2010Q2 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2010Q2.xlsx', range =
cell_cols("A:B"))

CW2010Q3 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2010Q3.xlsx', range =
cell_cols("A:B"))

CW2010Q4 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2010Q4.xlsx', range =
cell_cols("A:B"))

CW2011Q1 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2011Q1.xlsx', range =
cell_cols("A:B"))

CW2011Q2 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2011Q2.xlsx', range =
cell_cols("A:B"))

CW2011Q3 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2011Q3.xlsx', range =
cell_cols("A:B"))

CW2011Q4 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2011Q4.xlsx', range =
cell_cols("A:B"))

CW2012Q1 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2012Q1.xlsx', range =
cell_cols("A:B"))

CW2012Q2 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2012Q2.xlsx', range =
cell_cols("A:B"))

CW2012Q3 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2012Q3.xlsx', range =
cell_cols("A:B"))

CW2012Q4 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2012Q4.xlsx', range =
cell_cols("A:B"))

CW2013Q1 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2013Q1.xlsx', range =
cell_cols("A:B"))

CW2013Q2 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2013Q2.xlsx', range =
cell_cols("A:B"))

CW2013Q3 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2013Q3.xlsx', range =
cell_cols("A:B"))

CW2013Q4 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2013Q4.xlsx', range =
cell_cols("A:B"))

CW2014Q1 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2014Q1.xlsx', range =
cell_cols("A:B"))
```

```
CW2014Q2 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2014Q2.xlsx', range =
cell_cols("A:B"))

CW2014Q3 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2014Q3.xlsx', range =
cell_cols("A:B"))

CW2014Q4 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2014Q4.xlsx', range =
cell_cols("A:B"))

CW2015Q1 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2015Q1.xlsx', range =
cell_cols("A:B"))

CW2015Q2 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2015Q2.xlsx', range =
cell_cols("A:B"))

CW2015Q3 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2015Q3.xlsx', range =
cell_cols("A:B"))

CW2015Q4 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2015Q4.xlsx', range =
cell_cols("A:B"))

CW2016Q1 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2016Q1.xlsx', range =
cell_cols("A:B"))

CW2016Q2 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2016Q2.xlsx', range =
cell_cols("A:B"))

CW2016Q3 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2016Q3.xlsx', range =
cell_cols("A:B"))

CW2016Q4 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2016Q4.xlsx', range =
cell_cols("A:B"))

CW2017Q1 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2017Q1.xlsx', range =
cell_cols("A:B"))

CW2017Q2 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2017Q2.xlsx', range =
cell_cols("A:B"))

CW2017Q3 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2017Q3.xlsx', range =
cell_cols("A:B"))

CW2017Q4 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2017Q4.xlsx', range =
cell_cols("A:B"))

CW2018Q1 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2018Q1.xlsx', range =
cell_cols("A:B"))

CW2018Q2 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2018Q2.xlsx', range =
cell_cols("A:B"))

CW2018Q3 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2018Q3.xlsx', range =
cell_cols("A:B"))

CW2018Q4 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2018Q4.xlsx', range =
cell_cols("A:B"))

CW2019Q1 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2019Q1.xlsx', range =
cell_cols("A:B"))

CW2019Q2 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2019Q2.xlsx', range =
cell_cols("A:B"))

CW2019Q3 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2019Q3.xlsx', range =
cell_cols("A:B"))

CW2019Q4 <- read_xlsx('/[REDACTED]/AQI Data/CBSA Crosswalk/ZIP_CBSA_2019Q4.xlsx', range =
cell_cols("A:B"))



CW2010Q1$qtr <- 1
```

```
CW2010Q2$qtr <-  2
CW2010Q3$qtr <-  3
CW2010Q4$qtr <-  4
CW2011Q1$qtr <-  5
CW2011Q2$qtr <-  6
CW2011Q3$qtr <-  7
CW2011Q4$qtr <-  8
CW2012Q1$qtr <-  9
CW2012Q2$qtr <-  10
CW2012Q3$qtr <-  11
CW2012Q4$qtr <-  12
CW2013Q1$qtr <-  13
CW2013Q2$qtr <-  14
CW2013Q3$qtr <-  15
CW2013Q4$qtr <-  16
CW2014Q1$qtr <-  17
CW2014Q2$qtr <-  18
CW2014Q3$qtr <-  19
CW2014Q4$qtr <-  20
CW2015Q1$qtr <-  21
CW2015Q2$qtr <-  22
CW2015Q3$qtr <-  23
CW2015Q4$qtr <-  24
CW2016Q1$qtr <-  25
CW2016Q2$qtr <-  26
CW2016Q3$qtr <-  27
CW2016Q4$qtr <-  28
CW2017Q1$qtr <-  29
CW2017Q2$qtr <-  30
CW2017Q3$qtr <-  31
CW2017Q4$qtr <-  32
CW2018Q1$qtr <-  33
CW2018Q2$qtr <-  34
CW2018Q3$qtr <-  35
CW2018Q4$qtr <-  36
CW2019Q1$qtr <-  37
CW2019Q2$qtr <-  38
CW2019Q3$qtr <-  39
```

```
CW2019Q4$qtr <-  40

names(CW2010Q1) <- c("Zip","CBSA.Code","qtr")
names(CW2010Q2) <- c("Zip","CBSA.Code","qtr")
names(CW2010Q3) <- c("Zip","CBSA.Code","qtr")
names(CW2010Q4) <- c("Zip","CBSA.Code","qtr")
names(CW2011Q1) <- c("Zip","CBSA.Code","qtr")
names(CW2011Q2) <- c("Zip","CBSA.Code","qtr")
names(CW2011Q3) <- c("Zip","CBSA.Code","qtr")
names(CW2011Q4) <- c("Zip","CBSA.Code","qtr")
names(CW2012Q1) <- c("Zip","CBSA.Code","qtr")
names(CW2012Q2) <- c("Zip","CBSA.Code","qtr")
names(CW2012Q3) <- c("Zip","CBSA.Code","qtr")
names(CW2012Q4) <- c("Zip","CBSA.Code","qtr")
names(CW2013Q1) <- c("Zip","CBSA.Code","qtr")
names(CW2013Q2) <- c("Zip","CBSA.Code","qtr")
names(CW2013Q3) <- c("Zip","CBSA.Code","qtr")
names(CW2013Q4) <- c("Zip","CBSA.Code","qtr")
names(CW2014Q1) <- c("Zip","CBSA.Code","qtr")
names(CW2014Q2) <- c("Zip","CBSA.Code","qtr")
names(CW2014Q3) <- c("Zip","CBSA.Code","qtr")
names(CW2014Q4) <- c("Zip","CBSA.Code","qtr")
names(CW2015Q1) <- c("Zip","CBSA.Code","qtr")
names(CW2015Q2) <- c("Zip","CBSA.Code","qtr")
names(CW2015Q3) <- c("Zip","CBSA.Code","qtr")
names(CW2015Q4) <- c("Zip","CBSA.Code","qtr")
names(CW2016Q1) <- c("Zip","CBSA.Code","qtr")
names(CW2016Q2) <- c("Zip","CBSA.Code","qtr")
names(CW2016Q3) <- c("Zip","CBSA.Code","qtr")
names(CW2016Q4) <- c("Zip","CBSA.Code","qtr")
names(CW2017Q1) <- c("Zip","CBSA.Code","qtr")
names(CW2017Q2) <- c("Zip","CBSA.Code","qtr")
names(CW2017Q3) <- c("Zip","CBSA.Code","qtr")
names(CW2017Q4) <- c("Zip","CBSA.Code","qtr")
names(CW2018Q1) <- c("Zip","CBSA.Code","qtr")
names(CW2018Q2) <- c("Zip","CBSA.Code","qtr")
names(CW2018Q3) <- c("Zip","CBSA.Code","qtr")
names(CW2018Q4) <- c("Zip","CBSA.Code","qtr")
```

```
names(CW2019Q1) <- c("Zip","CBSA.Code","qtr")

names(CW2019Q2) <- c("Zip","CBSA.Code","qtr")

names(CW2019Q3) <- c("Zip","CBSA.Code","qtr")

names(CW2019Q4) <- c("Zip","CBSA.Code","qtr")

CBSAmaster <-
rbind(CW2010Q1,CW2010Q2,CW2010Q3,CW2010Q4,CW2011Q1,CW2011Q2,CW2011Q3,CW2011Q4,CW2012Q1,CW2012Q2,C
W2012Q3,CW2012Q4,


CW2013Q1,CW2013Q2,CW2013Q3,CW2013Q4,CW2014Q1,CW2014Q2,CW2014Q3,CW2014Q4,CW2015Q1,CW2015Q2,CW2015Q
3,CW2015Q4,


CW2016Q1,CW2016Q2,CW2016Q3,CW2016Q4,CW2017Q1,CW2017Q2,CW2017Q3,CW2017Q4,CW2018Q1,CW2018Q2,CW2018Q
3,CW2018Q4,

                    CW2019Q1,CW2019Q2,CW2019Q3,CW2019Q4)

rm(CW2010Q1,CW2010Q2,CW2010Q3,CW2010Q4,CW2011Q1,CW2011Q2,CW2011Q3,CW2011Q4,CW2012Q1,CW2012Q2,CW20
12Q3,CW2012Q4,


CW2013Q1,CW2013Q2,CW2013Q3,CW2013Q4,CW2014Q1,CW2014Q2,CW2014Q3,CW2014Q4,CW2015Q1,CW2015Q2,CW2015Q
3,CW2015Q4,


CW2016Q1,CW2016Q2,CW2016Q3,CW2016Q4,CW2017Q1,CW2017Q2,CW2017Q3,CW2017Q4,CW2018Q1,CW2018Q2,CW2018Q
3,CW2018Q4,

   CW2019Q1,CW2019Q2,CW2019Q3,CW2019Q4)



CBSAmaster <- CBSAmaster %>% select(Zip,qtr,CBSA.Code)

CBSAmaster <- CBSAmaster[CBSAmaster$CBSA.Code %in% unique(AQIdata$CBSA.Code),]

#appears crosswalk 38... 2019 Quarter 2 had best Zip to CBSA to AQI  for all data

CBSAmaster <- CBSAmaster[CBSAmaster$qtr==38,]



+++++++++++++++ End File +++++++++++++++


+++++++++++++++ Start File ++++++++++++++
#Disseration Paper 3 MHS Data person long part 2----
# Pre-Analysis Preparatory Tasks ----

## Prep the cyberspace----
options(scipen=999) ## forces full display of results, all digits
setwd('/[REDACTED]/Working')
### clean up the environment/remove old objects ----
rm(list=ls())
gc()

## Load Packages----
library(lubridate) #date handling
library(dplyr) #data wrangling
library(data.table) #better format for fast data indexing

#load working data files ----
load("personFile.RData")
load("eventTable.RData")

#long form person data part 2
personFile$startPer <- ((personFile$startcy-2010)*12)+personFile$startcm #create start period
(startPer) variable
```

```
personFile$endPer <- ((personFile$endcy-2010)*12)+personFile$endcm #create end period (endPer)
variable
personFile$BDoffset <- ((year(personFile$patdob)-2010)*12)+month(personFile$patdob) #create a
Birthday offset (BDoffset) variable that adjusts the given period to figure the childs age in
months

personLong <- as.data.table(rbind(rep("",10)))
names(personLong) <-
c("x_edipn","per","age","sex","branch","rank","EFzip","TXzip","PFzip","event")

current_percent <- 0
last_printed_percent <- -1
ipR <- 237336L
while (ipR<=460119) {
  if (personFile$endPer[ipR]<1 || personFile$startPer[ipR]>120) {
    ipR <- ipR+1L
    next
  }
  reps <- (min(120,personFile$endPer[ipR])-max(1,personFile$startPer[ipR]))+1
  output <- data.table("x_edipn"=c(rep(personFile$x_edipn[ipR],reps)),

"per"=max(1,personFile$startPer[ipR]):(max(1,personFile$startPer[ipR])+reps-1),

"age"=(max(1,personFile$startPer[ipR]):(max(1,personFile$startPer[ipR])+reps-1))-
personFile$BDoffset[ipR],
                       "sex"=rep(NA,reps),
                       "branch"=rep(NA,reps),
                       "rank"=rep(NA,reps),
                       "EFzip"=rep(NA,reps),
                       "TXzip"=rep(NA,reps),
                       "PFzip"=rep(personFile$d_zip_cd[ipR],reps),

"event"=as.numeric(eventTable[which(eventTable$x_edipn==personFile$x_edipn[ipR]),(max(1,personFil
e$startPer[ipR])+1):(min(120,personFile$endPer[ipR])+1)]))
  output <- output[-which(output$event==1),]
  personLong <- as.data.table(rbind(personLong,output))

  ipR <- ipR+1L
  current_percent <- floor((ipR / nrow(personFile)) * 100)
  if (current_percent != last_printed_percent) {
    cat(sprintf("[%s] Progress: %d%%\n", Sys.time(), current_percent))
    last_printed_percent <- current_percent
  }
}
save(personLong,file='/[REDACTED]/Working/personLongPt2.RData')
+++++++++++++++ End File +++++++++++++++


+++++++++++++++ Start File +++++++++++++++

#Disseration Paper 3 MHS Data person long part 2a----
# Pre-Analysis Preparatory Tasks ----

## Prep the cyberspace----
options(scipen=999) ## forces full display of results, all digits
setwd('/[REDACTED]/Working')
### clean up the environment/remove old objects ----
rm(list=ls())
gc()

## Load Packages----
library(lubridate) #date handling
library(dplyr) #data wrangling
library(data.table) #better format for fast data indexing

#load working data files ----
load("personFile.RData")
load("eventTable.RData")

#long form person data part 2a -> accidently excluded all individuals who are not in the event
table... this (a) version looks specifically for those individuals
```

```
personFile$startPer <- ((personFile$startcy-2010)*12)+personFile$startcm #create start period
(startPer) variable
personFile$endPer <- ((personFile$endcy-2010)*12)+personFile$endcm #create end period (endPer)
variable
personFile$BDoffset <- ((year(personFile$patdob)-2010)*12)+month(personFile$patdob) #create a
Birthday offset (BDoffset) variable that adjusts the given period to figure the childs age in
months

personLong <- as.data.table(rbind(rep("",10)))
names(personLong) <-
c("x_edipn","per","age","sex","branch","rank","EFzip","TXzip","PFzip","event")

current_percent <- 0
last_printed_percent <- -1
ipR <- 237336L
while (ipR<=460119) {
  if (length(which(eventTable$x_edipn==personFile$x_edipn[ipR]))>0) {
    ipR <- ipR+1L
    next
  }
  if (personFile$endPer[ipR]<1 || personFile$startPer[ipR]>120) {
    ipR <- ipR+1L
    next
  }
  reps <- (min(120,personFile$endPer[ipR])-max(1,personFile$startPer[ipR]))+1
  output <- data.table("x_edipn"=c(rep(personFile$x_edipn[ipR],reps)),

"per"=max(1,personFile$startPer[ipR]):(max(1,personFile$startPer[ipR])+reps-1),

"age"=(max(1,personFile$startPer[ipR]):(max(1,personFile$startPer[ipR])+reps-1))-
personFile$BDoffset[ipR],
                       "sex"=rep(NA,reps),
                       "branch"=rep(NA,reps),
                       "rank"=rep(NA,reps),
                       "EFzip"=rep(NA,reps),
                       "TXzip"=rep(NA,reps),
                       "PFzip"=rep(personFile$d_zip_cd[ipR],reps),
                       "event"=rep(0,reps))
  personLong <- as.data.table(rbind(personLong,output))

  ipR <- ipR+1L
  current_percent <- floor((ipR / nrow(personFile)) * 100)
  if (current_percent != last_printed_percent) {
    cat(sprintf("[%s] Progress: %d%%\n", Sys.time(), current_percent))
    last_printed_percent <- current_percent
  }
}
save(personLong,file='/[REDACTED]/Working/personLongPt2a.RData')

+++++++++++++++ End File +++++++++++++++


+++++++++++++++ Start File +++++++++++++++

#Disseration Paper 3 MHS Data Prep (join person long files and prep) ----
# Pre-Analysis Preparatory Tasks ----

## Prep the cyberspace----
options(scipen=999) ## forces full display of results, all digits
setwd('/[REDACTED]/Working')
### clean up the environment/remove old objects ----
rm(list=ls())
gc()

## Load Packages----
library(lubridate) #date handling
library(dplyr) #data wrangling
library(data.table) #better format for fast data indexing
library(zipcodeR) #Zip Code handleling and information lookup

## Load long file parts
```

```
load('/[REDACTED]/Working/personLongPt1.RData')
p1 <- personLong
load('/[REDACTED]/Working/personLongPt1a.RData')
p1a <- personLong
load('/[REDACTED]/Working/personLongPt2.RData')
p2 <- personLong
load('/[REDACTED]/Working/personLongPt2a.RData')
p2a <- personLong
load('/[REDACTED]/Working/personLongPt3.RData')
p3 <- personLong
load('/[REDACTED]/Working/personLongPt3a.RData')
p3a <- personLong
load('/[REDACTED]/Working/personLongPt4.RData')
p4 <- personLong
load('/[REDACTED]/Working/personLongPt4a.RData')
p4a <- personLong
load('/[REDACTED]/Working/personLongPt5.RData')
p5 <- personLong
load('/[REDACTED]/Working/personLongPt5a.RData')
p5a <- personLong
load('/[REDACTED]/Working/personLongPt6.RData')
p6 <- personLong
load('/[REDACTED]/Working/personLongPt6a.RData')
p6a <- personLong
load('/[REDACTED]/Working/personLongPt7.RData')
p7 <- personLong
load('/[REDACTED]/Working/personLongPt7a.RData')
p7a <- personLong
load('/[REDACTED]/Working/personLongPt8.RData')
p8 <- personLong
load('/[REDACTED]/Working/personLongPt8a.RData')
p8a <- personLong
load('/[REDACTED]/Working/personLongPt9.RData')
p9 <- personLong
load('/[REDACTED]/Working/personLongPt9a.RData')
p9a <- personLong
load('/[REDACTED]/Working/personLongPt10.RData')
p10 <- personLong
load('/[REDACTED]/Working/personLongPt10a.RData')
p10a <- personLong

personLong <- rbind(p1,p1a,
                        p2,p2a,
                        p3,p3a,
                        p4,p4a,
                        p5,p5a,
                        p6,p6a,
                        p7,p7a,
                        p8,p8a,
                        p9,p9a,
                        p10,p10a)
rm(p1,p1a,p2,p2a,p3,p3a,p4,p4a,p5,p5a,p6,p6a,p7,p7a,p8,p8a,p9,p9a,p10,p10a) # n= 35,312,635
months in 979,307 children


##Exclusions----
personLong <- personLong %>% dplyr::arrange(x_edipn,as.numeric(per))
personLong <- personLong[-(1:19),] #removing 19 empty rows
personLong <- personLong[as.numeric(personLong$age)>=48,] #removing 8,330,701 months (including
226,514 total chilren) where child was younger than inclusion criteria; n = 26,981,915 months in
752,793 children
personLong <- personLong[as.numeric(personLong$age)<=216,] #removing 2,475,969 months (including
46,291 total chilren) where child was older than inclusion criteria; n = 24,505,946 months in
706,502 children
personLong <- personLong[-which(grepl("[A-Z]",personLong$EFzip,ignore.case = TRUE)),] # removing
169 months (including 0 total chilren) where event file zipcode contained letters (not a
zipcode); n= 24,505,777 months in 706,502 children
personLong <- personLong[-which(grepl("[A-Z]",personLong$TXzip,ignore.case = TRUE)),] # removing
167 months (including 4 total chilren) where event file treatment zipcode contained letters (not
a zipcode); n= 24,505,610 months in 706,498 children
```

```
personLong <- personLong[-which(grepl("[A-Z]",personLong$PFzip,ignore.case = TRUE)),] # removing
1,386 months (including 165 total chilren) where patient file zipcode contained letters (not a
zipcode); n= 24,504,224 months in 706,333 children

### add in a consolidated Zip code variable for matching to MHA and AQI
personLong$Zip <-
ifelse(personLong$event==0,personLong$PFzip,ifelse(zip_distance(personLong$EFzip,personLong$TXzip
)$distance<50|is.na(zip_distance(personLong$EFzip,personLong$TXzip)$distance),personLong$EFzip,pe
rsonLong$TXzip))

### add MHA columns
personLong <- left_join(personLong,MHAzip,by="Zip")

### remove duplicate events
x <- 1
problem <- personLong %>% slice(0)
while (x<=nrow(personLong)) {
  if (personLong$event[x]==0) {
    x <- x+1
    if(x>nrow(personLong)){break}
    next
  }
  if (personLong$event[x+1]==0) {
    x <- x+2
    if(x>nrow(personLong)){break}
    next
  }
  if
(personLong$x_edipn[x]==personLong$x_edipn[x+1]&&personLong$per[x]==personLong$per[x+1]&&personLo
ng$MHA.Name[x]==personLong$MHA.Name[x+1]) {
    personLong <- personLong[-(x+1),]
    x <- x+1
    if(x>nrow(personLong)){break}
    next
  }
  problem <- rbind(problem,personLong[x,])
  x <- x+1
  if(x>nrow(personLong)){break}
  next
}


### join AQI data
per2qtr <- testZip %>% group_by(per) %>% summarise(qtr=mean(qtr))
per2qtr <- as.character(per2qtr)

personLong$per <- as.numeric(personLong$per)

personLong <- left_join(personLong,CBSAmaster,by=c("Zip"),multiple = "first")
personLong <- left_join(personLong,AQIdata,by=c("CBSA.Code","per"))

save(personLong,file='/[REDACTED]/Working/personLongJoined.RData')

### break out Aim 1 data
aim1 <- personLong %>% group_by(MHA.Name,per) %>% summarize(events=sum(as.numeric(event),na.rm =
TRUE),n=n(),AQImax=mean(AQImax),AQI=mean(AQI))
aim1 <- aim1 %>% arrange(MHA.Name,as.numeric(per))
aim1$rate <- aim1$events/aim1$n
save(aim1,file='/[REDACTED]/Aim1.RData')

aim1a <- personLong %>% group_by(MHA.Name) %>% summarize(events=sum(as.numeric(event),na.rm =
TRUE),n=n(),AQImax=mean(AQImax),AQI=mean(AQI))
aim1a$rate <- aim1a$events/aim1a$n
aim1a$MHA.grp <-
ifelse(is.na(aim1a$MHA.Name),NA,ifelse(substr(aim1a$MHA.Name,1,6)=="UNKNOW",NA,ifelse(substr(aim1
a$MHA.Name,1,6)=="COUNTY","X","MHA")))
save(aim1a,file='/[REDACTED]/Aim1a.RData')

+++++++++++++++ End File +++++++++++++++
```

```
+++++++++++++++ Start File +++++++++++++++

#Disseration Paper 3 MHS Aim 1 ----
# Pre-Analysis Preparatory Tasks ----

## Prep the cyberspace----
options(scipen=999) ## forces full display of results, all digits
setwd('/[REDACTED]/Working')
### clean up the environment/remove old objects ----
rm(list=ls())
gc()

## Load Packages----
library(readxl) #import Excel files
library(lubridate) #date handling
library(dplyr) #data wrangling
library(tidyverse) #data wrangling
library(data.table) #better format for fast data indexing
library(zipcodeR) #Zip Code handleling and information lookup
library(ggplot2) #graphics and plotting

## Load Data
load('/[REDACTED]/Aim1.RData')
load('/[REDACTED]/Aim1a.RData')

## Create location-rate table
rateTable <- aim1 %>% pivot_wider(names_from=MHA.Name,id_cols=per,values_from=rate)
rateTable <- as.data.table(rateTable)
save(rateTable,file='/[REDACTED]/Working/rateTable.RData')

##plotting variables
aim1$mo <- as.factor(((aim1$per-1)%%12)+1)
aim1$yr <- as.character(2010+floor(((aim1$per-1)/12)))
aim1$st <- substr(aim1$MHA.Name,nchar(aim1$MHA.Name)-1,nchar(aim1$MHA.Name))

#aim1b <- aim1 %>% group_by(st) %>%
summarise(events=sum(events),n=sum(n),AQImax=sum(AQImax*n,na.rm =
TRUE)/sum(n),AQI=sum(AQI*n,na.rm = TRUE)/sum(n))
## Plot Rates


top5loc <- aim1 %>% group_by(MHA.Name) %>% summarise(events=sum(events,na.rm =
TRUE),n=sum(n,na.rm = TRUE))
top5loc$rate <- top5loc$events/top5loc$n
top5loc <- top5loc %>%  arrange(desc(rate)) %>% head(5)
top5loc$yrRate <- top5loc$rate*12

bot5loc <- aim1 %>% group_by(MHA.Name) %>% summarise(events=sum(events,na.rm =
TRUE),n=sum(n,na.rm = TRUE))
bot5loc$rate <- bot5loc$events/bot5loc$n
bot5loc <- bot5loc %>%  arrange(desc(rate)) %>% tail(7)
bot5loc <- bot5loc[c(-4,-7),]
bot5loc$yrRate <- bot5loc$rate*12

list <- rbind(top5loc[,1],bot5loc[,1])
plotdata <- aim1 %>% filter(MHA.Name %in% unlist(list$MHA.Name))
avgRate <- aim1 %>% group_by(yr)  %>% summarise(n=sum(n),events=sum(events)) %>%
mutate(rate=(events/n)*12)
avgRate$MHA.Name <- "Avg Rate"
plotdataA <- plotdata %>% group_by(MHA.Name,yr) %>% summarise(n=sum(n),events=sum(events)) %>%
mutate(rate=(events/n)*12)

ggplot(plotdataA, aes(x=yr,y=rate,group=MHA.Name)) +
  geom_line(data=avgRate,y=avgRate$rate, x=avgRate$yr, color="red", alpha=0.5, linetype =
"longdash") +
  geom_line()

+++++++++++++++ End File ++++++++++++++


+++++++++++++++ Start File +++++++++++++++
```

```
#Disseration Paper 3 MHS Aim 2 ----
# Pre-Analysis Preparatory Tasks ----

## Prep the cyberspace----
options(scipen=999) ## forces full display of results, all digits
setwd('/[REDACTED]/Working')
### clean up the environment/remove old objects ----
rm(list=ls())
gc()

## Load Packages----
library(readxl) #import Excel files
library(lubridate) #date handling
library(dplyr) #data wrangling
library(tidyverse) #data wrangling
library(data.table) #better format for fast data indexing
library(zipcodeR) #Zip Code handleling and information lookup
library(ggplot2) #graphics and plotting
library(car) # for recoding data
library(zoo) # for carrying forward or backward to fill in NA demographics
library(lme4)   ### multilevel modeling software
library(Matrix) ### needed for lme4
library(lmerTest) ### to get df and t/p values for lme4 output
library(psych)  ### descriptives
library(r2mlm)  ### R2 values for linear 2L models
library(MuMIn) ### for R2 values for Binomal Multi-Level models using r.squaredGLMM()



## Load Data
load('/[REDACTED]/Aim1.RData')
load('/[REDACTED]/Working/rateTable.RData')
load('/[REDACTED]/Working/personLongJoined.RData')
```

```
## Remove 64,492 months (4,722 unique children) with no locations; 24,503,730 mo & 706,333
children -> 24,439,238 mo & 701,611 children

aim2 <- personLong[!is.na(personLong$EFzip)|!is.na(personLong$TXzip)|!is.na(personLong$PFzip),]

rm(personLong)


## Exclusions Prep

aim2$consec <- as.numeric(0)

current_percent <- 0

last_printed_percent <- -1

x <- 1L

while (x<=nrow(aim2)) {

  if (x==1) {set(aim2,x,19L,1)

    x <- x+1L

    next

  }

  ifelse(aim2$x_edipn[x]==aim2$x_edipn[x-1]&&aim2$per[x]==aim2$per[x-
1]+1,set(aim2,x,19L,aim2[[19L]][x-1L]+1),set(aim2,x,19L,1))

  x <- x+1L

  if (x>nrow(aim2)) {break}

  current_percent <- floor((x / nrow(aim2)) * 100)

  if (current_percent != last_printed_percent) {

    cat(sprintf("[%s] Progress: %d%%\n", Sys.time(), current_percent))

    last_printed_percent <- current_percent

  }

}



## Remove 17yo Cadets and AD from list (have no initial billing zip... only treatement zip which
is a Basic Training site or acadamy)

## removes 539 mo (244 individuals): 24,439,238 mo & 701,611 children -> 24,438,699 & 701,367
children

cutlist <- aim2[is.na(aim2$Zip),]

cutlist <- cutlist[as.numeric(cutlist$age)>=204,]

cutlist <- cutlist[as.numeric(cutlist$consec)<=12,]

cutlist <- as.data.table(unique(cutlist$x_edipn))

names(cutlist) <- "x_edipn"

aim2 <- anti_join(aim2,cutlist)
```

```
rm(cutlist)


#remove 71 months (14 unique children) with missing consoladated Zip data: 24,438,699 & 701,367 children -> 24,438,628 & 701,353 children

aim2 <- aim2[!is.na(aim2$Zip),]


#remove months overseas zipcodes

##remove 294,244 months (13,313 unique children) stationed in europe "09": 24,438,628 & 701,353 children ->  24,144,384 months & 688,040 children

aim2 <- aim2[-(grep("^09",aim2$Zip)),]

##remove 634,265 months (24,329 unique children) stationed in the pacific (including HI, US territories, and AK) "96": 24,144,384 months & 688,040 children ->  23,510,119 months & 663,711 children

aim2 <- aim2[-(grep("^96",aim2$Zip)),]


#remove all children who never has an exacerbation

##remove 10,203,825 months (397,229 unique children) with missing demographic data: 23,510,119 months & 663,711 children  -> 13,306,294 & 266,482 children

cutlist <- aim2 %>% group_by(x_edipn) %>% summarise(events=sum(as.numeric(event)))

cutlist <- cutlist[cutlist$events==0,1]

aim2 <- anti_join(aim2,cutlist)

rm(cutlist)


#remove children that have zipcodes that are not real or dont align with any Military Housing Area

##remove 4,385 months (165 unique children) with problematic zip codes:  13,306,294 months & 266,482 children  -> 13,298,312 months & 266,317 children

cutlist <- aim2[is.na(aim2$MHA.Name),]

cutlist <- as.data.frame( unique(cutlist$x_edipn))

names(cutlist) <- "x_edipn"

aim2 <- anti_join(aim2,cutlist)

rm(cutlist)


#deduplicate event months

## removes 61,604 months (0 unique children) with duplicate event months:  13,298,312 months & 266,317 children  -> 13,236,708 months & 266,317 children

setkey(aim2, x_edipn, per)

aim2 <- unique(aim2, by = c("x_edipn", "per"))
```

```
# Add PCS variable

aim2$pcs <- as.numeric(0)

current_percent <- 0

last_printed_percent <- -1

x <- 1L

while (x<=nrow(aim2)) {

  if (x==1) {set(aim2,x,20L,0)

    x <- x+1L

    next

  }

  if (aim2$x_edipn[x]!=aim2$x_edipn[x-1]) {set(aim2,x,20L,0)

    x <- x+1L

    if (x>nrow(aim2)) {break}

    next

  }

  if (aim2$MHA.Name[x]==aim2$MHA.Name[x-1]) {set(aim2,x,20L,0)

    x <- x+1L

    if (x>nrow(aim2)) {break}

    next

  }

  if (aim2$MHA.Name[x]!=aim2$MHA.Name[x-1]&&aim2$MHA.Name[x-1]==aim2$MHA.Name[x+1])
{set(aim2,x,20L,0.1)

    set(aim2,x+1L,20L,0)

    x <- x+2L

    if (x>nrow(aim2)) {break}

    next

  }

  if (aim2$Zip[x]!=aim2$Zip[x-1]&&aim2$Zip[x]==aim2$Zip[x+1]) {set(aim2,x,20L,1)

    x <- x+1L

    if (x>nrow(aim2)) {break}

    next

  }

  x <- x+1L

  if (x>nrow(aim2)) {break}

  current_percent <- floor((x / nrow(aim2)) * 100)
```

```
  if (current_percent != last_printed_percent) {
    cat(sprintf("[%s] Progress: %d%%\n", Sys.time(), current_percent))
    last_printed_percent <- current_percent
  }
}


#rerun consec after dedup
aim2$consec <- as.numeric(0)
current_percent <- 0
last_printed_percent <- -1
x <- 1L
while (x<=nrow(aim2)) {
  if (x==1) {set(aim2,x,19L,1)
    x <- x+1L
    next
  }
  ifelse(aim2$x_edipn[x]==aim2$x_edipn[x-1]&&aim2$per[x]==aim2$per[x-
1]+1,set(aim2,x,19L,aim2[[19L]][x-1L]+1),set(aim2,x,19L,1))
  x <- x+1L
  if (x>nrow(aim2)) {break}
  current_percent <- floor((x / nrow(aim2)) * 100)
  if (current_percent != last_printed_percent) {
    cat(sprintf("[%s] Progress: %d%%\n", Sys.time(), current_percent))
    last_printed_percent <- current_percent
  }
}


ExcHlpr <- aim2 %>% group_by(x_edipn) %>%
summarise(consec=max(consec),events=sum(as.numeric(event)),pcs=sum(pcs),n=n())


#subset down to those with at least 1 pcs
## removes 11,427,305 months (236,318 unique children) with no PCSs: 13,236,708 months & 266,317
children  -> 1,809,403 months & 29,999 children
cutlist <- as.data.table(ExcHlpr[ExcHlpr$pcs<1,1])
aim2x <- anti_join(aim2,cutlist)
rm(cutlist)
```

```
ExcHlpr <- aim2x %>% group_by(x_edipn) %>%
summarise(consec=max(consec),events=sum(as.numeric(event)),pcs=sum(pcs),n=n())


#remove childen with less than 24 months consectutive data

## removes 93,030 months (4,674 unique children) with consec <24 months: 1,809,403 months &
29,999 children  -> 1,716,373 months & 25,325 children

cutlist <- as.data.table(ExcHlpr[ExcHlpr$consec<24,1])

aim2x <- anti_join(aim2x,cutlist)

rm(cutlist)


ExcHlpr <- aim2x %>% group_by(x_edipn) %>%
summarise(consec=max(consec),events=sum(as.numeric(event)),pcs=sum(pcs),n=n())


#add cumlative pcs

aim2x$cumpcs <- as.numeric(0)

current_percent <- 0

last_printed_percent <- -1

x <- 1L

while (x<=nrow(aim2x)) {

  if (x==1) {set(aim2x,x,21L,floor(aim2x[[20L]][x]))

    x <- x+1L

    next

  }

  if (aim2x$x_edipn[x]!=aim2x$x_edipn[x-1]) {set(aim2x,x,21L,floor(aim2x[[20L]][x]))

    x <- x+1L

    if (x>nrow(aim2x)) {break}

    next

  }

  if (aim2x$x_edipn[x]==aim2x$x_edipn[x-1])
{set(aim2x,x,21L,floor(aim2x[[20L]][x])+aim2x[[21L]][x-1])

    x <- x+1L

    if (x>nrow(aim2x)) {break}

    next

  }

  current_percent <- floor((x / nrow(aim2x)) * 100)

  if (current_percent != last_printed_percent) {
```

```
    cat(sprintf("[%s] Progress: %d%%\n", Sys.time(), current_percent))
    last_printed_percent <- current_percent
  }
}



#add months since last pcs
aim2x$sincepcs <- as.numeric(0)
current_percent <- 0
last_printed_percent <- -1
x <- 1L
while (x<=nrow(aim2x)) {
  current_percent <- floor((x / nrow(aim2x)) * 100)
  if (current_percent != last_printed_percent) {
    cat(sprintf("[%s] Progress: %d%%\n", Sys.time(), current_percent))
    last_printed_percent <- current_percent
  }
  if (x==1) {set(aim2x,x,22L,0)
    x <- x+1L
    next
  }
  if (aim2x$x_edipn[x]!=aim2x$x_edipn[x-1]) {set(aim2x,x,22L,0)
    x <- x+1L
    if (x>nrow(aim2x)) {break}
    next
  }
  if (aim2x$x_edipn[x]==aim2x$x_edipn[x-1]&&aim2x[[21L]][x]==0) {set(aim2x,x,22L,0)
    x <- x+1L
    if (x>nrow(aim2x)) {break}
    next
  }
  if (aim2x$x_edipn[x]==aim2x$x_edipn[x-1]&&aim2x[[20L]][x]==1) {set(aim2x,x,22L,0)
    x <- x+1L
    if (x>nrow(aim2x)) {break}
    next
```

```
  }
  if (aim2x$x_edipn[x]==aim2x$x_edipn[x-1]&&aim2x[[21L]][x]>=1) {set(aim2x,x,22L,aim2x[[22L]][x-
1]+1)
    x <- x+1L
    if (x>nrow(aim2x)) {break}
    next
  }
}


##fixing branch demographics
set(aim2x,1131366L,5L,"N")
set(aim2x,910419L,5L,"A")
set(aim2x,86394L,5L,"C")
aim2x$br <- car::recode(aim2x$branch,"'V'=NA;'X'=NA;'Z'=NA")
aim2x$rnk <- car::recode(aim2x$rank,"'XX'=NA")


## Specify demographic columns
demographic_cols <- c("sex", "rank", "branch", "br", "rnk")


## Fill missing data forward and backward within each individual
aim2x <- aim2x[order(x_edipn), (demographic_cols) := lapply(.SD, function(z)
{zoo::na.locf(zoo::na.locf(z, na.rm = FALSE), fromLast = TRUE)}), by = x_edipn, .SDcols =
demographic_cols]
rm(demographic_cols)


#loading in local rates for each month
rateLong <- pivot_longer(rateTable,2:341)
names(rateLong) <- c("per","MHA.Name","rate")
aim2x <- left_join(aim2x,rateLong)
rm(rateTable,rateLong)


#removing children with local rates of "0" or "1"
## removes 306,586 months (4,209 unique children) in loctions with a monthly rate of 0 or 1:
1,716,373 months & 25,325 children  -> 1,409,787 months & 21,116 children
cutlist <- unique(aim2x[aim2x$rate==0|aim2x$rate==1,1])
aim2x <- anti_join(aim2x,cutlist)
rm(cutlist)
```

```
#checking for lonely (less than 5) PSUs

testPSU <- aim2x %>% group_by(MHA.Name,per) %>% summarise(n=n(),rate=mean(rate))


#removing children who ever resided in a "county cost group"

## removes 354,045 months (5,135 unique children) where children resided in county cost groups:
1,409,787 months & 21,116 children  -> 1,055,742 months & 15,981 children

cutlist <- unique(aim2x[grep("^COUN",aim2x$MHA.Name),1])

aim2x <- anti_join(aim2x,cutlist)

rm(cutlist)


#checking imputed demographics

aim2x$checkRnk <- ifelse(aim2x$rank==aim2x$rnk|aim2x$rank=="XX",1,0)

aim2x$checkBr <- ifelse(aim2x$branch==aim2x$br|aim2x$branch=="V",1,0)


#create an list of unique IDs of final set

aim2kids <- unique(aim2x[,1])

save(aim2kids,file='/[REDACTED]/aim2kids.RData')


#load in PCSmaster file

load('/[REDACTED]/PCSmaster.RData')

names(PCSmaster) <- c("x_edipn","per","Mpcs","Mcumpcs","Msincepcs","MsincepcsNA")

aim2x <- left_join(aim2x,PCSmaster)


save(aim2x,file = '/[REDACTED]/aim2x.RData')


#prep regression data

d1 <- aim2x %>%
select(x_edipn,per,age,sex,br,rnk,rate,event,pcs,cumpcs,sincepcs,AQI,AQImax,Mpcs,Mcumpcs,Msincepc
s,MsincepcsNA)


##recoding categorical variables

d1$FEM_eff <- as.numeric(car::recode(d1$sex,"'M'=-1;'F'=1")) #Male (ref) = -1

d1$FEM_dum <- as.numeric(car::recode(d1$sex,"'M'=0;'F'=1")) #Male (ref) = 0


## Branch of Service where (F) "Air Force" is the reference value
```

```
d1$br_ARMY_eff <- as.numeric(car::recode(d1$br,"'A'=1;'C'=0;'F'=-1;'H'=0;'M'=0;'N'=0")) #Army

d1$br_CG_eff <- as.numeric(car::recode(d1$br,  "'A'=0;'C'=1;'F'=-1;'H'=0;'M'=0;'N'=0")) #Coast
Guard

d1$br_PHS_eff <- as.numeric(car::recode(d1$br, "'A'=0;'C'=0;'F'=-1;'H'=1;'M'=0;'N'=0")) #Public
Health Service

d1$br_MAR_eff <- as.numeric(car::recode(d1$br, "'A'=0;'C'=0;'F'=-1;'H'=0;'M'=1;'N'=0")) #Marines

d1$br_NAVY_eff <- as.numeric(car::recode(d1$br,"'A'=0;'C'=0;'F'=-1;'H'=0;'M'=0;'N'=1")) #Navy

d1$br_ARMY_dum <- as.numeric(car::recode(d1$br,"'A'=1;'C'=0;'F'=0;'H'=0;'M'=0;'N'=0")) #Army

d1$br_CG_dum <- as.numeric(car::recode(d1$br,  "'A'=0;'C'=1;'F'=0;'H'=0;'M'=0;'N'=0")) #Coast
Guard

d1$br_PHS_dum <- as.numeric(car::recode(d1$br, "'A'=0;'C'=0;'F'=0;'H'=1;'M'=0;'N'=0")) #Public
Health Service

d1$br_MAR_dum <- as.numeric(car::recode(d1$br, "'A'=0;'C'=0;'F'=0;'H'=0;'M'=1;'N'=0")) #Marines

d1$br_NAVY_dum <- as.numeric(car::recode(d1$br,"'A'=0;'C'=0;'F'=0;'H'=0;'M'=0;'N'=1")) #Navy


## Rank where (OS) "Officer Senior" is the reference value

d1$rnk_CD_eff <- as.numeric(car::recode(d1$rnk, "'CD'=1;'EJ'=0;'ES'=0;'WO'=0;'OJ'=0;'OS'=-1"))
#Cadet

d1$rnk_EJ_eff <- as.numeric(car::recode(d1$rnk, "'CD'=0;'EJ'=1;'ES'=0;'WO'=0;'OJ'=0;'OS'=-1"))
#Enlisted Junior

d1$rnk_ES_eff <- as.numeric(car::recode(d1$rnk, "'CD'=0;'EJ'=0;'ES'=1;'WO'=0;'OJ'=0;'OS'=-1"))
#Enlisted Senior

d1$rnk_WO_eff <- as.numeric(car::recode(d1$rnk, "'CD'=0;'EJ'=0;'ES'=0;'WO'=1;'OJ'=0;'OS'=-1"))
#Warrent Officer

d1$rnk_OJ_eff <- as.numeric(car::recode(d1$rnk, "'CD'=0;'EJ'=0;'ES'=0;'WO'=0;'OJ'=1;'OS'=-1"))
#Officer Junior

d1$rnk_CD_dum <- as.numeric(car::recode(d1$rnk, "'CD'=1;'EJ'=0;'ES'=0;'WO'=0;'OJ'=0;'OS'=0"))
#Cadet

d1$rnk_EJ_dum <- as.numeric(car::recode(d1$rnk, "'CD'=0;'EJ'=1;'ES'=0;'WO'=0;'OJ'=0;'OS'=0"))
#Enlisted Junior

d1$rnk_ES_dum <- as.numeric(car::recode(d1$rnk, "'CD'=0;'EJ'=0;'ES'=1;'WO'=0;'OJ'=0;'OS'=0"))
#Enlisted Senior

d1$rnk_WO_dum <- as.numeric(car::recode(d1$rnk, "'CD'=0;'EJ'=0;'ES'=0;'WO'=1;'OJ'=0;'OS'=0"))
#Warrent Officer

d1$rnk_OJ_dum <- as.numeric(car::recode(d1$rnk, "'CD'=0;'EJ'=0;'ES'=0;'WO'=0;'OJ'=1;'OS'=0"))
#Officer Junior

## Rank: Enlisted Status where (CD,OS,OJ,&WO) "Officers" are the reference values

d1$rnk_ENLST_eff <- as.numeric(car::recode(d1$rnk, "'CD'=-1;'EJ'=1;'ES'=1;'WO'=-1;'OJ'=-1;'OS'=-
1")) #Enlisted Status Effect coded

d1$rnk_ENLST_dum<- as.numeric(car::recode(d1$rnk, "'CD'=0;'EJ'=1;'ES'=1;'WO'=0;'OJ'=0;'OS'=0"))
#Enlisted Status dummy coded

## Catergorize sincePCS to allow for non-linear time effect
```

```
d1$pm00 <- as.numeric(car::recode(d1$Msincepcs, "-137:-1 = -1; 0 = 1; 1:12 = 0; 13:118 = -1"))

d1$pm01 <- as.numeric(car::recode(d1$Msincepcs, "-137:-1 = -1; 0 = 0; 1 = 1; 2:12 = 0; 13:118 = -
1"))

d1$pm02 <- as.numeric(car::recode(d1$Msincepcs, "-137:-1 = -1; 0:1 = 0; 2 = 1; 3:12 = 0; 13:118 =
-1"))

d1$pm03 <- as.numeric(car::recode(d1$Msincepcs, "-137:-1 = -1; 0:2 = 0; 3 = 1; 4:12 = 0; 13:118 =
-1"))

d1$pm04 <- as.numeric(car::recode(d1$Msincepcs, "-137:-1 = -1; 0:3 = 0; 4 = 1; 5:12 = 0; 13:118 =
-1"))

d1$pm05 <- as.numeric(car::recode(d1$Msincepcs, "-137:-1 = -1; 0:4 = 0; 5 = 1; 6:12 = 0; 13:118 =
-1"))

d1$pm06 <- as.numeric(car::recode(d1$Msincepcs, "-137:-1 = -1; 0:5 = 0; 6 = 1; 7:12 = 0; 13:118 =
-1"))

d1$pm07 <- as.numeric(car::recode(d1$Msincepcs, "-137:-1 = -1; 0:6 = 0; 7 = 1; 8:12 = 0; 13:118 =
-1"))

d1$pm08 <- as.numeric(car::recode(d1$Msincepcs, "-137:-1 = -1; 0:7 = 0; 8 = 1; 9:12 = 0; 13:118 =
-1"))

d1$pm09 <- as.numeric(car::recode(d1$Msincepcs, "-137:-1 = -1; 0:8 = 0; 9 = 1; 10:12 = 0; 13:118
= -1"))

d1$pm10 <- as.numeric(car::recode(d1$Msincepcs, "-137:-1 = -1; 0:9 = 0; 10 = 1; 11:12 = 0; 13:118
= -1"))

d1$pm11 <- as.numeric(car::recode(d1$Msincepcs, "-137:-1 = -1; 0:10 = 0; 11 = 1; 12 = 0; 13:118 =
-1"))

d1$pm12 <- as.numeric(car::recode(d1$Msincepcs, "-137:-1 = -1; 0:11 = 0; 12 = 1; 13:118 = -1"))

#Z score metrical scores

d1$zAGE <- as.numeric(scale(as.numeric(d1$age), scale = TRUE))

d1$zAQI <- as.numeric(scale(sqrt(d1$AQI), scale = TRUE))

d1$zAQImax <- as.numeric(scale(sqrt(d1$AQImax), scale = TRUE))

d1$zRATE <- as.numeric(scale(sqrt(d1$rate), scale = TRUE))


d1$event <- as.numeric(d1$event)

save(d1,file = '/[REDACTED]/d1.RData')



# Intercept Only Model ----

M0 <- glmer(event ~ 1 + (1|x_edipn), data=d1, family = binomial)

save(M0,file = '/[REDACTED]/ppr3 data/M0.RData')



M0variances = as.data.frame(VarCorr(M0))
```

```
M0cluster_var = M0variances[1,'vcov']
resid_var = (pi^2)/3
M0ICC <- M0cluster_var/(M0cluster_var + resid_var) # ICC = 9.48%
r.squaredGLMM(M0) #R2= 0.02139574

# M1
M1 <- glmer(event ~ per + zAGE + FEM_eff + zAQI + zAQImax + zRATE +
              br_ARMY_eff + br_NAVY_eff + br_MAR_eff + br_CG_eff + br_PHS_eff +
              rnk_ENLST_eff + zAGE * FEM_eff +
              (1|x_edipn),
            data=d1, family = binomial)
summary(M1)
save(M1,file = '/[REDACTED]/ppr3 data/M1.RData')

Anova(M)
# approx R2
r.squaredGLMM(M1, null = M0) # R2 =  0.03899835

# M2x= M1 + L2 time variable
M2x <- glmer(event ~ per + zAGE + FEM_eff + zAQI + zAQImax + zRATE +
              br_ARMY_eff + br_NAVY_eff + br_MAR_eff + br_CG_eff + br_PHS_eff +
              rnk_ENLST_eff + zAGE * FEM_eff + Mcumpcs +
              (1|x_edipn),
            data=d1, family = binomial)
summary(M2x)
save(M2x,file = '/[REDACTED]/ppr3 data/M2x.RData')



# approx R2
r.squaredGLMM(M2x, null = M0) # R2 =  0.03884428

# M3x= M2x + L1 categorical time variable
M3x <- glmer(event ~ per + zAGE + FEM_eff + zAQI + zAQImax + zRATE +
               br_ARMY_eff + br_NAVY_eff + br_MAR_eff + br_CG_eff + br_PHS_eff +
               rnk_ENLST_eff +
```

```
                zAGE * FEM_eff + Mcumpcs + pm00 + pm01 + pm02 + pm03 + pm04 + pm05 +
                pm06 + pm07 + pm08 + pm09 + pm10 + pm11 + pm12 +
                (1|x_edipn),
              data=d1, family = binomial)
summary(M3x)
save(M3x,file = '/[REDACTED]/ppr3 data/M3x.RData')


# approx R2
r.squaredGLMM(M3x, null = M0) # R2 =  0.04034494



anova(M1,M2x) #p = <.001
anova(M2x,M3x) #p = <.001


#Plotting
p1data <- read_xlsx('/[REDACTED]/ppr3 data/Paper 3 Tables.xlsx',sheet = 4)
p1data$order <- 1:nrow(p1data)
# p1data[21,2] <- "Don't Know Type"
# p1data[22,2] <- "Refused to Answer"
# p1data[4:5,1] <- "Gap in\nInsurance\nCoverage"
# p1data[16:22,1] <- "Insurance\nType"
# p1data[26:27,1] <- "Parental\nVeteran\nStatus"
p1data <- p1data %>% mutate(Variable=factor(Variable,levels =
rev(Variable)),Category=factor(Category,levels = unique(p1data$Category)))


p1 <- ggplot(p1data)+
  geom_hline(yintercept = 1, color="red")+
  geom_hline(yintercept = c(0.5,2), linetype= "longdash", alpha=.5)+
  geom_errorbar(aes(x=Variable,y=OR,ymin = LB,ymax = UB),width=.2)+
  geom_point(aes(x=Variable,y=OR), shape = ifelse(is.na(p1data$p),17,ifelse(p1data$p<0.05,8,16)))
+
  scale_y_continuous(breaks = c(.5,1,1.5,2,2.5),limits = c(.3,2.4),labels = c("0.5\nHalf
as\nLikely","1\nEqually\nLikely","1.5","2\nTwice as\nLikely","2.5")) +
  coord_flip()+
  facet_grid(rows=vars(Category), scales = "free_y", space = "free",switch = "y") +
  theme_bw()+
```

```
  theme(strip.placement = "outside", strip.text.y.left = element_text(angle = 0)) +


  #annotate(geom = "text",x=14,y=1.25,label="n=2; OR= 13.73, LL= 1.12, UL= 167.53")+

  labs(y = "Model-Implied Odds Ratio (95% CI)", x = NULL, title = "Model-Implied Odds
Ratios\nfrom the Final Regresson Model", caption = "Note. n= 1,055,742 months (L1) and 15,981
children (L2); 'Ref' = Refence Value and is marked with a '▲';\nSignificant values (p < .05) are
marked with an asterisk; Not-significant values (p > .05) are marked '●'.")


ggsave(filename="ppr3plt1a.png",plot = p1,path = '/[REDACTED]',width = 6.5,height = 8.5,units =
"in")


## Plot 2 Model 3 interactions

### GRAPH 1 line plot for a binary x continuous variable interaction effect ----

### (a) extract interaction and create a new dataset using 'effects' package ----

intdata_ageXfem <- as.data.frame(effect(term="zAGE:FEM_eff", # INTERACTION TERM AS IT APPEARS IN
MODEL

                                        xlevels= list(FEM_eff=c(-1, 1)), #specify levels of
moderator

                                        mod=M3x)) #specify model

### (b) make categorical/binary variable a 'factor' non-numeric variable for graphing ----

intdata_ageXfem$Fem_as_factor <- as.factor(intdata_ageXfem$FEM_eff)

### (c) create labels for the categorical/binary variable for graphing ----

intdata_ageXfem$Fem_as_factor <- as.factor(car::recode(intdata_ageXfem$Fem_as_factor,

                                                       "

                                                           '-1' = 'Male';

                                                           '1' = 'Female'

                                                           "))

### (d) plot ----


intdata_ageXfemOR <- intdata_ageXfem

intdata_ageXfemOR$fit <- exp(intdata_ageXfemOR$fit)

intdata_ageXfemOR$upper <- exp(intdata_ageXfemOR$upper)

intdata_ageXfemOR$lower <- exp(intdata_ageXfemOR$lower)



p2 <- ggplot(intdata_ageXfemOR, # check your dataset name!

       aes(x = zAGE, y = fit,  # continuous predictor

           colour = Fem_as_factor,
```

```
          linetype = Fem_as_factor)) + # categorical predictor (moderator)

  xlab("L1 Child Age in Months (Z)") + # x-axis label (must be a continuous predictor)

  ylab("Likelihood of Facility-Treated Astham Exacerbation\n(Model-Implied OR) with 95% CIs") + #
y-axis label (outcome) \n creates a line break

  labs(fill = "Gender") +     # legend title label

  labs(color = "Gender") +    # legend title label, repeat for each line characteristic

  labs(linetype = "Gender") + # legend title label, repeat for each line characteristic

  labs(alpha = "Gender") +    # legend title label, repeat for each line characteristic

  geom_point() +

  geom_line(size=1) +

  geom_ribbon(aes(ymin=lower, ymax=upper, fill=Fem_as_factor), # categorical predictor (different
lines)

              alpha=0.2) + #alpha =transparency

  scale_color_manual(values=c("salmon", "skyblue")) + # number of colors = number of groups

  scale_fill_manual(values=c("salmon", "skyblue")) + # number of colors = number of groups

  scale_linetype_manual(values=c("solid","dotted")) + # types of lines = number of groups

  scale_x_continuous(breaks = c(-3, -2, -1, 0, 1, 2, 3)) +

  scale_y_continuous(limits = c(1.02,1.08), breaks = c(1.02, 1.04, 1.06, 1.08)) +

  theme_bw() + # for black & white background and gridlines

  #theme_classic() + # other popular background, no gridlines

  theme(axis.text.x = element_text(size = 10, color = "black")) +

  theme(axis.text.y = element_text(size = 10, color = "black")) +

  theme(axis.title.x = element_text(size = 12, face="bold")) +

  theme(axis.title.y = element_text(size = 12, face="bold")) +

  theme(legend.position="bottom") + # placement of legend

  theme(legend.background = element_blank(),

        legend.box.background = element_rect(colour = "black")) + # border for legend

  theme(legend.text = element_text(size = 10)) +

  theme(legend.title = element_text(size = 12, face="bold"))


ggsave(filename="ppr3plt2.png",plot = p2,path = '/[REDACTED]',width = 6.5,height = 8.5,units =
"in")

+++++++++++++++ End File +++++++++++++++
```

Chapter 5 – Conclusion

This work aimed to determine if geographic relocation increased the likelihood of pediatric asthma. Using Bronfenbrenner's Ecological Systems Theory and a novel application of the Ecological Transition concept, we examined geographic relocation's physical and psychosocial effects on children with asthma. This established a solid theoretical foundation that guided inclusion and exclusion criteria, variable selection, and an analytical approach for the other studies. The cross-sectional analysis of the Asthma Call-Back Survey data served as proof of concept of joining air quality data at the individual level. It was determined that children of veteran parents experienced asthma exacerbation at the same rate as children of non-veteran parents. The final study built off the approach of the second and found that geographic relocations increased the likelihood of facility-treated asthma exacerbations in children of military families.

One of the biggest implications for the study of pediatric asthma outcomes is the theoretical approach. It addresses social triggers of asthma exacerbation that the child may not even be directly exposed to, along with triggers from the physical environment. This approach will facilitate future studies by identifying seemingly disparate factors that may drive asthma outcomes.

Implications for clinical practice start with the knowledge that asthma exacerbation is more likely in the first few months following a geographic relocation. Families who have children with asthma should be made aware of the increased risk during geographic relocations. A potential mitigation strategy may be to establish contact with the gaining clinic ahead of the move to shorten or eliminate the time a healthcare provider does not cover the child.

This work leads to two areas of future work. First would be to retest the air quality variable. In the second study, the annual average of the monthly maximum Air Quality Index (AQI) was significant, and the monthly max AQI in the third study was not significant. It is possible that AQI may only be predictive when it measures chronic high exposures. The future study would be the same as the third, except instead of the local monthly daily average and max AQI for each child, it would be that child's monthly max AQI averaged for their last twelve months.

Another area of future work would be to look at how parent deployment affects facility-tread asthma exacerbation. Using Ecological Systems Theory as a framework for social interactions at the child's meso- and exosystem may cause an increased likelihood of asthma exacerbation due to significant stress. This may also be tested with geographic relocation to help explain the increased likelihood of facility-treated asthma exacerbations.

In conclusion, the findings from this study added to the existing literature on pediatric asthma and geographic relocations. This understanding is important for healthcare providers and policymakers alike. It remains a significant area of research due to the high prevalence of military family geographic relocation and the high prevalence of asthma.