ABSTRACT

Title of thesis: INPATIENT MORTALITY IN EMERGENCY CARE: IS COMPETITION ALWAYS GOOD?

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The objective of this study was to measure the association between regional competition and emergency care outcomes. Competition was measured using the Herfindahl-Hirschman Index for three hospital referral regions in Maryland. Preliminary regression analysis using a logistic binary model showed that higher competition was associated with lower odds of mortality. Further investigation suggested that competition could be endogenous. Further regression analysis using an instrumental variable of hospital system affiliation and two-stage least squares estimation showed that lower competition was associated with lower odds of mortality for sepsis and trauma (OR = 0.7, p-value <0.001, OR = 0.5, p-value <0.001, respectively). Future investigation perhaps on a national level could help identify a stronger, more uniform association between competition and emergency care outcomes including large scale events, and as such provide policy guidance for quality of emergency care.

INPATIENT MORTALITY IN EMERGENCY CARE: IS COMPETITION ALWAYS GOOD?

By

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And to Mom, for taking me to the library.

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2SLS	Two-Stage Least Squares Estimation
ACA	Affordable Care Act
AHA	American Hospital Association
AHRQ	Agency for Healthcare Research & Quality
CDC	Centers for Disease Control and Prevention
CMS	Centers for Medicare & Medicaid Services
ECSC	Emergency Care Sensitive Condition
ED	Emergency Department
EDGT	Early Goal-Directed Therapy
HHS	U.S. Department of Health and Human Services
HCUP	Healthcare Cost and Utilization Project
HHI	Herfindahl-Hirschman Index
HSCRC	Health Services Cost Review Commission
HRR	Hospital Referral Region
IOM	Institute of Medicine
OLS	One-Stage Least Squares Estimation
SID	State Inpatient Database
STEMI	ST-Segment Elevation Myocardial Infarction

1: Introduction and Background

With the increased focus on aligning quality and cost in healthcare, many hospitals have consolidated into hospital systems over the past two decades (Cuellar & Gertlar, 2003). This wave of mergers and acquisitions adds a competitive dimension to the quality of care paradigm, generating debate about the relationship between competition and delivery of healthcare. Basic economic theory posits that increased competition among providers generates higher quality (Baker, 2001); but this may not be true in unplanned critical illness due to (1) the immediate demand given the sudden occurrence of illness, (2) the lack of transparency in health care price and quality and overall inability of patient to consider emergency medical care as a consumer good, and (3) reliance on cooperation between multiple components of the healthcare sector as well as between multiple hospitals to provide optimal medical care. For sudden, critical illness and injury, appropriate and timely emergency care is the difference between life and death - underscoring the need to explicitly examine the role of competition in emergency care-specific outcomes.

It is possible for competition to drive quality in healthcare markets for scheduled and elective services (Kessler & McClellan, 2000; Sari, 2002; Porter & Teisberg, 2006; Cooper, Gibbons, Jones, McGuire, 2010). For planned care, consumers have the opportunity to research and choose the best facility based on a variety of perceived and technical hospital quality indicators (Miller, 1996). In the traditional economic theory of market competition, consumers are assumed to have full information to the quality of services that they purchase (Robinson, 1988), but this not always be in the case in healthcare. Planned care is foreshadowed whereas critical incidents that necessitate emergency care are unlikely to be known by the individual before its occurrence (Lien, Chou & Liu, 2009). As a result, emergency care is inherently different. In cases of sudden, serious illness or injury, the provision of emergency care is intrinsically geography- and time-bound (Carr, Caplan, Pryor & Branas, 2006). The innate differences between planned and unscheduled care require a framework that addresses the unique challenges of the emergency care system.

In the landmark emergency care report, the Institute of Medicine's (2006) call for greater coordination between emergency care services suggests that cooperation in the emergency care system results in positive outcomes. It is much easier to build an organized and effective system of care when the scope is within a single, integrated hospital system, rather than a number of competing hospitals vying for greater market shares and profit margins. The U.S. economy typically relies on market competition. However, in health care, competition pits clinician against clinician, and hospital against hospital (Nugent, 2003). These conflicting financial interests render it difficult, if not impossible, to fulfill the IOM's (2006) vision of a high quality, coordinated emergency care system (Enthoven & Tollen, 2005).

The need for improvement in quality and safety of health care has been reiterated by federal, state, industry, and non-government agencies (Institute of Medicine, 2001; Agency for Healthcare Research and Quality, 2005). Increasingly stressed healthcare budgets (Kaiser Health News, 2012) coupled with national pressures for quality improvement force states and hospitals to reevaluate policies and allocation of resources. Despite the considerable number of performance improvement activities (Hibbard, Stockard & Tusler, 2003) and development of emergency department (ED) therapeutic interventions (Kaji et al., 2010; Cairns & Glickman, 2010), there are often consequential delays in treatment for emergency care sensitive conditions, including sepsis, trauma, acute ischemic stroke, cardiac arrest, and ST-segment elevation myocardial infarction. This lack of coordination is reflective of not only the emergency care system, but a larger, systemic failure in the current health care delivery system in the United States.

The Affordable Care Act (ACA) reiterates the need for care coordination (Kaiser Family Foundation, 2014; Balto & Kovacs, 2013), spurring a frenzy of hospital mergers (Dafny, 2014). While the appropriate level of competition in healthcare is largely inconclusive (Gaynor & Town, 2012; Dafny, 2014), one may consider the notion that healthcare competition may not be intrinsically good or bad (Dash & Meredith, 2010). An examination of the impact of competition on quality and patient outcomes, specifically in emergency care, is warranted. To bridge this gap, this study examined the association between regional levels of competition and mortality for emergency care sensitive conditions using inpatient data from the state of Maryland.

Adopting a macro-oriented approach, the State of Maryland's innovative hospital payment system incorporates uniform rate-setting to control costs and improve the overall quality of care in Maryland hospitals (Health Services Cost Review Commission, 2011). As the nation watches the Maryland model unfold, other states may be interested in experimenting with rate-setting systems. Under the regulated payment system, the state of Maryland allows for a unique analytical study of the relationship between hospital competition and emergency care outcomes.

2: Review of Healthcare Competition and Emergency Care Literature

Competition holds the promise of bringing the socially optimal combination of price and quality (Baker, 2001). Previous studies have found positive effects of competition on quality, social welfare, mortality and price (Gaynor & Town, 2012; Kessler & McClellan, 2000; Miller, 1996; Bloom, Propper, Seiler, Van Rennan, 2010). Consolidated systems can raise prices through its dominant market influence (Capps, 2010; Melnick, Shen & Wu, 2011; Balto & Kovacs, 2013; Rosenthal, 2014), increasing costs for consumers.

The American Hospital Association (AHA) (2014) defines a system as a “multihospital system with two or more hospitals owned, leased, sponsored or contract managed by a central organization … but does not preclude network participation.” As hospital mergers and acquisitions take place, systems of care are formed among the various hospitals. A study of hospital consolidation in the nation’s 306 hospital referral regions (HRR) found that hospital prices in concentrated local healthcare markets were significantly higher (Robinson, 2011). While large health systems are capable of creating economies of scale, these cost savings may not be passed onto consumers (Gaynor & Town, 2012). In essence, hospital competition allows providers to compete on not only price but also quality indicators (Miller, 1996), potentially driving improvements in delivery of care.

In contrast to the U.S.’s traditionally free-market, competitive approach towards the economy, many of the ACA reforms drive market consolidation in the healthcare market (Gottlieb, 2012; George, 2013; Pope, 2014). Hospitals face ACA-related challenges (Pope, 2014), including reduced Medicare reimbursements (Congressional

Budget Office, 2010), improving operational efficiency through smooth care transitions (Balto & Kovacs, 2013; HHS, 2014), and managing population health (Dafny, 2014). These goals are designed to improve care of coordination among providers and generate high quality care (Anderson, 2014).

From a systemic perspective, the U.S. healthcare system's lack of coordination presents a significant and fundamental challenge in delivery of quality care and ensuring patient safety (Institute of Medicine, 2001). While hospital consolidation emerges as the healthcare industry's premier solution to these reforms and emerging threats, other methods of achieving the ACA's goals of operational efficiency and smooth care transitions include use of health information exchanges, communal learning networks and accountability (HHS, 2014), ultimately revolving around the idea of collaboration among multiple hospitals.

The logic behind hospital consolidation complements the ACA's goals of improving care coordination (Kaiser Family Foundation, 2013); integrated hospitals can provide seamless transitions in care. Consolidated systems are able to create economies of scale (Balto & Kovacs, 2013) and produce better outcomes (Cutler & Morton, 2013; Romano & Balan, 2010; Tsi & Jha, 2014). Findings from disease management literature support this; patients with moderate to severe illness experience benefits from coordinated care (Wennberg & Wennberg, 2003). Within integrated systems, hospitals are financially incentivized to work together to offer a continuum of care (Wan, Lin & Ma, 2001) by pooling resources and increasing clout.

Despite the overall fragmentation of the health care delivery system, notable healthcare delivery systems throughout the country improved quality and patient outcomes, cut costs, or both through its organizational processes (Shih, Davis, Shoenbaum, Gauthier, Nuzman & McCarthy, 2008). These high-performing health systems reveal the ability of integrated health systems to achieve coordination of care (Shih et al., 2008). The Geisinger Health System, a commonly highlighted example of positive hospital consolidation outcomes (Tsi & Jha, 2014), implemented a coordinated bundle of evidence-based best practices, resulting in a “100 percent lower in-hospital mortality [and] 21 percent decrease in patients with any complications” (McCarthy, Mueller & Wrenn, 2009). Furthermore, average length of stay, hospital readmissions, and overall treatment costs have all decreased substantially (Menninger, 2009). Similarly, the Mayo Clinic developed its model of integrated care, as documented in its *Mayo Clinic Model of Care*, to achieve quality improvement initiatives. The system’s redesigned care processes to improve the timeliness of heart attack treatment, by reducing door-to-balloon time from 92 minutes to 60 minutes (McCarthy, Mueller & Wrenn, 2009). The correlation between integrated hospital systems and positive performances can prompt further consolidation to take place, but also spur collaboration among different hospital systems to achieve the same system-based outcomes for the entire population.

2.1 Hospital Consolidation Trends

Adopting this rationale, healthcare markets across the nation are undergoing a considerable number of mergers, transforming previously independent hospitals into a health system centered on inpatient institutions (Cutler & Morton, 2013). In the pre-ACA period of 1999 to 2003, the typical metropolitan statistical area experienced a reduction from six to four competing local hospital systems (Vogt & Town, 2006), reducing the number of solo hospitals (Cuellar & Gertlar, 2003). This trend continues into the next decade; from 2007 to 2012, 432 mergers and acquisitions were announced, involving 832 hospitals (Cutler & Morton, 2013).

This anticompetitive trend is reflected at the state level as well. In 2012, only 15 of Maryland's 46 general hospitals were independent (Gantz, 2012). These remaining independent hospitals in Maryland are at risk for financial insolubility as they cope with the pervasive problems of reduced reimbursement rates, weak negotiating clout, and lack of resources to meet the ACA's mandates of increased reporting and adoption of electronic health records (Weintraub, 2010). A prominent organizational strategy to enhance capabilities or procurement is to form partnerships with other organizations (Provan, 1984), leading to horizontal integration. Horizontal integration takes place when organizations, hospitals in this case, at the same level merge together (Investopedia, 2014). For example, Sibley Memorial Hospital joined the Johns Hopkins Health System, located in Baltimore, MD, to generate "more efficient, integrated regional health care services for patients" (Sibley Memorial Hospital, 2010). Similarly, Regional Health System, Meritus Health and Western Maryland Health System are in strategic discussions to create a regional alliance between the three independent hospitals (Meritus Health, 2014). As the number of independent, unattached hospitals diminish, patients will ascertain the proposed consolidation benefits along with its unintended consequences.

Antitrust laws exist to protect consumers from higher prices resulting from monopolistic activity (Balto & Kovacs, 2013), such as mergers and acquisitions. Under the premise of a competitive environment, a greater number of firms will promote economic welfare and efficiency, because it becomes more difficult for firms to coordinate behaviors, (Bazzoli Marx, Arnould & Manheim, 1995, 1995) such as price setting. However, this also makes it more difficult for the firms to facilitate care coordination or resource sharing, creating quality concerns (Bodenheimer, 2008).

As policymakers and hospital industry debate over extent to which government regulation is needed to regulate healthcare market consolidation (Bazzoli et al., 1995; Ho & Hamilton, 2000), it is important to consider the endogeneity of healthcare competition. Both competition and consolidation approaches offer quality improvements, suggesting that a contextual framework may be appropriate in examining this intricate relationship in emergency care.

Demand for healthcare is considered largely inelastic (Newhouse & Phelps, 1974; Ringel, Hosek, Vollard & Mahnovski, 2002), but price elasticity may be even more rigid in emergency care. The unplanned nature and severity of emergency care is exposed to substantial time and geography constraints. For instance, the closest facility could be considered the “best” facility, opposed to hospital quality and condition-specific considerations. Hospital Compare, a CMS innovation for information about quality of care, states that the website’s resources may be used as guidance for planned health care needs, but recommends the nearest hospital in an emergency. This juxtaposition signifies the need to differentiate between planned and unplanned care, when assessing quality and outcomes.

2.2 Delivery of Emergency Care

The ACA reforms are centered on aims of care coordination, quality, and cost-cutting but frame around chronic disease management and scheduled care considerations, rather than emergency care. The ACA’s goals are largely influenced by minimizing economic costs opposed to years of productive life lost, implications of a poorly-functioning emergency care system. For planned care, coordination and operational efficiency among accountable care organizations (ACOs) and patient-centered medical homes promote the creation of “teams,” creating the notorious silos in healthcare. Because there is no competitive advantage in sharing information between different teams that do not share common goals, information is not shared and there is little interoperability among these providers.

The consequences of this fragmentation and lack of communication in emergency care systems is intensified in this context. Acute unscheduled care poses significant and stringent time-bounds in order to improve patient outcomes and requires intensive resources. For instance, a car crash instigates a bystander to call 9-1-1 for help. The injured individual is taken to the nearest hospital, with little to no regard for the patient’s preference for treatment location, especially if the patient is unable to communicate. The nearest hospital may not offer the subspecialty care required for the individual’s condition – requiring a compromise between the hospital’s desire for greater economic gain and the patient’s best interest. The hospital needs to be willing to give away the patient, a source of revenue, to another facility that can better meet his or her needs to ensure good patient outcomes. In this sense, the emergency care system requires substantial continuum of care – the ED and emergency medical services (EMS) should pass on information to promote greater coordination of care and ultimately, ensure improved population health.

The ED plays a unique and substantial role in this framework of population health outcomes. The ED represents the most available and immediate source of care for critical, acute illness, while simultaneously serving as a gateway for inpatient admissions, offering access to specialty and diagnostic services (Braithwaite, Pines, Asplin & Epstein, 2011). Emergency care utilization is a function of the severity of patient's complaint, time, and proximity (Ragin et al., 2005; Richardson & Hwang, 2001).

The ED functions in a comprehensive capacity; it is a critical staging area for unplanned and acute illness (Schurr, Hsia, Burstin, Schull & Pines, 2013) and a safety net provider. For uninsured patients, the ED can function as a source of usual care (Emergency Medical Treatment & Labor Act, 2003). As a result, high ED utilization trends reflect its integral role on the healthcare spectrum. Since 1997, the annual number of ED visits has increased by 23% (Niska, Bhuiya & Xu, 2010), comprising of nearly all growth for inpatient hospital admissions (Morganti et al., 2013). Depending on the type of facility, between 30 to 75 percent of inpatient stays originate from the ED (Pines, 2006), with a national average of 12.5 percent of inpatient admissions. Inpatient admissions serve as the bulk of the hospital's revenue, amassing to 31 percent of national healthcare spending (Morganti et al., 2013).

While previous studies yield inconclusive results about the financial impact of EDs, whether it accrues profits for the hospital from high costs of care and or incurs losses from its higher severity patient mix (Wilson & Cutler, 2014), the ED acts as an important decision maker for inpatient admissions (Morganti et al., 2013). Furthermore, implementation of the ACA is predicted to increase profits for hospital-based EDs (Wilson & Cutler, 2014). With this financial leverage at stake, hospitals compete for greater market shares, subsequently spurring a high level of internal rivalry in emergency care.

It is important to distinguish between the levels of reimbursement for different conditions – naturally, most health systems focus on improving outcomes for more expensive conditions. However, these lucrative conditions do not comprise of unplanned critical illness. Without the opportunity for greater economic gains, emergency care systems have little incentive to change and implement more patient-centered and population-health focus. The hospital costs for treating septicemia, an emergency care sensitive condition and one of the leading causes of mortality (Centers for Disease Control & Prevention, 2009), is regulated at an average of $19,075 (HSCRC, 2013) in Maryland. On the other hand, a cesarean delivery has associated charges of $23,173 (HSCRC, 2013). The difference in pricing between these two common inpatient conditions reflects the greater profitability in planned and elective care, including procedures such as transplants, chemotherapy, and cardiac surgery, and the need to redesign incentives for emergency care systems to deliver high-quality care.

Coupling the IOM (2006) report on the future of emergency care with the ACA's National Quality Strategy, the emergency care system and the overall health system face analogous challenges and opportunities, underscoring the need for greater coordination of care between the two entities. Reports of substandard and inconsistent emergency care (Plantz, Kreplick, Panacek, Mehta, Adler & McNamara, 1997) serve as impetus for quality improvements. The National Quality Strategy aims to improve access, safety, care coordination, and use of evidence-based interventions to deliver high quality care (HHS, 2011); these objectives are all transferrable to the delivery of emergency care.

Emergency care is inherently team-based, involving multiple providers and interactions between pre-hospital emergency medical services, nurses, and emergency physicians (Schurr et al., 2013; Pines, 2006). High-quality emergency care and smooth transitions requires different systems to interact and work with one another. Additionally, therapeutic interventions for emergency conditions may require substantial resources. A ST-segment elevation myocardial infarction (STEMI) requires percutaneous coronary intervention (PCI), involving both the ED and cardiology units (Rathore et al., 2009), serving as impetus for developing multidisciplinary teams.

Through a cooperative stance, providers may ascertain quality improvements through care coordination, information and resource sharing. On a macro scale, cooperation among medical personnel, suppliers, and facilities in disasters and large scale emergencies is necessary for patient triage and medical surge (Waeckerle, 1991; Jacobs, Ramp & Breay, 1979). After all, the best way to prepare for a large scale disaster is to create an emergency care system that functions effectively on an everyday basis (Kellerman, 2006).

2.3 Emergency Care Sensitive Conditions

Toward the overarching goal of preparedness, the medical community can examine and enhance the emergency system's functions and outcomes on a day to day basis. Despite these beneficent intentions, quality measurement for emergency care requires more refinement. CMS's Physician Quality Reporting Initiative Program and Hospital Compare, as well as accrediting agencies including the Joint Commission, provide quality measures. However, many of the proposed measures do not reflect the systemic nature of emergency care problems and outcomes, in addition to integrating the goal of providing high-value, integrated emergency care (Schurr et al., 2013).

Positive emergency care outcomes reflect the ability of the whole emergency system to provide coordinated, quality care, opposed to just examining the capabilities or processes of a single facility. The emergency care sensitive conditions (ECSC) framework identifies conditions for which rapid diagnosis and timely intervention significantly impact patient outcome (Carr et al., 2010). The development of this quality measurement paradigm is analogous to AHRQ's ambulatory care sensitive conditions, for which high quality preventative care may reduce hospitalizations (National Quality Measures Clearinghouse, 2014). ECSCs include ischemic stroke, cardiac arrest, sepsis, trauma, and STEMI – the outcomes of these time-sensitive conditions can reflect high-quality emergency care.

For these emergency conditions, the patient would be taken to the most appropriate facility based on the severity of the condition or facilities' distances (Institute of Medicine, 2006) in efforts to promote better quality care and outcomes. It emphasizes the concepts of cooperation and commitment to safety, in order to get the patients the right care at the right place at the right time (Kellermann & Martinez, 2011).

Appropriate treatment for emergency care sensitive conditions may require a substantial number of resources, in addition to rapid diagnosis, creating a need for different emergency care services to collaborate in order to promote patient outcomes. The trauma system's success in significantly reducing mortality for traumatic injuries (MacKenzie et al., 2006) highlights the benefits of regionalization towards providing patients with the resources they require in a timely manner (Myers, Branas, Kallan, Wiebe, Nance & Carr, 2011). Because not all hospitals contain trauma centers or resources to adequately care for trauma patients, there has been significant system planning to ensure efficient and effective delivery of care (Branas, MacKenzie & ReVelle, 2000). Through this approach towards population outcomes, the trauma system can serve as impetus for development of coordinated systems towards the goal of improving population health, for other unplanned critical illness, such as acute ischemic stroke, STEMI, and cardiac arrest.

Stroke and STEMI can be detected by ambulance staff to an extent (Harbison, Hossain, Jenkinson, Davis, Louw & Ford, 2003; Eckstein, Cooper, Nguyen & Pratt, 2009) indicating a minor difference between these two condition from cardiac arrest and sepsis, which require more equipment and tests to diagnose. Furthermore, the diagnostic opportunity during paramedic transport reinforces the need for greater system communication and collaboration to ensure that stroke and STEMI patients are delivered to the most capable facility. Stroke patients that receive early stroke treatment, tissue plasminogen activator (rt-PA) have better outcomes, if treatment is administered within 90 minutes (Marler et al., 2000). Ambulance staff, as well as patients' families, can perform a face arm speech test for suspected stroke patients (Harbison et al., 2003) and with adequate knowledge of stroke symptoms. This can eliminate the need for transfers from within facilities or to another hospital, in order for the stroke patient to receive the necessary treatment. Similarly, STEMI can be diagnosed by an ambulance ECG (Eckstein et al., 2009) to ensure that the patient receives the necessary reperfusion therapy. For stroke and STEMI patients, hospitals that have the resources to effectively treat these conditions are obviously better suited and can promote improved patient outcomes. These evidence-based strategies demonstrate reduced odds of mortality and can be considered in emergency care system models to improve collaboration between 9-1-1 dispatchers, EMS staff, EDs and hospitals.

Cardiac arrest has considerably high rates of mortality (McNally et al., 2009). Its high fatality rate poses a significant public health burden. In out-of-hospital cardiac arrests, induced hypothermia has demonstrated improved outcomes and survival (Bernard et al., 2002). However, only nine hospitals in the state of Maryland offer therapeutic hypothermia resources, implying the need for collaboration and resource sharing among providers in the state.

While the etymology of the term ‘emergency care’ fixates on the emergency department, quality care and patient outcomes are a byproduct of the whole emergency care system. The U.S. healthcare system is highly fragmented and variable (IOM, 2006), resulting in inefficient and poor quality care. Upon consideration of emergency preparedness and the ECSC framework, themes of cooperation and collaboration emerge. As quality measures are beginning to shift towards assessing and incentivizing care coordination, meaningful measures must also include the most basic outcomes measure on the lowest end of the quality spectrum, mortality.

2.4 Sepsis – A Public Health Concern

There are a number of ED interventions that have demonstrated reduced mortality and improved outcomes for patients with acute, time-sensitive conditions (Kaji et al., 2010) but have not been implemented nationally. Sepsis, a costly condition, remains a major public health concern (Angus, 2010; Rhee, Gohil & Klompas, 2014). The condition manifests itself as a potentially life-threatening complication of a severe infection (Al-Khafaji, Sharma & Eschun, 2014), characterized by pathogenic microorganisms (Weidemann, 2007). Without adequate medical attention, the immune system remains in a state of dysregulated inflammation (Rhee et al., 2014) and triggers widespread inflammation and subsequent cellular injury in body tissues (Chang, Lynm &

Glass, 2010). This may lead the development of one or multiple organ dysfunctions (American College of Chest Physicians/Society of Critical Care Medicine Consensus Conference, 1992), acting in a cascade ranging from systemic inflammatory response syndrome to septic shock (Bone, 1991).

There are a number of proven emergency department interventions designed to reduce mortality and improve outcomes for patients with acute, time-sensitive illnesses (Cairns & Glickman, 2010; Kai et al., 2010). Despite twenty years of extensive research, therapeutic approaches to sepsis have not been successfully translated to the clinical setting (Rittirsch, Fierl, Ward, 2008). Rivers et al. (2001) introduced Early Goal Directed Therapy in 2001 as a protocol-based resuscitation, involving the use of a central venous catheter, blood transfusions, medications, and involvement of critical-care clinicians. In this landmark study, Rivers et al. (2001) suggest that the use of Early Goal-Directed Therapy (EGDT) provide significant benefits for sepsis patient mortality outcomes, later serving as one the "cornerstone of the Surviving Sepsis Campaign guidelines" (Levinson, Casserly & Levy, 2011).

While there remains controversy over sepsis coding methodology (Gaieski et al., 2013; Angus et al., 2001; Wang, Shapiro, Angus & Yealy, 2007; Dombrovskiy et al., 2007; Martin, Mannino, Eaton & Moss, 2003) and care mandates (Rhee et al., 2014; Peake et al., 2014; Yealy et al.; 2014), "increased [awareness] and recognition of novel therapeutic strategies have led to renewed focus by hospitals to improve outcomes in patients with sepsis" (Gaiski et al., 2013).

2.4.1 Sepsis Incidence and Mortality

Despite national attention on quality improvement and the condition itself, sepsis incidence and mortality rates continue to increase (Gaiski et al., 2013; Martin, Mannino, Eaton & Moss, 2003; Hall, Williams, DeFrances & Golonskiy, 2011). Kaiser Permanente (2012) attributes sepsis to causing more deaths in California hospitals than stroke, heart disease or cancer. Despite the decrease in the case fatality rate, researchers found that the national rates of death from severe sepsis increased (Gaieski et al., 2013). The number of hospitalizations for septicemia or sepsis as a first-linked or principal diagnosis increased to 727,000 cases in 2008 (Hall et al., 2011). Sepsis hospitalization rates more than doubled from 2000 through 2008 (Hall et al., 2011) in conjunction with national rates of sepsis mortality increasing (Gaeiski et al., 2013).

As with any condition, it is important to consider other factors that may contribute to the increased incidence. Previous studies have indicated that increased rates of sepsis incidence can be attributed to an aging population with an increasing burden of disease (Hall et al., 2011; Martin et al., 2003; McBean & Rasamani, 2001), increased awareness (Gaieski et al., 2013), greater use of invasive procedures, immunosuppressive drugs, use of chemotherapy and transplantation, microbial resistance to antibiotics (Hall et al., 2011) and improvement in coding practices for reimbursement schemes (Gaieski et al., 2013; Rhee et al., 2014). In essence, patients with sepsis face significant healthcare challenges ranging on the spectrum of functional disability to death.

While anyone is susceptible to sepsis, the elderly and those with compromised immune systems are at greater risk for developing complications (Ayres, 1985; Hall et al., 2011) and significantly contribute to causes of death for patients admitted to intensive care units (Bochud & Calandra, 2003). Those aged 65 and older had much higher hospitalization rates than those under 65 (Hall et al., 2011). Furthermore, those aged 65 and older hospitalized for sepsis faced a 20 percent mortality rate compared to three percent for other hospitalizations (Hall et al., 2011). As the aging population continues to grow, with estimates of the elderly expected to comprise of 20 percent of the total population in 2050 (Ortman, Velkhoff & Hogan, 2014), indicates that sepsis may be of even greater concern in the future.

Sepsis is difficult to predict, diagnose and treat (Centers for Disease Control and Prevention, 2014), resulting in a high mortality rate and potentially diminished quality of life (Yende & Angus, 2007). While death is the most apparent and obvious end point of sepsis, it is important to acknowledge the other consequences of the disease's symptoms of organ dysfunction including neurological impairment, respiratory impairment and renal failure (Yende & Angus, 2007).

2.4.2 War on Sepsis

Sepsis awareness efforts like the Surviving Sepsis Campaign and STOP Sepsis Collaborative are coordinated alliances that encourage collaboration to reduce sepsis mortality (Vassalos & Rooney, 2013; United Hospital Fund, 2014). Despite the controversy of best practices for sepsis coding and therapeutic intervention, analysis of sepsis outcomes can provide insight on the potential benefits of hospital system cooperation on a local healthcare market for emergency care conditions.

Variations in healthcare and inconsistent care practices generate serious concerns about quality of care (Wennberg & Wennberg, 2003). Wennberg (2002) concedes that wide variations in everyday practice are unwarranted in the field of clinical science. Baicker, Chandra & Skinner (2005) noted the differences in treatments and effective care among HRRs, indicating geographic disparities. The implications of variations in clinical interventions can be observed in a variety of fields. Morris (2004) detected errors in clinical setting were linked to the lack of clinical standardization for iatrogenic illness. Similarly, proven interventions for altering the sepsis care pathway exist (Rivers et al., 2001; Yealy et al., 2014; Peake et al., 2014) but there is no national standard for sepsis treatment.

There remains relative ambiguity in denominating a standard sepsis treatment for widespread use. Early aggressive volume resuscitation under the premise of EGDT remains the basis of standard sepsis treatment (Rice & Bernard, 2007) as part of the bundle treatment. A bundle is a group of interventions that product synergistic outcomes when implemented together, rather than individually (Zambon, Ceola, Almeida-de-Castro, Gullo & Vincent, 2008). Recent publications of the ProCESS (Yealy et al., 2014) and ARISE (Peake et al., 2014) trials, reexamining the traditional sepsis bundle treatments, suggest the use of EGDT in sepsis care best practices may be questionable. This is reminiscent of the since-retired pneumonia quality measure, yielding unintended consequences of antibiotic resistance (Schurr et al., 2013). This historical precedence and current ambiguity towards appropriate clinical interventions renders uncertainty towards current sepsis mandates and best practices.

Despite the relative feasibility of implementing a sepsis bundle in the emergency department and intensive care unit setting (Nguyen, Corbett, Steele, Banta, Clark, Hayes & Edwards, 2007; Zambon et al., 2008), compliance rates remain relatively low (Miguel-Yanes, Andueza-Lillo, Gonzalez-Ramallo, Pastor & Munoz, 2006; Zambon et al., 2008; Gao et al. 2005). This can be attributed to a variety of factors, including lack of education

(Ferrer et al., 2008) and inconclusiveness about sepsis best practices (Yealy et al., 2014; Peake et al., 2014) and coding (Gaieski et al., 2013). This lack of general compliance even years after the Surviving Sepsis Campaign guidelines' implementation reveal the need to simplify the bundle to increase its clinical accessibility (Zambon et al., 2008). Hospitals and physicians face a tremendous challenge in diagnosing and treating a disease rapidly and accurately, with minimal guidance.

Previous studies indicate the rate of compliance with the 6-hour and 24-hour sepsis bundles to be 52% and 30%, respectively (Gao, Melody, Daniels, Giles & Fox, 2005). Furthermore, 39% of acute adult emergency patients were admitted to the intensive care unit late into the clinical care pathway (McQuillan et al., 1998) These findings reiterate the need for improving the structure and process of delivery of care (McQuillian et al., 1998). Despite the controversy over the EGDT mandate and the results of the ProCESS and ARISE trials, sepsis bundles demonstrate clinical effectiveness in reducing hospital mortality of sepsis patients (Gao et al., 2005).

In response to the Institute of Medicine's (2001) call for delivering high quality medical care, hospital systems honed in on quality improvement initiatives under the premise of improving outcomes while reducing costs (Shortell, Bennett & Byck, 2001). Several hospital systems engaged in efforts to reduce sepsis mortality through improving early detection and appropriate treatment strategies. Rincon, Bourke & Ikeda (2007) suggest that centralized remote identification of at-risk sepsis patients can improve compliance to sepsis management and best practices. The implementation of a multicenter sepsis bundle at Intermountain Health System resulted in a 59% relative reduction in hospital adjusted mortality rate (Miller et al., 2013). Intermountain Health

System includes 18 intensive care units (ICU) and 11 hospitals in Utah and Idaho (Miller et al., 2013). Similarly, Kaiser Permanente's systematic approach to sepsis identification and management reduced mortality from 24.6% in March 2008 to 11.5% in December 2010 (Crawford, Skeath & Whippy, 2012). This multicenter approach could serve as an organizational framework for other emergency care systems and conditions. In conjunction with these health systems' sepsis initiatives, Penn Medicine's implementation of an algorithm for an early warning system to identify sepsis patients has led to a 4% decrease in sepsis mortality (McCann, 2014). These coordinated efforts and progress towards sepsis reduction reflects the abilities of collaborative and integrated health systems to streamline delivery of care, producing better outcomes (Cutler & Morton, 2013; Bodenheimer, 2008).

2.5 The State of Maryland's Initiative

Quality improvement in sepsis and other emergency care conditions can take place through coordinated clinical efforts as well as policy levers. Hospital costs totaled $387 billion in 2011 (Torio & Andrews, 2013), indicating that costs and quality may be better addressed simultaneously in improvement initiatives. High levels of healthcare spending, accounting for nearly two-fifths of overall U.S. economic activity (KFF, 2012), invite reforms.

Many cite the traditional fee-for-service payment system as the culprit for increased health spending, without corresponding improvements in health outcomes (Orszag & Ellis, 2007). In contrast to the fee-for-service approach of rewarding providers on case volume, Maryland's innovative payment model realigns hospital payments to improve quality of healthcare (HSCRC, 2011). Akin with the ACA's goals of reducing healthcare expenditures and improving health outcomes, the Centers for Medicare and

Medicaid Services (2014) and the state of Maryland established a partnership to develop the nation's only uniform payment regulation system, in which all third parties pay the same rates.

Established in 1971, Maryland's rate-setting system allows the state to control and budget hospital costs (Shurkin, 2014) and more recently, set goals that emphasize quality, not quantity in care (Coyle, 2014). In the past few decades, Maryland has demonstrated success in reducing costs per admission (Anderson, Chaulk & Fowler, 1993) and growth (Murray, 2014), from 24 percent above the national average in 1977 to 11 percent below the national average within two decades (McDonough, 1995). Currently, the system has "saved the sate more than $45 billion in health care costs" (Coyle, 2014).

Maryland's All Payer-Model serves as impetus and potential framework for improving delivery of care (Rajkumar et al., 2014). Maryland hospitals have retained their "reputation for clinical excellence" (Coyle, 2014). The U.S. News & World Report (2014) ranks Johns Hopkins Hospital within the top three performers along with a number of Joint Commission accredited facilities. This partnership between Maryland and CMS can reveal the advantageous link between hospital payment systems and improved health outcomes (Murray, 2014) to serve as a potential model for the rest of the nation.

2.5.1 Sepsis in Maryland

Under the new Medicaid waiver effective January 2014, the state of Maryland is charged with the task of reducing infections and hospital-acquired infections by 30 percent within five years (Centers for Medicare and Medicaid Services, 2014). The current HSCRC quality- and performance-based initiatives identify postoperative sepsis as a patient safety indicator (HSCRC, 2013; AHRQ, 2009), revealing the state's quality improvement enterprise. Going forward, the Maryland Hospital Association and Maryland Patient Safety Center developed Improving Sepsis Survival, a federal-industry sepsis mortality reduction initiative for Maryland hospitals (Maryland Hospital Association, 2014) to meet this target. Sepsis, the most expensive condition treated in hospitals, amounting to over $20 billion in 2011 (Torio & Andrews, 2013), along with its high disease burden, renders it an extremely effectual target in meeting the Medicare Waiver's financial and quality targets.

The Maryland Patient Safety Center operates as a non-for-profit organization and is listed as a Patient Safety Organization by the Agency for Healthcare Research and Quality under the provisions of Patient Safety and Quality Improvement Act of 2005 (Maryland Patient Safety Organization, 2014). Functioning as an American Hospital Association ally, the Maryland Hospital Association is an independent organization focused on serving as Maryland's hospitals and health systems' advocate (Maryland Hospital Association, 2014). The collaboration between these two independent organizations signifies the need, and inherent ability, for quality improvement paradigms to scale beyond just the health system.

Beginning in July 2014, ten Maryland hospitals participated in the initiative's first cohort (Maryland Patient Safety Center, 2014), including hospital systems and independent hospitals. In the Baltimore Hospital Referral Region, participating hospitals include: Carroll Hospital Center, Johns Hopkins Hospital, LifeBridge Health System's Northwest Hospital, LifeBridge Health System's Sinai Hospital of Baltimore and University of Maryland Baltimore Washington Medical Center. Additionally, Holy Cross

Hospital and MedStar Montgomery Medical Center in the Takoma Park Hospital Referral Region are participants as well. The unique mix of hospitals in bed size, affiliation with a health system, location, and reputation allows the sepsis collaborative implementation to not only be more generalizable, but also represents the statewide, collaborative aspect of improving healthcare. As future cohorts unveil, it may become possible to assess the impact of the collaborative on not only sepsis mortality but also guide future quality improvement paradigms.

2.6 Conceptual Framework

Recent hospital consolidation trends bring attention to the role of competition and its influence on delivery of care and controlling costs. There is no consensus, however, as to the appropriate level of competition in health care to facilitate delivery of care. Previous studies have examined the association between competition and price, attempting to extract the influence of cost on the overarching healthcare problem. However, quality problems remain pervasive in the U.S. healthcare system. A number of studies found positive effects of competition on patient outcomes, but cannot be generalized beyond the planned care setting. Consequently, questions remain about the role of competition on emergency care outcomes.

The role of emergency care and its associated challenges, especially in the context of delivery of quality care, remains undetermined. As an essential part of the healthcare system, the ED provides a variety of challenges and opportunities to move forward in the quality of care dialogue. However, a better understanding of the role of competition in emergency care is important, demanding the need for further research in this sector. This retrospective data analysis examined the effect of hospital competition on emergency care outcomes, providing implications for coordination and competition in emergency care.

2.7 Specific Aims

In light of the limitations in previous literature and exigency for a better understanding of quality in emergency care, this study examined the association between hospital competition within a region and inpatient outcomes for emergency care sensitive conditions. If such a relationship exists, this study sought to measure this effect. This cross-sectional, observational data analysis assessed the association of competition on emergency care patient outcomes, focusing on inpatient hospital mortality for five emergency care sensitive conditions: sepsis, trauma, acute ischemic stroke, cardiac arrest and STEMI. In essence, the study sought to characterize the role of competition in emergency care for patient outcomes.

3: Methodology

3.1 Research Question

1. Is there an association between health system competition and emergency care outcomes?

3.2 Study Design

A retrospective regression analysis assessed the effect of hospital system competition for a given hospital referral region on inpatient mortality originating from the emergency department. The analysis focused on the following conditions: Sepsis, trauma, acute ischemic stroke, cardiac arrest, and ST-segment elevation myocardial infarction. This data analysis was conducted using the Agency for Healthcare Research and Quality's Healthcare Costs and Utilization Project, State Inpatient Database (SID) file for

Maryland for dates of service 2012, American Hospital Association, and Dartmouth Atlas of Healthcare.

The SID is collected annually by the Agency for Healthcare Research and Quality, and contains the universe of inpatient admissions to community hospitals for all payer types. The SID data is supplemented by descriptive hospital information from the American Hospital Association (AHA) to enable more in-depth empirical analyses of the role of hospital system competition on emergency care inpatient mortality.

This database contained detailed diagnostic, billing, and patient demographic information for 695,207 inpatient episodes in the 2012 year, of which 70,677 cases were used for the emergency conditions being considered in this study. The Maryland SID is composed of more than 200 variables, including up to 30 International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) diagnoses, discharge status from the ED, admission type (e.g. emergency, urgent, elective), patient demographics (e.g., gender, age, race, urban-rural designation of patient residence, national quartile of median household income for patient's ZIP code), expected payment source (e.g. Medicare, Medicaid, private insurance), admission type and hospital identifiers allowing supplementary hospital-level information (e.g. bed size, teaching status, hospital ownership, and hospital system affiliation) to be linked.

3.3 Analytic Approach

This study examined the association between hospital system competition, the main predictor variable, and inpatient hospital mortality for emergency care sensitive conditions, the study's outcome variable. The conceptual framework is depicted in Figure 1.1. Using AHA data on nonfederal, short-term general and specialty hospitals, the study's analytical database categorized the individual hospitals into hospital systems to calculate a competition measure for the corresponding local healthcare markets. For the purpose of this study, the local healthcare market is delineated as the hospital referral region, as defined by the Dartmouth Atlas of Healthcare (Wennberg & Cooper, 1996).

The study used the Herfindahl-Hirschman Index (HHI) to measure competition and subsequently analyze its association with inpatient hospital mortality for emergency care conditions (Cutler & Morton, 2013). Association between inpatient hospital mortality and the independent variable of hospital competition is examined with the use of a multivariable binary logistic regression model. HHIs were also calculated for inpatient admissions originating from the ED as well as specific conditions under study. These modifications of competition allowed for a comparative analysis of the role of competition, specifically in emergency care.

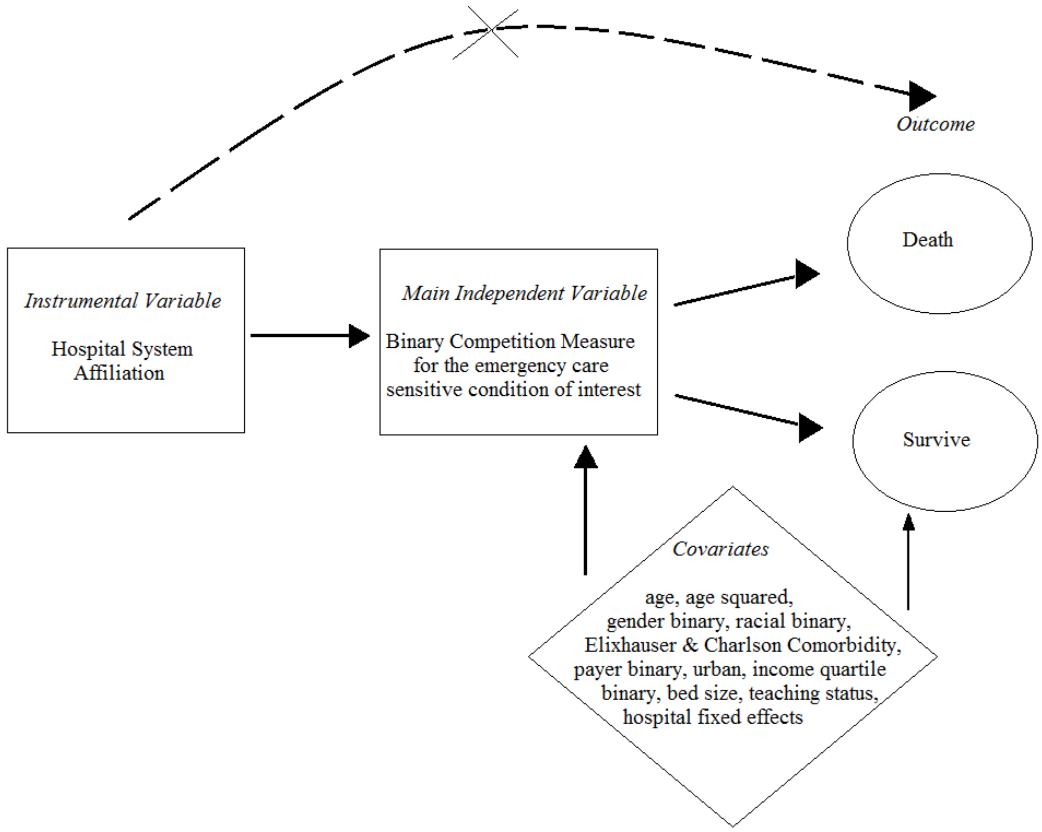

Figure 3.1: Conceptual framework of the regression analysis. Including the instrumental variable of hospital system affiliation, main explanatory variable of regional competition, acting as endogenous, covariates, and the outcome variable of mortality.

3.4 Study Population

The dataset for inpatient admissions, originating from the emergency department, that fit the emergency conditions of interest, contained a total of 70,677 observations. The parameters for study population selection is highlighted in Figure 3.2.

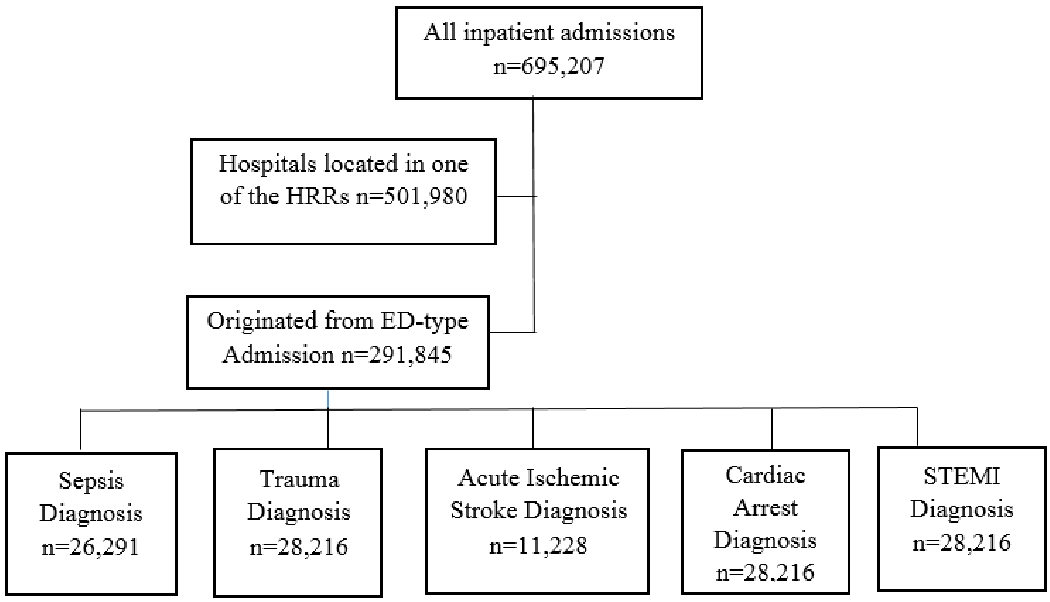

Figure 3.2: Selection of study population and number of observations for each condition. Data was obtained from the Maryland SID 2012 data. Patients with limited demographic information were excluded.

The study population included patients classified with ICD-9 codes for the following emergency care sensitive conditions: sepsis, trauma, acute ischemic stroke, cardiac arrest, and STEMI as characterized in Appendix C. The sepsis cohort contained 26,291 observations, 28,216 observations for trauma, 11,228 observations for acute ischemic stroke, 2,125 observations for cardiac arrest, and 2,817 observations for STEMI.

3.4.1 Coding Methodology

While there remains a general consensus that the incidence of sepsis is increasing (Hall et al., 2011; Centers for Disease Control and Prevention, 2009; Gaiseki et al., 2013), there is substantial variability in the actual incidence and mortality rates, depending on coding methodology (Gaieski et al., 2013). The lack of widely accepted definitions of sepsis and its complications has made it difficult to obtain accurate estimates of its incidence and mortality (Bochud & Calandra, 2007). One study examining sepsis coding variability utilized different sepsis coding schemes and found that the annual average incidence of sepsis varied as much as 3.5-fold (Gaieski et al., 2013). Despite the introduction of the new ICD-9 codes designated for sepsis, severe sepsis, and septic shock diagnoses; these codes are not used uniformly and still require the use of supplemental infection codes (Gaieski et al., 2013). The accuracy of ICD-9 CM coding remains controversial and may underestimate the true incidence and burden of clinical sepsis (Martin et al., 2003; Rhee et al., 2014).

Rather than relying on a single coding methodology for sepsis, this study integrated two validated sepsis coding methodologies from Dombrovskiy et al. (2007)'s longitudinal study of sepsis hospitalization and mortality and Elixhauser et al.-generated septicemia HCUP brief (2011). Because Elixhuaser et al. focused only on septicemia, Dombrovskiy's methodology is incorporated with Elixhauser's codes to reflect the full cascade of sepsis. Therefore, the ICD-9 CM codes of interest ranges from the systemic inflammatory response to septic shock, to include varying degrees of sepsis severity.

The use of an integrated coding paradigm provided a more comprehensive and accurate assessment on sepsis, based on the available variables in the data abstract for the purpose of this study. To validate this coding scheme, the sepsis diagnosis codes were cross-referenced with AHRQ's (20009) Patient Safety Indicator brief for postoperative sepsis codes, excluding the codes for shock – other and postoperative shock. The ICD-9

CM codes present in all three methodologies are considered for this study, with minor exceptions. The three excluded ICD-9 CM codes were irrelevant to this study. Elixhauser et al.'s use of newborn septicemia is not considered, because the study's working dataset only contained patients over the age of 18. These identified ICD-9 CM codes exclude Dombrovskiy et al.'s categorization of severe sepsis with organ dysfunction codes, since this study merely examined the incidence and mortality of all sepsis cases, regardless of severity. For future studies that seek to differentiate between sepsis-severity outcomes, it would be useful to include the Dombrovskiy's distinction of organ dysfunction-sepsis cases.

A similar and simpler literature review process was used to identify ICD-9 CM codes for the other emergency conditions. For trauma, two trauma benchmarking studies were referenced (Benns, Carr, Kallan & Sims, 2013; Phillips, Clark, Nathens, Shiloach & Freel, 2008). For acute ischemic stroke, the study adopted Kokotailo & Hill's (2005)'s suggested stroke codes, while accepting the authors' noted slight bias towards more severe strokes, since patients with mild symptoms may not seek treatment. Cardiac arrest was operationalized through a single ICD-9 code (Carr et al., 2009). STEMI patients were identified with Steinberg et al.'s (2008) coding paradigm.

With the looming ICD-10 compliance deadline approaching, it is important to consider the clinical and quality implications of this pervasive coding variability. Under the Health Insurance Portability and Accountability Act, covered entities are required to transition to ICD-10 by October 2015 (Centers for Medicare & Medicaid Services, 2014). This mandate will most likely bring even more ambiguity to sepsis and other complex, multistage conditions coding by researchers and clinicians. Coding variability remains an area of future study and refinement as this transition unfolds.

3.5 Measures

Key variables of interest include: system competition, system affiliation, and inpatient mortality for the emergency conditions of interest. These variables were all derived from SID, and supplementary hospital characteristics.

3.6 Outcome Variable: Inpatient Mortality for Emergency Conditions

The main outcome being studied is inpatient mortality for emergency care conditions. The outcomes of mortality are classified as survive or died, rendering it as a dichotomous outcome. Therefore, mortality is inherently categorized as a binary variable to indicate the patient’s outcome.

The study considered inpatient mortality from emergency-type admissions, for sepsis, trauma, acute ischemic stroke, cardiac arrest and STEMI, as classified by the ICD-9 CM codes in the medical record’s listed diagnoses from SID. The 2012 Maryland SID file lists up to 30 diagnoses for each patient - the study considered all 30 in the analyses. Because of the natural disease pathway of sepsis, the condition often emerges after initial hospitalization, rather than acting as the principal cause for admission. Therefore, sepsis is often listed as a secondary diagnosis instead of primary (Hall et al., 2011). Being able to consider all 30 diagnoses in Maryland’s dataset allowed for a more comprehensive analysis of the incidence and mortality rates of emergency conditions. Furthermore, it provided greater depth to the study by enabling analyses of any interactions between the different emergency care sensitive conditions.

The study examined the case fatality rate, the ratio of cases for the condition of interest ending in death to the total number of condition-specific cases in the hospital referral region. Hospital standardized mortality ratios can be used to assess hospital performance (Berthelot, Lang, Quan & Stelfox, 2014), and correlating to this study, hospital system performance in HRRs.

3.7 Key Independent Variable: Competition at the Hospital Referral Region Level

This study defined the local healthcare market at the HRR level. The HRR deliniation is useful towards the study's goals of understanding the association between competition and patients' outcomes, especially when time-sensitive and geographic constraints are critical factors. The HRR definition also provides a larger, more systemic perspective of the healthcare market, allowing implications about hospital consolidation and care coordination to be ascertained.

Following the geographical methodology of previous studies of hospital consolidation (Cutler & Morton, 2013; Robinson, 2011), the HRR unit provides a geographic unit to analyze the local hospital market structures in the state. The Dartmouth Atlas of Healthcare demarcates 306 HRRs in the national healthcare market, three of which are located in Maryland. The 2012 Maryland SID data was mapped to the designated Dartmouth HRRs, using the admitting hospital's zip code to identify the patient's HRR designation, rather than the patient zip code to better reflect healthcare utilization patterns and associated outcomes.

The use of HRRs to define the market area is commonly used in studies of regional variation (Wennberg et al., 2002; Lee et al., 2012; O'Hare et al., 2010; Song et al., 2010; Robinson, 2011) in quality of care (Fisher et al., 2003). Using a multifaceted algorithm of commuting patterns of patients to major referral hospitals (Wennberg & Fisher, 2003), hospital referral regions are generated to represent regional healthcare markets where patients seek tertiary care (Wennberg & Cooper, 1996). HRRs "contain at least one hospital that performs major cardiovascular procedures and neurosurgery" (Wennberg & Cooper, 1996). Because the HRR represents a larger healthcare market, this study utilized this broader market area definition to conduct an in-depth analysis of competition among hospital systems.

3.7.1 Maryland Geography at the Hospital Referral Region Level

In terms of topography, Maryland is diverse and is naturally divided by the Chesapeake Bay, resulting in a natural, geographically-defined HRR on the Eastern Shore, Salisbury, and two other HRRs, Baltimore and Takoma Park, on the West side of the Bay. Maps of the state's three HRRs are shown in Figures 1 and 2. The Baltimore HRR has the largest resident population (Wennberg & Cooper, 1996). It encompasses Baltimore City, the most populated city in the state (U.S. Census Bureau). As the second-most populated HRR, Takoma Park contains Prince George's County, which has the second-largest population in Maryland. Finally, the Salisbury HRR reflects the population patterns of the state's Eastern shore counties – it is considerably less populous than the more metropolitan areas in Maryland (U.S. Census Bureau). Located bayside, the Salisbury HRR encompasses more miles of shoreline (Maryland Geological Survey, 2007). It is geographically isolated from the rest of the state and contains lower rates of developed residential and non-residential land than the counties in the Baltimore and Takoma Park HRRs (Maryland Department of Planning, 2010).

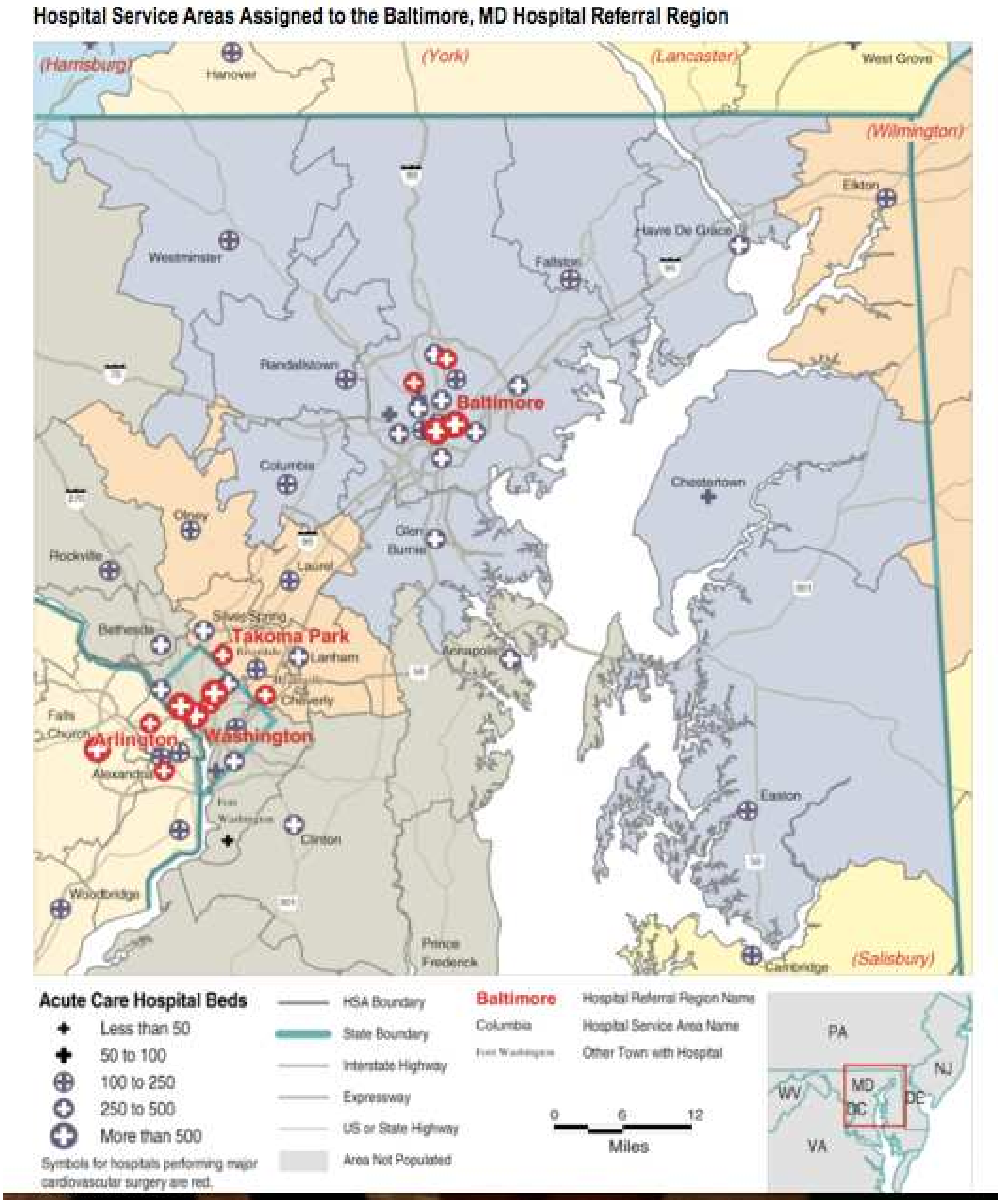

Figure 3.3. Map of the Baltimore and Takoma Park Hospital Referral Regions.

***Note.* Data source: Dartmouth Atlas of Health Care, 1996.**

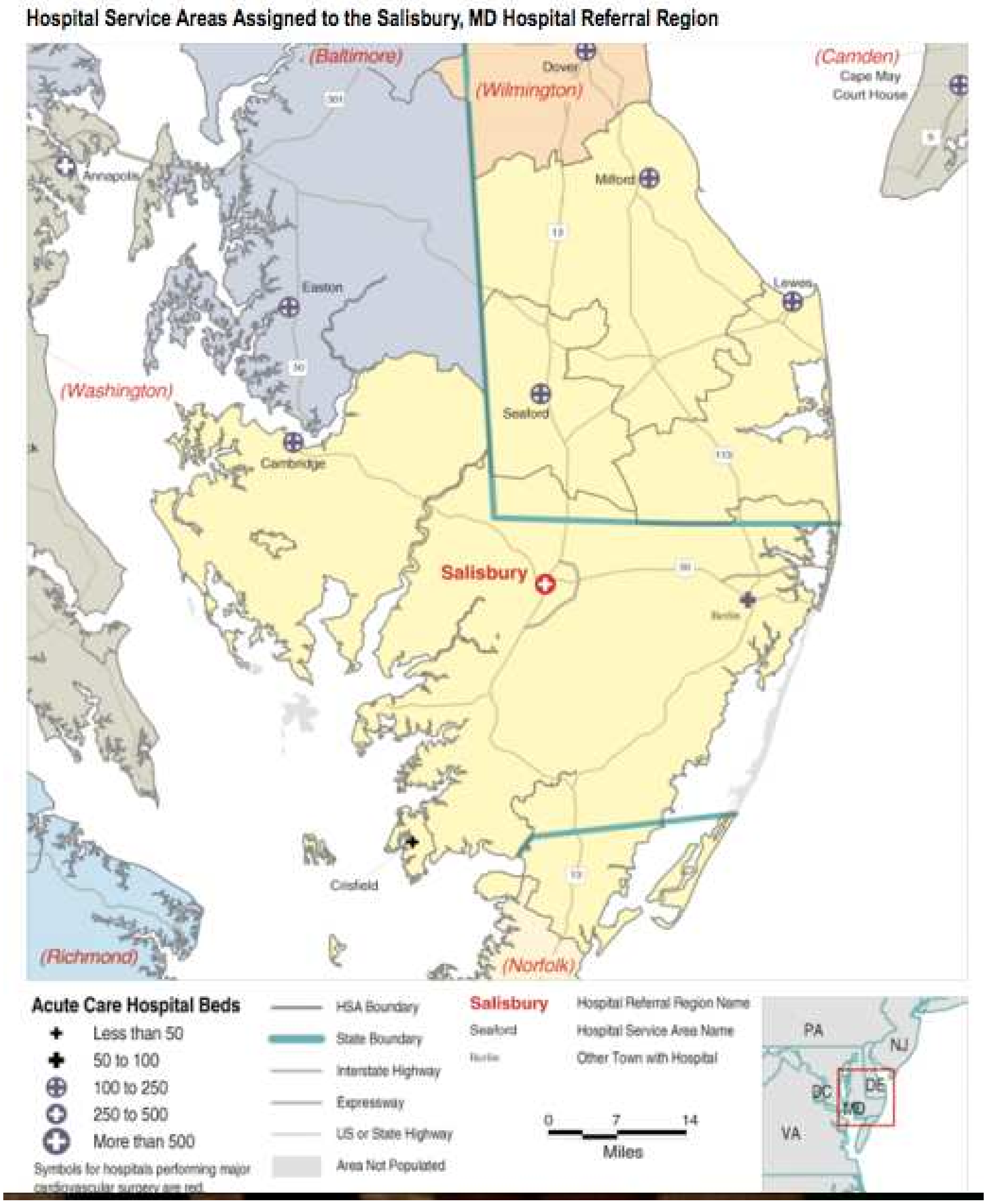

Figure 3.4. Map of the Salisbury Hospital Referral Region.

Note. **Data source: Dartmouth Atlas of Health Care, 1996.**

The following table obtained from the Dartmouth Atlas of Health Care details the HRRs' population and healthcare characteristics (Wennberg & Cooper, 1996).

Hospital Referral Region	Resident Population	Acute Care Beds per 1000	Expenditures per capita
Baltimore	2,247,761	3.1	1,116
Salisbury	305,907	2.8	998
Takoma Park	778,169	2.7	703

As the largest and most populous HRR, Baltimore contains seven hospital systems and three independent hospitals. The Baltimore HRR encompasses the University of Maryland Medical System and Johns Hopkins Health System, which are considered to be rivals (Appleby, 2012). There are a total of 23 hospitals in the Baltimore HRR, all located within the states. The Takoma Park HRR contains four hospital systems and one independent hospital. Finally, the Salisbury HRR contains two hospital systems and one independent hospital. It is important to note that the Salisbury HRR contains two hospitals located in Delaware as well. Without the availability of Delaware data, these out-of-state hospitals were excluded from the study's parameters.

Geospatial information from the Dartmouth Atlas of Healthcare provided a contextual understanding of the HRRs' healthcare utilization trends. In the 1992 fiscal year, the Baltimore HRR's Medicare reimbursements per enrollee was $4,481, significantly higher than the national average of $3,650. Along the same lines, the HRR has more acute care beds, acute hospital employees, registered nurses in acute care hospital, adjusted total acute care hospital expenditures, physician workforce, specialist physicians, and number of medical discharges than other South Atlantic HRRs. These initial population-level statistics reveal that Baltimore has traditionally been a more resource-intensive and high-spending HRR than other HRRs in the South Atlantic region, and particularly when compared to the other HRRs in the state.

For this study, the competition index was calculated at the HRR level, allowing regional variation analyses of hospital system competition and population-level patient outcomes. Because emergency care necessitates immediate medical attention, the patient is restricted to proximate hospitals, likely enclosed in the geographic bounds of the HRR.

3.8 Competition Index

The Herfindahl-Hirschman Index (HHI) is used to quantify the competitive environment in each HRR. HHI is the most common measure of competition and used by the Department of Justice and Federal Trade Commission. HHI captures the number and relative size of firms (Baker, 2001) to describe the market competition and inter-market variation in competition (Sari, 2002).

This study calculated the competition index using hospital systems' market shares within the three HRRs. Because the study focused on the impact of hospital system competition, the study compares patient outcomes by hospital system rather than individual hospitals. Therefore, Holy Cross Hospital in Silver Spring is classified as part of the Trinity Health System, Laurel Regional Hospital and Prince George's Hospital Center are both part of Dimensions Healthcare System, MedStar Montgomery Medical Center is part of MedStar Health, and Washington Adventist Hospital is part of Adventist Healthcare. Doctors Community Hospital operates as the only independent hospital in the Takoma Park HRR, in which the study considered an individual entity and unaffiliated with a health system. In the Salisbury HRR, it contains three independent hospitals. The competition index calculation considered each hospital individually.

For the competition index calculation, the whole hospital system is considered to better serve the purpose of the study. The use of the hospital system variable provided a better indicator of coordination of care as well as level of market concentration. With the focus on care coordination, collaborative hospital systems claim to better serve patients and communities through its geographic influence. By deriving the competition index at the hospital system level, this study hoped to reflect the true structure and quality of care of the local healthcare market.

The competition index reflects the aggregate hospital systems' market shares for three separate parameters: all inpatient admissions, all inpatient admissions originating from the ED, and all inpatient admissions originating from the ED for the conditions of interest. Mathematically, the competition index is the sum of the all hospital systems' squared market shares (Pearlstein et al., 2002). The spectrum of competitiveness in the market can be categorized into three categories: Unconcentrated (HHI between 100 and 1500), moderately concentrated (HHI between 1500 and 2500), highly concentrated (HHI above 2500) (Department of Justice, 2014). In essence, the lower the HHI, the more competitive the market is. HHI increases as both the numbers of firms in the market decreases, and as the disparity in size between the contributing firms increases (Department of Justice).

For the sake of simplicity and enhanced readability, this study translated HHI into a zero to one range. Therefore, an HHI of one indicates that there is one single monopolistic hospital system dominating the market, and a minimal, if any, level of competition from other providers. On the other hand, a low HHI of 0.2 indicates that there are a substantial number of providers in the market, representing numerous health systems or independent hospitals.

3.8.1 Modified HHIs

Considering the innate differences between planned care and emergency care, this study sought to explore the role of competition specifically in the emergency care sector. Through an original modified-HHI paradigm, this study manipulated hospital system market shares to fit the emergency care and disease-specific contexts, subsequently producing varying levels of competition. The study's use and creation of modified-HHI methodology is novel for healthcare sectors, especially for emergency care.

In this study, the modified-HHI approach funneled the competition measure from a general portrayal of health systems' market shares in the HRR to specifically assess emergency department admissions of interest. This provided a preliminary approach towards understanding the level of competition for emergency care in contrast to the overall inpatient system. As the emergency department continues to evolve, the modified-HHI methodology can provide a juxtaposition between ED and inpatient admissions in general.

To extend the use of this modified-HHI methodology, this study calculated disease-specific HHIs for the emergency care sensitive conditions of interest rather than just analyzing discharges for all conditions. Furthermore, HHI calculation for the five emergency care conditions provided for an analysis of the potential variation in competition for different diseases. The modified-HHI methodology lends a more narrow focus towards the study's area of interest in emergency care. Future studies that seek to assess the impact of competition for a discrete population and conditions of interest, pediatrics for instance, can utilize this study's modified-HHI paradigm for greater insight.

3.8.2 Calculation of HHI

HHI calculation requires determining the market shares of hospitals or health systems in the specified HRR. The market share of each facility is based on the number of discharges. The following equation depicts this process.

$$Market\ share\colon \frac{\#\ of\ discharges\ at\ one\ hospital}{\#\ of\ discharges\ within\ the\ HRR}$$

The market share of each facility is squared, and the resulting amounts are then totaled for the HRR, resulting in the subsequent equation.

$$\begin{aligned} &HRR\ Market\ Shares \\ &\quad = Facility\ A's\ Market\ Share^2 + Facility\ B's\ Market\ Share^2 \\ &\quad + Facility\ C's\ Market\ Share^2 + Facility\ (n-1)'s\ Market\ Share^2 \end{aligned}$$

The HHI reflects the level of competition in the HRR, suggesting that one region may be more competitive than another. The facility market shares were modified to reflect the various competition and disease parameters, to produce more ED-specific competition indices. These considerations for the modified-HHI methodology is shown in Figure 4. The of the use modified-HHIs provides an analytical visualization of competition in terms of the state's geography.

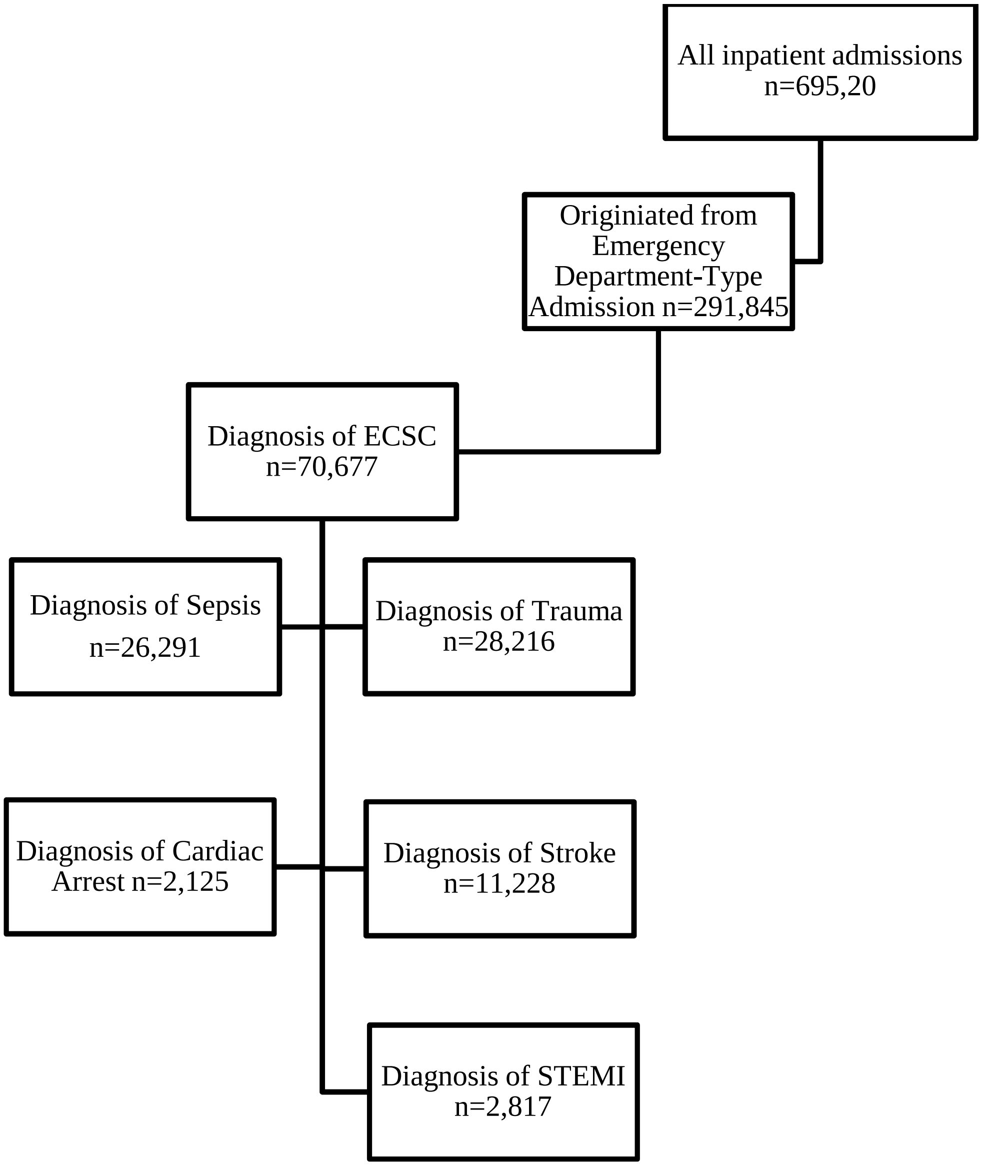

Figure 3.5. Calculation of Competition Index. First, the inpatient admissions are considered, then only admissions originating from the Emergency Department, and then the condition-specific parameters.

3.9 Covariates

To diminish the potential for confounding, the regression analyses controlled for a variety of patient, episode, and provider characteristics. Potential confounders were selected based on literature and included patient- and hospital-level characteristics. Given that variable mortality rates may reflect differences in study populations and settings, rather than a lack of association, it is necessary to take these covariates into account.

3.9.1 Patient-Level Covariates

Patient-case mix and demographic covariates included gender, age, race, and median income quartile based on the patient zip code. Using information retrieved from the SID, the variables of gender, age, and race were included to account for possible differences in the HRR study populations' in demographic profiles. The median income quartile of the patient's zip code was defined in four quadrants: 0 – 25 percentile, 26 – 50 percentile, 51 – 75 percentile, and 76 – 100 percentile.

In this study, weekend admission was considered as a patient-level variable. Weekday and weekend admission has been identified as a risk factor for patients presenting with unplanned critical illness, resulting in variability in emergency care outcomes (Carr, Reilly, Schwab, Branas, Geiger & Wiebe, 2011; Bell & Redelmeir, 2011; Shulkin, 2008; Cram, Hillis, Barnett & Rosenthal, 2004).

Because comorbidity is an important confounder in clinical and epidemiological studies (Schneeweiss, Seeger, Maclure. Wang, Avorn & Glynn, 2001), controlling for patient comorbidity allows a more accurate analysis using the claims-based data. Comorbidity measures were validated by "how well they predict worse health outcomes, health care utilization, and increased health care expenditures" (Schneeweiss et al., 2001). Comorbidity covariates included all components of the Charlson Comorbidity

Index (Charlson, Szatrowski, Peterson & Gold, 1994). The AHRQ-sponsored supplemental comorbidity software provided the Elixhauser Comorbidity algorithm to develop measures for risk-adjustment. Combining the Charlson and Elixhauser Comorbidity Indices enabled comparisons of mortality among the different conditions, while controlling for underlying health status and illness severity.

3.9.2 Hospital Characteristics as Covariates

The AHA Directory and HCUP AHA Linkage file supplements the SID with hospital-level information, including bed size, teaching status, type of control, and hospital affiliation, allowing more in-depth empirical analysis. In the context of this study, hospital characteristics may act as confounders and proxies for hospital quality.

For the hospital characteristic variable of "type of control," the study referred to the AHD profiles. This study supplemented the AHD information by examining the HSCRC Community Benefits Report Narratives as well. The ACA requires designated non-profit hospitals to submit a Community Health Needs Assessment (CNHA) and HSCRC collects these reports. The CNHA report includes all 32 hospitals captured in the analysis, indicating a not-for-profit status. However, one variation to note is Johns Hopkins Bayview Hospital. AHD lists Bayview as private whereas the AHA profile lists as a not-for-profit. Because of the discrepancy, the evidence of the AHA profile and CHNA report suggests that Bayview is a not-for-profit organization. In the overall scheme of the analysis, the other 31 hospitals are all listed as not-for-profit, rather than private, relegating it difficult to use the "type of control" variable as an adjustor in the analysis. In terms of an executive decision, this study categorized Johns Hopkins Bayview Hospital as a voluntary not-for-profit organization as well, due to its submission of CNHA documents and the AHA classification. Because of the uniform non-profit status, hospital ownership was not a relevant control in this study.

The Salisbury HRR is on a significantly smaller scale than Baltimore, subsequently the Salisbury HRR lacks some hospital characteristics that are important controls in this study. Salisbury does not contain any teaching hospitals or hospitals affiliated with a health system. In this study, teaching status acts as a hospital quality characteristic that may confound and affect mortality. Teaching status may be correlated with competitiveness as well (Pines, 2006). Additionally, the Salisbury HRR is comprised of independent hospitals. However, this study aims to study the role of competition and quality, for which hospital system affiliation may impact one or both variables. Because the overall objective of this analysis is to examine the relationship between competition and mortality for emergency care conditions, the inclusion of teaching status and hospital system affiliation as controls facilitates a better understanding of the impact of hospital characteristics on patient outcomes and quality of care.

The number of hospitals categorized as teaching and affiliated with a hospital system varies by the HRR. Small and differentiated sizes led to unstable estimates of the association between hospital characteristics and the study outcome. In using teaching status and hospital system affiliation, the effect of the hospital characteristics and stability of the estimates are minimized.

3.9.2 Creation of Binary Covariates

For the regression analysis, the categorical covariates were transformed into binary variables. These categorical variables, such as payer or gender, do not have a real numerical relationship with one another. Therefore, the creation of dummy variables converts the variable into a binary variable for more accurate statistical analyses (Pasta, 2009). For nominal variables with multiple levels, including race and median income quartile, binary variables can be created to represent each level or category.

Gender, race, payer, urban or rural patient location, median income percentiles of patient zip code, hospital system affiliation, weekend admission, and teaching status are depicted as binary variables in the regression analyses, enabling the use of a single regression equation to represent the associated groups.

3.9.3 Creation of Binary HHI

Initially, the main explanatory variable, HHI, began as a continuous variable and became categorical, namely three regions. The continuous competition index can be scaled from zero to one, reflecting the spectrum of competition in the local healthcare market. Preliminary analyses using the continuous competition index yielded convoluted and insignificant results, suggesting further refinement of the competition index. In the scope of this study, Maryland encompasses three HRRs - significantly limiting the ability of HHI to be used as a continuous variable and therefore supporting its transformation into a binary variable.

Accordingly for analytical purposes, binary HHI variables were created. The binary HHI variable distinguished between high and low level of competition in the HRRs. While the three continuous modified-HHI variables represented the differing levels of competition in the inpatient, emergency, and disease-specific contexts, the binary high and low competition categories allows more accurate assessment of the HRRs' level of competition, by simplifying the competition relationship.

For future studies that incorporate a larger scope of geographic markets across states or regions, the use of the continuous modified-HHIs may provide a more comprehensive approach because of the greater numbers of HRRs and associated competition indices. Regardless, this study's various HHI-adjustments revealed the ability of the competition index to fit a variety of study specifications.

3.10 Statistical Analysis

For this study, the sample means and standard deviations were calculated to provide descriptive statistics of population characteristics within the three HRRs. A Pearson's chi-square test was utilized to compare the distributions to ascertain any significant differences in ECSC mortality among the HRRs.

Two-sample t-tests were conducted to assess the demographic and hospital facility differences and any significant differences among HRRs. Two HRRs were modeled simultaneously in the two-sample t-test, providing an examination of the Baltimore HRR against Salisbury HRR, Baltimore against Takoma Park, and Salisbury and Takoma Park. The associated means, standard deviations, and p-values indicated any significant differences between the regions to reveal the makeup of the regions. For example, a significant difference in bed size between Baltimore and Salisbury suggested that it may be a potential confounder; therefore, inclusion as a covariate as a control for the regressions.

An initial analysis using a Chi-Square Test compared the binary competition variable with mortality. Binary logistic regressions with controls were conducted to examine the association between hospital system competition and inpatient mortality for emergency care sensitive conditions. The analyses were conducted at the HRR level for the five conditions. The main predictor in this study was the binary regional competition variable, as defined by the 2012 Maryland SID file and Dartmouth Atlas of Healthcare.

For these models, the use of the binary competition variable is framed that the high level of competition is the control and the low level of competition is the reference group. The stepwise regression models included covariates for case-mix, severity, and hospital quality adjustments. The use of covariates attenuates biasness from potential confounders, and allows a better understanding of the effect of solely competition on inpatient mortality. In the stepwise regressions, the covariates are added by groups relating to patient demographics, severity of disease, and hospital characteristics to study the effect of different sets of controls on inpatient mortality. The use of stepwise regressions provided insight on the interactions between the patient- and hospital-level covariate domains, regional competition, and mortality. Table 2.1 outlines the specific covariates included in each model.

Model	Covariates Included
Basic	Competition binary
Demographics	Age, age squared, gender binary, racial binary
Comorbidity	Elixhauser and Charlson Comorbidity Indices
Demographics+	Demographics, payer binary, urban, income quartile binary
Demographics+, Comorbidity	Demographics+, comorbidity
Facility	Bed size, teaching status
Facility+	Hospital fixed effects
Demographics+. Comorbidity, Facility	Demographics+, comorbidity, facility

The stepwise regression included seven models: basic, demographics, comorbidity, demographics +, facility, facility + and demographics + comorbidity and facility. These different models included varying characteristics that may confound the outcome. The basic model regression only includes the binary competition variable. For demographics, the model includes the binary competition variable and age, age squared, gender binary variable, and racial binary variables as covariates. The comorbidity model includes the binary competition variable and Elixhauser and Charlson Comorbidity Indices as covariates. The demographics+ model builds upon the original demographics step, and adds payer, urban, and income quartile binary variables. Furthermore, the demographics+, comorbidity model combines the covariates in those two models. The facility model focuses on hospital characteristics and includes the binary competition variable with the bed size and teaching status of the hospital. Finally, the demographics+, comorbidity, facility model integrates the covariates in those three models together, to provide a summation of all listed covariates.

The facility+ model used hospital fixed effects, to control for unobservable characteristics at the hospital level. The hospital fixed effects model created a binary variable for each hospital. However, this may bias the results because it essentially controls for hospital quality, which may be related to the mortality outcome.

3.11 Instrumental Analysis of Hospital System Affiliation

This study serves as a natural experiment, in which the Maryland All-Payer Model's regulated payment system have created an economic environment somewhat akin to a randomized experiment (Angrist & Krueger, 2001). Through the state's uniform rate-setting policy, the independent variable of competition is essentially configured to be volume-based, rather than price or quality-driven. This study exploits the state of Maryland's payment system to identify empirically the impact of uniform-rate setting and hospital competition on inpatient mortality for unplanned, critical illness.

In the state of Maryland, the All-Payer Model sets uniform rates for hospitals; therefore, competitive mechanisms in the state's healthcare market are different than markets in other states. With hospital payment prices fixed, this creates a level paying plane where hospitals cannot compete based on price. As a result, quantity is the only factor that fluctuates for hospitals, creating an environment of primarily volume-based competition. The process of determining hospital competition is affected by the uniform payment system and correlated with the study's outcome of inpatient mortality.

The possibility of inconsistent parameter estimation exists due to a possible endogenous regressor. An inconsistent estimate, produced by the stepwise regressions, may only measure the magnitude of the association, rather than the association's magnitude in conjunction with the direction of the causation (Cameron, 2013). For example, an odds ratio point estimate may reveal a significant association between contrasting regional levels of competition and mortality, but not necessarily in the correct direction. As a result, statistical effectiveness is misplaced and the results generated are inconsistent (Bowden & Turkington, 1990).

By using instrumental variables analysis, the multivariable logistic regressions can show more consistent parameter estimations to overcome measurement errors in the explanatory variable (Angrist & Krueger, 2001) and subsequently determine the true value of the parameter. An understanding of hospital competition activity supports the premise of competition as an endogenous variable – competition acts as the main explanatory variable but is jointly determined by the study's dependent variable (Verbeek, 2008) of mortality, reinforcing the need to identify a logical instrumental variable and re-estimate the models accounting for this previously unaccounted for variable. Hospital system affiliation is largely correlated with hospital competition; larger, consolidated systems create asymmetry in market shares, and subsequently reduce the level of competition in the HRR. With this institutional knowledge, the variable of hospital system affiliation was included as an additional covariate to indicate facilities belonging to a hospital system. As an instrumental variable, this new variable of hospital system affiliation should be correlated with the endogenous variable of competition, and potentially correlated with the study's outcome variable, but only through the endogenous competition variable.

3.12 Two-Stage Least Squares Estimation

To test the endogeneity of this relationship between hospital system affiliation, hospital system competition, and inpatient mortality, 2-Stage Least Squares Estimation and the Durbin-Wu-Hausman Test were used. For the 2-Stage Least Squares Estimation (2SLS), the One-Stage Least Square (OLS) estimates were first produced for a condition of interest, then the Two-Stage Least Squares (2SLS) estimates were subsequently calculated as well. The Durbin-Wu-Hausman Test for Instrumental Endogeneity was used to validate the use of instrumental variables analysis. The 2SLS estimate uses instruments to control for possible endogeneity of the regressor, and if endogenous, then the OLS estimates will be inconsistent with the 2SLS results, so the two estimates will be different.

3.13 Hausman Test of Endogeneity

The Durbin-Wu-Hausman Test for instrumental endogeneity was used to test the potentially endogenous variable of hospital competition. Because the dataset only contains observations from the 2012 year, panel data analysis for testing endogeneity cannot be used, as it is created to model parameters over time. For subsequent analyses with multiple years of SID data, the panel data model analyses will be a better fit.

The original Hausman Endogeneity Test equation (Hausman, 1978) is:

$$H = (\beta_{2SLS} - \beta_{OLS})'[V_{2SLS} - V_{OLS})^{-1}(\beta_{2SLS} - \beta_{OLS}) \overset{d}{\rightarrow} \chi^2 rank(V)$$

However, this study only focuses on one potential instrumental variable, hospital system affiliation, rendering the first derivative of the coefficients unnecessary. Therefore, the Durban-Wu-Hausman test equation is simplified for this study's purposes. Fortunately, the Hausman test is particularly easy to calculate by hand because there is only one component of the parameter tested, opposed to the use of multiple instrumental variables (Cameron & Trivedi, 2006). As a result, the Hausman Test equation is:

$$H = \frac{\left(\hat{\theta} - \tilde{\theta}\right)^2}{(\tilde{s} - \hat{s})^2}$$

The OLS estimates, represented by $\tilde{\theta}$ and $\tilde{s}$ and the 2SLS regression estimates, $\hat{\theta}$ and $\hat{s}$, for the systems' coefficients for the different conditions can be used in this equation to calculate the Hausman Test Statistic and test for endogeneity, after completing a 2SLS estimation.

Instrumental variable analysis was used to specifically address potential bias due to hospital system affiliation, which could not be controlled with the existing hospital characteristic control variables. Instrumental variables can be used to identify a causal effect of a treatment on outcomes, but requires an instrument that correlates with the independent variable of interest, hospital system competition in the HRR, but does not directly affect the outcome of mortality, except through its influence on the likelihood of hospital system affiliation. In essence, an instrumental variable is correlated to the endogenous main independent variable, hospital competition, but uncorrelated with the dependent variable. For this study, the instrumental variable of hospital system affiliation and competition are correlated, therefore impacting mortality of emergency care conditions through the endogenous variable of competition.

Instrumental variables analysis is a quasi-experimental technique that mimics randomness, allowing more accurate results to be extrapolated. Since instrumental variable properties represent consistency and convergence properties, this instrument was applied to the stepwise binary logistic regressions of interest to yield more accurate parameter estimates.

4: Results

4.1 Computation

All statistical analyses were performed using SAS 9.3 (SAS Institute Inc., Cary, NC). Two-tailed statistical significance level, α, was defined at 0.05.

4.2 Binary Competition Measure

Under the binary competition approach, the competition index becomes an independent dummy variable to reflect the high and low levels of competition. With a fixed reference group, a binary variable facilitated the interpretation of results by comparing an HRR with high competition against an HRR with low competition. For the purpose of this study, the Takoma Park and Baltimore HRRs were grouped together in the low competition group. Takoma Park has an overall HHI of 0.253 for all inpatient admissions, comparable to Baltimore's HHI of 0.181. In contrast to this, Salisbury's HHI is 0.753, reflecting a low competition market. The various modified HHIs are shown in Table 4.1. By analyzing the relative change in mortality, the binary competition variable enabled interpretations in the scope of competition level and greater or less likelihood of mortality for the ECSC.

	Baltimore	Salisbury	Takoma Park
HHI for All Inpatient Admissions	0.181	0.753	0.253
HHI for All Inpatient Admissions, Originating from ED	0.191	0.689	0.210
HHI for All Inpatient Admissions, Originating from ED, with Sepsis	0.185	0.614	0.249
HHI for All Inpatient Admissions, Originating from ED, with Trauma	0.273	0.629	0.272
HHI for All Inpatient Admissions, Originating from ED, with Acute Ischemic Stroke	0.216	0.639	0.209
HHI for All Inpatient Admissions, Originating from ED, with Cardiac Arrest	0.189	0.771	0.243
HHI for All Inpatient Admissions, Originating from ED, with STEMI	0.238	0.902	0.253

Table 4.1. Modified Competition Index Measures for the HRRs by Condition.

4.3 Descriptive Statistics

Descriptive summary statistics for the variables and covariates were examined for the five emergency conditions. From 695,207 observations, 70,677 cases were identified within the study's parameters of the disease conditions of interest originating from the emergency department. This study also excluded any episodes that had missing patient-level information. Sepsis and trauma reported relatively similar case volumes, with 26,291 and 28,216 cases respectively. On the other hand, cardiac arrest and STEMI experienced relatively similar, and lower, volumes of 2,125 and 2,817 respectively. The study's analytical dataset also included 11,228 stroke observations.

The study population's descriptive statistics, stratified by condition and HRR, are reported in Tables 4.2 to 4.6.

Condition = Sepsis	Baltimore (N= 18,593)			Salisbury (N=1,439)			Takoma Park (N=6,259)		
	Mean	**Std Dev**	**Pr > |t|**	**Mean**	**Std Dev**	**Pr > |t|**	**Mean**	**Std Dev**	**Pr > |t|**
Died during hospitalization	0.12	0.33	<.0001	0.13	0.33	<.0001	0.12	0.32	<.0001
Age	63	19	<.0001	67	17	<.0001	64	20	<.0001
Female	0.50	0.50	<.0001	0.48	0.50	<.0001	0.53	0.50	<.0001
Admission day is a weekend	0.26	0.44	<.0001	0.28	0.45	<.0001	0.26	0.44	<.0001
Bed Size	366	214	<.0001	271	130	<.0001	289	126	<.0001
Competition Index for all inpatient	0.18	-	<.0001	0.75	-	<.0001	0.25	-	<.0001
Competition Index for inpatient from ED	0.19	-	<.0001	0.70	-	<.0001	0.21	-	<.0001
Competition Index for Sepsis	0.19	-	<.0001	0.61	-	<.0001	0.24	-	<.0001
Elixhauser index	10.63	10.61	<.0001	11.16	9.93	<.0001	9.27	8.53	<.0001
Charlson index	7.79	9.66	<.0001	7.69	8.44	<.0001	6.52	7.90	<.0001
White	0.60	0.49	<.0001	0.74	0.44	<.0001	0.34	0.48	<.0001
Black	0.35	0.48	<.0001	0.23	0.42	<.0001	0.50	0.50	<.0001
Hispanic	0.01	0.11	<.0001	0.02	0.13	<.0001	0.09	0.29	<.0001
Asian	0.01	0.11	<.0001	0.00	0.04	0.1574	0.03	0.18	<.0001
Native American	0.00	0.04	<.0001	0.00	0.03	0.3175	0.01	0.08	<.0001
Other	0.02	0.13	<.0001	0.01	0.11	<.0001	0.03	0.17	<.0001
Medicare	0.60	0.49	<.0001	0.68	0.47	<.0001	0.58	0.49	<.0001
Medicaid	0.16	0.37	<.0001	0.07	0.26	<.0001	0.14	0.34	<.0001
Private	0.22	0.42	<.0001	0.23	0.42	<.0001	0.27	0.44	<.0001
Other	0.02	0.14	<.0001	0.01	0.09	0.0003	0.01	0.11	<.0001
Urban	0.97	0.16	<.0001	0.54	0.50	<.0001	1.00	0.07	<.0001
Rural	0.03	0.16	<.0001	0.46	0.50	<.0001	0.00	0.07	<.0001
Income percentile 0-25	0.18	0.39	<.0001	0.15	0.36	<.0001	0.03	0.17	<.0001
Income percentile 26-50	0.15	0.36	<.0001	0.53	0.50	<.0001	0.02	0.14	<.0001
Income percentile 51-75	0.26	0.44	<.0001	0.28	0.45	<.0001	0.33	0.47	<.0001
Income percentile 76-100	0.40	0.49	<.0001	0.03	0.18	<.0001	0.62	0.49	<.0001
Hospital System	0.90	0.29	<.0001	-	-	-	0.84	0.36	<.0001
Teaching hospital	0.84	0.37	<.0001	-	-	-	0.73	0.44	<.0001

Table 4.2 Descriptive statistics for Sepsis.

Condition = Trauma	Baltimore (N= 22,446)			Salisbury (N=1,527)			Takoma Park (N=4,234)		
	Mean	**Std Dev**	**Pr > |t|**	**Mean**	**Std Dev**	**Pr > |t|**	**Mean**	**Std Dev**	**Pr > |t|**
Died during hospitalization	0.03	0.17	<.0001	0.02	0.15	<.0001	0.02	0.15	<.0001
Age	57	25	<.0001	66	21	<.0001	60	24	<.0001
Female	0.46	0.50	<.0001	0.54	0.50	<.0001	0.49	0.50	<.0001
Admission day is a weekend	0.30	0.46	<.0001	0.28	0.45	<.0001	0.29	0.45	<.0001
Sepsis	0.04	0.20	<.0001	0.07	0.25	<.0001	0.07	0.26	<.0001
Trauma	1.00	0.00	.	1.00	0.00	.	1.00	0.00	.
Stroke	0.03	0.17	<.0001	0.06	0.24	<.0001	0.03	0.16	<.0001
Cardiac Arrest	0.01	0.10	<.0001	0.01	0.12	<.0001	0.01	0.09	<.0001
STEMI	0.00	0.06	<.0001	0.01	0.08	0.00	0.00	0.06	0.00
Bed Size	480	240	<.0001	275	127	<.0001	268	99	<.0001
Competition Index for all inpatient	0.18	0.00	<.0001	0.75	0.00	<.0001	0.25	0.00	<.0001
Competition Index for inpatient from ED	0.19	0.00	<.0001	0.70	0.00	<.0001	0.21	0.00	<.0001
Competition Index for Trauma	0.27	0.00	<.0001	0.63	0.00	<.0001	0.27	0.00	<.0001
Elixhauser index	5.36	7.93	<.0001	6.77	7.90	<.0001	5.30	6.62	<.0001
Charlson index	3.34	6.50	<.0001	4.35	6.69	<.0001	3.29	6.09	<.0001
White	0.66	0.47	<.0001	0.83	0.38	<.0001	0.46	0.50	<.0001
Black	0.29	0.45	<.0001	0.12	0.33	<.0001	0.41	0.49	<.0001
Hispanic	0.03	0.16	<.0001	0.03	0.17	<.0001	0.08	0.27	<.0001
Asian	0.01	0.09	<.0001	0.00	0.04	0.08	0.02	0.15	<.0001
Native American	0.00	0.05	<.0001	0.00	0.03	0.32	0.00	0.06	0.00
Other	0.02	0.14	<.0001	0.02	0.13	<.0001	0.02	0.15	<.0001
Medicare	0.45	0.50	<.0001	0.60	0.49	<.0001	0.48	0.50	<.0001
Medicaid	0.17	0.37	<.0001	0.06	0.25	<.0001	0.14	0.35	<.0001
Private	0.33	0.47	<.0001	0.31	0.46	<.0001	0.36	0.48	<.0001
Other	0.05	0.22	<.0001	0.02	0.15	<.0001	0.02	0.13	<.0001
Urban	0.95	0.22	<.0001	0.53	0.50	<.0001	0.98	0.13	<.0001
Rural	0.05	0.22	<.0001	0.47	0.50	<.0001	0.02	0.13	<.0001
Income percentile 0-25	0.18	0.38	<.0001	0.17	0.38	<.0001	0.04	0.20	<.0001
Income percentile 26-50	0.15	0.35	<.0001	0.45	0.50	<.0001	0.02	0.15	<.0001
Income percentile 51-75	0.26	0.44	<.0001	0.30	0.46	<.0001	0.32	0.47	<.0001
Income percentile 76-100	0.41	0.49	<.0001	0.08	0.27	<.0001	0.62	0.49	<.0001
Hospital System	0.92	0.25	<.0001	0.00	0.00	.	0.89	0.30	<.0001
Teaching hospital	0.92	0.28	<.0001	0.00	0.00	.	0.86	0.35	<.0001

Table 4.3 Descriptive Statistics for Trauma

Condition = Stroke	Baltimore (N=8,569)			Salisbury (N=961)			Takoma Park (N=1,698)		
	Mean	Std Dev	Pr > |t|	Mean	Std Dev	Pr > |t|	Mean	Std Dev	Pr > |t|
Died during hospitalization	0.04	0.20	<.0001	0.04	0.18	<.0001	0.04	0.21	<.0001
Age	71	15	<.0001	73	13	<.0001	72	14	<.0001
Female	0.53	0.50	<.0001	0.51	0.50	<.0001	0.57	0.49	<.0001
Admission day is a weekend	0.25	0.43	<.0001	0.25	0.43	<.0001	0.26	0.44	<.0001
Bed Size	361	201	<.0001	279	125	<.0001	270	112	<.0001
Competition Index for all inpatient	0.18	-	<.0001	0.75	-	<.0001	0.25	-	<.0001
Competition Index for inpatient from ED	0.19	-	<.0001	0.70	-	<.0001	0.21	-	-
Competition Index for Stroke	0.22	-	<.0001	0.64	-	<.0001	0.21	-	-
Elixhauser index	7.77	7.81	<.0001	7.47	6.83	<.0001	7.22	6.65	<.0001
Charlson index	6.83	7.21	<.0001	6.63	6.80	<.0001	6.34	6.80	<.0001
White	0.63	0.48	<.0001	0.78	0.41	<.0001	0.37	0.48	<.0001
Black	0.33	0.47	<.0001	0.19	0.39	<.0001	0.51	0.50	<.0001
Hispanic	0.02	0.14	<.0001	0.02	0.14	<.0001	0.06	0.23	<.0001
Asian	0.01	0.09	<.0001	0.00	0.03	0.3176	0.04	0.19	<.0001
Native American	0.00	0.04	0.0005	0.00	0.03	0.3176	0.00	0.04	0.0833
Other	0.01	0.11	<.0001	0.01	0.09	0.0046	0.02	0.15	<.0001
Medicare	0.70	0.46	<.0001	0.76	0.43	<.0001	0.68	0.47	<.0001
Medicaid	0.09	0.29	<.0001	0.04	0.19	<.0001	0.09	0.28	<.0001
Private	0.19	0.40	<.0001	0.19	0.39	<.0001	0.23	0.42	<.0001
Other	0.02	0.13	<.0001	0.01	0.10	0.0015	0.00	0.07	0.0046
Urban	0.95	0.22	<.0001	0.53	0.50	<.0001	1.00	0.05	<.0001
Rural	0.05	0.22	<.0001	0.47	0.50	<.0001	0.00	0.05	0.0253
Income percentile 0-25	0.16	0.37	<.0001	0.17	0.38	<.0001	0.02	0.13	<.0001
Income percentile 26-50	0.15	0.35	<.0001	0.48	0.50	<.0001	0.03	0.17	<.0001
Income percentile 51-75	0.29	0.45	<.0001	0.30	0.46	<.0001	0.35	0.48	<.0001
Income percentile 76-100	0.41	0.49	<.0001	0.04	0.20	<.0001	0.60	0.49	<.0001
Hospital System	0.91	0.27	<.0001	0.00	0.00	-	0.82	0.38	<.0001
Teaching hospital	0.88	0.32	<.0001	0.00	0.00	-	0.75	0.44	<.0001

Table 4.4 Descriptive Statistics for Acute Ischemic Stroke.

Condition = Cardiac Arrest	Baltimore (N= 1,174)			Salisbury (N=166)			Takoma Park (N=345)		
	Mean	**Std Dev**	**Pr > |t|**	**Mean**	**Std Dev**	**Pr > |t|**	**Mean**	**Std Dev**	**Pr > |t|**
Died during hospitalization	0.63	0.48	<.0001	0.57	0.50	<.0001	0.61	0.49	<.0001
Age	63	19	<.0001	64	17	<.0001	68	16	<.0001
Female	0.44	0.50	<.0001	0.41	0.49	<.0001	0.46	0.50	<.0001
Admission day is a weekend	0.26	0.44	<.0001	0.31	0.47	<.0001	0.27	0.44	<.0001
Bed Size	401	224	<.0001	308	101	<.0001	288	108	<.0001
Competition Index for all inpatient	0.18	-	.	0.75	-	-	0.25	-	-
Competition Index for inpatient from ED	0.19	-	<.0001	0.70	-	-	0.21	-	-
Competition Index for Cardiac Arrest	0.19	-	<.0001	0.77	-	-	0.24	-	-
Elixhauser index	8.38	8.96	<.0001	9.34	9.24	<.0001	8.38	6.88	<.0001
Charlson index	6.51	8.59	<.0001	6.93	8.91	<.0001	6.96	8.00	<.0001
White	0.54	0.50	<.0001	0.67	0.47	<.0001	0.26	0.44	<.0001
Black	0.42	0.49	<.0001	0.28	0.45	<.0001	0.62	0.49	<.0001
Hispanic	0.01	0.09	0.00	0.02	0.13	0.08	0.06	0.24	<.0001
Asian	0.01	0.09	0.00	0.01	0.08	0.32	0.03	0.18	0.00
Native American	0.00	0.04	0.16	0.00	0.00	.	0.01	0.08	0.16
Other	0.02	0.14	<.0001	0.02	0.13	0.08	0.03	0.16	0.00
Medicare	0.57	0.49	<.0001	0.63	0.49	<.0001	0.62	0.49	<.0001
Medicaid	0.18	0.38	<.0001	0.07	0.25	0.00	0.11	0.31	<.0001
Private	0.23	0.42	<.0001	0.29	0.45	<.0001	0.27	0.44	<.0001
Other	0.01	0.12	<.0001	0.02	0.13	0.08	0.00	0.00	-
Urban	0.97	0.16	<.0001	0.53	0.50	<.0001	0.99	0.08	<.0001
Rural	0.03	0.16	<.0001	0.47	0.50	<.0001	0.01	0.08	0.16
Income percentile 0-25	0.24	0.43	<.0001	0.16	0.36	<.0001	0.04	0.19	0.00
Income percentile 26-50	0.16	0.36	<.0001	0.49	0.50	<.0001	0.03	0.16	0.00
Income percentile 51-75	0.25	0.43	<.0001	0.29	0.45	<.0001	0.39	0.49	<.0001
Income percentile 76-100	0.35	0.48	<.0001	0.07	0.25	0.00	0.55	0.50	<.0001
Hospital System	0.91	0.27	<.0001	0.00	0.00	-	0.86	0.34	<.0001
Teaching hospital	0.86	0.35	<.0001	0.00	0.00	-	0.79	0.41	<.0001

Table 4.5 Descriptive statistics for Cardiac Arrest.

Condition = STEMI	Baltimore (N = 2,173) Mean	Std Dev	Pr > |t|	Salisbury (N = 247) Mean	Std Dev	Pr > |t|	Takoma Park (N = 397) Mean	Std Dev	Pr > |t|
Died during hospitalization	0.12	0.32	<.0001	0.13	0.34	<.0001	0.15	0.36	<.0001
Age	67	15	<.0001	67	14	<.0001	67	15	<.0001
Female	0.41	0.49	<.0001	0.38	0.49	<.0001	0.38	0.49	<.0001
Admission day is a weekend	0.27	0.44	<.0001	0.30	0.46	<.0001	0.27	0.45	<.0001
Admission type	1.00	0.00	-	1.00	0.00	-	1.00	0.00	-
Bed Size	360	200	<.0001	332	66	<.0001	302	109	<.0001
Competition Index for all inpatient	0.18	-	<.0001	0.75	-	-	0.25	0.00	-
Competition Index for inpatient from ED	0.19	-	<.0001	0.70	-	-	0.21	0.00	-
Competition Index for STEMI	0.24	-	<.0001	0.90	-	-	0.25	0.00	-
Elixhauser index	7.44	9.30	<.0001	5.86	6.91	<.0001	6.41	7.61	<.0001
Charlson index	7.06	9.45	<.0001	5.39	6.50	<.0001	5.76	7.13	<.0001
White	0.69	0.46	<.0001	0.77	0.42	<.0001	0.39	0.49	<.0001
Black	0.26	0.44	<.0001	0.16	0.37	<.0001	0.45	0.50	<.0001
Hispanic	0.01	0.12	<.0001	0.03	0.17	0.01	0.09	0.29	<.0001
Asian	0.01	0.10	<.0001	0.00	0.06	0.32	0.05	0.21	<.0001
Native American	0.00	0.06	0.01	0.00	0.00	-	0.02	0.12	0.01
Other	0.02	0.15	<.0001	0.04	0.20	0.00	0.01	0.10	0.05
Medicare	0.55	0.50	<.0001	0.56	0.50	<.0001	0.53	0.50	<.0001
Medicaid	0.10	0.30	<.0001	0.04	0.21	0.00	0.08	0.26	<.0001
Private	0.33	0.47	<.0001	0.38	0.49	<.0001	0.38	0.49	<.0001
Other	0.03	0.16	<.0001	0.02	0.13	0.05	0.01	0.10	0.05
Urban	0.95	0.22	<.0001	0.45	0.50	<.0001	0.99	0.07	<.0001
Rural	0.05	0.22	<.0001	0.55	0.50	<.0001	0.01	0.07	0.16
Income percentile 0-25	0.14	0.34	<.0001	0.18	0.38	<.0001	0.02	0.15	0.00
Income percentile 26-50	0.14	0.35	<.0001	0.43	0.50	<.0001	0.02	0.14	0.00
Income percentile 51-75	0.28	0.45	<.0001	0.31	0.46	<.0001	0.31	0.46	<.0001
Income percentile 76-100	0.44	0.50	<.0001	0.09	0.28	<.0001	0.65	0.48	<.0001
Hospital System	0.91	0.27	<.0001	0.00	0.00	-	0.86	0.34	<.0001
Teaching hospital	0.90	0.30	<.0001	0.00	0.00	-	0.90	0.30	<.0001

Table 4.6 Descriptive statistics for STEMI.

There are differences in mortality depending on the condition. Cardiac arrest has the highest mortality with means of 0.63, 0.57, and 0.61 for Baltimore, Salisbury and Takoma Park respectively. Sepsis and STEMI have similar mortalities. For both Baltimore and Salisbury, sepsis mortality means were 0.12 and STEMI mortality means were 0.13. For Takoma Park, sepsis mortality was 0.12 and STEMI was a bit higher, at 0.15. Trauma mortality was lowest in all three regions, with means of 0.03, 0.02, and 0.02 for Baltimore, Salisbury, and Takoma Park respectively. Mortality for acute ischemic stroke was also relatively low, with the average of 0.04 for all three regions.

The average age for all of the conditions was 60 years old, with the lowest of 57 years old for trauma patients in Baltimore. Overall, trauma patients presented with the lowest average age out of the conditions, ranging from 57 years old in Baltimore to 66 years old in Salisbury. Stroke patients had the highest average age, from 71 years old in Baltimore, 73 in Salisbury, and 72 in Takoma Park.

Overall, the distribution of gender for all conditions and HRRs is relatively uniform. The only exception is there are slightly fewer female STEMI cases in all HRRs, with a mean of 0.41 for Baltimore and 0.03 for Salisbury and Takoma Park, compared to means of approximate 0.5 for the other conditions.

The study's analytical dataset allowed comparisons of one condition to another, stratified by HRR. Cardiac arrest observations included sepsis and trauma diagnoses as well. Diagnoses of both cardiac arrest and sepsis were averaged at 0.32, 0.3, and 0.49 for Baltimore, Salisbury, and Takoma Park. Cases of both cardiac arrest and trauma were 0.13 for Baltimore and Salisbury and 0.1 for Takoma Park.

The study populations for all conditions in Baltimore and Salisbury are predominately White, comprising of over 50% of the case volume. The second largest racial group for Baltimore and Salisbury is African-American. In contrast to this, African-Americans make up the largest racial group in Takoma Park, with Whites as the second largest group.

The Baltimore and Takoma Park HRRs are comprised of nearly all patients from urban areas with means of 0.97 and higher, whereas only half of Salisbury patients are from urban areas, with means around 0.53. These location patterns are reflected in all five of the conditions examined. Patients listing Medicare as the primary payer comprise of a large share of admissions for all conditions.

There was a large amount of variation in comorbidity measures among different conditions, but not by HRR, with the exception of STEMI. For all the conditions, the Elixhauser Comorbidity Measure had higher means than the Charlson Comorbidity Index. Sepsis had the highest means among the conditions, with the regional means ranging from 9.26 to 11.16 for the Elixhauser measure and 6.52 to 7.79 for the Charlson Index. Cardiac arrest also had high comorbidity means; with regional means of 8.38 to 9.34 for the Elixhauser measure and 6.51 to 6.96 for the Charlson Index. The regional means for acute ischemic stroke were between 7.22 and 7.77 for the Elixhauser measure and 6.34 to 6.83 for the Charlson Index. Trauma had slightly lower comorbidity means, perhaps due to its truly unforeseen nature. The regional means for trauma were 5.3 to 6.77 for the Elixhauser measure and 3.29 to 4.35 for the Charlson Index. STEMI was the only condition that presented slightly larger regional differences in the comorbidity means. In Baltimore, the Elixhauser measure was 7.06, compared to 5.86 in Salisbury and

6.41 in Takoma Park. For the Charlson Index means, Baltimore was 7.06, Salisbury was 5.39, and Takoma Park was 5.76.

In terms of hospital characteristics, Baltimore contains the highest average bed size, Salisbury and Takoma Park had lower, and similar, bed size averages. However, the majority of hospitals in Baltimore and Takoma Park are teaching hospitals and belong to hospital systems, with means of ~0.91 for Baltimore and ~0.8 for Takoma Park, whereas none of the hospitals in Salisbury fit this criteria so the means are 0.

In summary, Baltimore is the largest HRR of the three. It has a higher number of observations for all conditions; the most noticeable difference is in trauma, for which Baltimore has 22,446 observations and Salisbury has 1,527. For all the conditions, Takoma Park has the second most number of observations, leaving Salisbury with the fewest.

4.4 Two-Sample T-Tests

Two-sample t-tests were used to assess regional variation in demographics and hospital characteristics. Tables 4.7 – 4.11 outline the significant differences, if any, for the covariates by condition among two HRRs at a time. The use of a two-sample t-test models the differences between the Baltimore and Salisbury HRRs, Baltimore and Takoma Park, and Salisbury and Takoma Park for sepsis, trauma, acute ischemic stroke, cardiac arrest, and STEMI.

Condition = Sepsis	Baltimore, Salisbury (N = 20,032)		Baltimore, Takoma Park (N = 24,852)		Salisbury, Takoma Park (N = 7,695)	
	t	***p***	***t***	***p***	***t***	***p***
Died during hospitalization	-0.47	0.636	0.4	0.692	-0.47	0.636
Age	-8	<.0001	-2	0.041	-8	<.0001
Female	-1.17	0.242	-4.64	<.0001	1.82	0.0695
Admission day is a weekend	-1.17	0.242	-0.46	0.642	-1.17	0.242
Sepsis	.	.	.	.	.	.
Trauma	-2.98	<.0001	1.25	0.212	-2.98	0.002
Stroke	-1.19	<.0001	0.09	0.929	-1.19	0.232
Cardiac Arrest	-1.39	0.163	0.34	0.736	-1.39	0.163
STEMI	0.91	0.36	-0.05	0.95	0.91	0.364
Bed Size	25	<.0001	34	<.0001	25	<.0001
Competition Index for all inpatient	-Infty	<.0001	-Infty	<.0001	-Infty	<.0001
Competition Index for inpatient from ED	-Infty	<.0001	-Infty	<.0001	-Infty	<.0001
Competition Index for Sepsis	-Infty	<.0001	-Infty	<.0001	-Infty	<.0001
Elixhauser index	-1.96	0.049	10.21	<.0001	-1.96	0.049
Charlson Index	0.42	0.677	10.4	<.0001	0.42	0.677
White	-11.57	<.0001	37.22	<.0001	-11.57	<.0001
Black	11.02	<.0001	-19.91	<.0001	11.02	<.0001
Hispanic	-1.04	0.299	-20.74	<.0001	-1.04	0.299
Asian	7.84	<.0001	-9.31	<.0001	7.84	<.0001
Native American	1.35	0.176	-4.23	<.0001	1.35	0.176
Other	1.62	0.105	-5.46	<.0001	1.62	0.105
Medicare	-6.93	<.0001	1.99	0.046	-6.93	<.0001
Medicaid	11.76	<.0001	4.91	<.0001	11.76	<.0001
Private	-0.81	0.01	-7.15	<.0001	-0.8	0.425
Other	3.88	0.0001	3.52	0.004	3.88	0.0001
Urban	32.67	<.0001	-15.23	<.0001	32.67	<.0001
Income percentile 0-25	2.81	0.005	43	<.0001	2.81	0.005
Income percentile 26-50	-28.09	<.0001	40.94	<.0001	-28.09	<.0001
Income percentile 51-75	-1.53	0.126	-9.63	<.0001	-1.5	0.134
Income percentile 76-100	61.06	<.0001	-30.7	<.0001	61.06	<.0001
Hospital System	409.83	<.0001	11.42	<.0001	310.12	<.0001
Teaching hospital	310.12	<.0001	16.79	<.0001	409.83	<.0001

Table 4.7. Two Sample T-Test for Sepsis.

Condition = Trauma	Baltimore, Salisbury (N = 23,973)		Baltimore, Takoma Park (N = 26,689)		Salisbury, Takoma Park (N = 5,770)	
	t	***p***	***t***	***p***	***t***	***p***
Died during hospitalization	1.7	0.089	1.5	0.132	-0.6	0.545
Age	-15	<.0001	-9	<.0001	8	<.0001
Female	-6.06	<.0001	-4.04	<.0001	3.1	0.001
Admission day is a weekend	1.68	0.092	0.66	0.508	-1.1	0.269
Sepsis	-3.88	0.0001	-6.63	<.0001	-0.25	0.803
Trauma	.	.	.	.	.	.
Stroke	-4.55	<.0001	1.51	0.131	4.92	<.0001
Cardiac Arrest	-1.55	<.0001	1.03	0.301	1.91	0.056
STEMI	-1.12	0.262	0.37	0.714	1.21	0.227
Bed Size	56	<.0001	96	<.0001	2	0.033
Competition Index for all inpatient	-Infty	<.0001	-Infty	<.0001	-Infty	<.0001
Competition Index for inpatient from ED	-Infty	<.0001	-Infty	<.0001	-Infty	<.0001
Competition Index for Trauma	-Infty	<.0001	-Infty	<.0001	-Infty	<.0001
Elixhauser index	-6.74	<.0001	0.49	0.621	6.5	<.0001
Charlson Index	-5.86	<.0001	0.48	0.631	5.67	<.0001
White	-16.88	<.0001	23.51	<.0001	29.73	<.0001
Black	18.45	<.0001	-15.17	<.0001	-25.51	<.0001
Hispanic	-1.18	0.236	-12.62	<.0001	-8.02	<.0001
Asian	5.14	<.0001	-5.71	<.0001	-7.93	<.0001
Native American	2.16	0.031	-1.15	0.251	-2.41	0.016
Other	1.32	0.186	-1.17	0.242	-1.86	0.06
Medicare	-11.7	<.0001	-3.91	<.0001	8.02	<.0001
Medicaid	15.39	<.0001	4.43	<.0001	-9.42	<.0001
Private	1.67	0.095	-3.06	0.002	-3.22	0.001
Other	6.83	<.0001	12.42	<.0001	0.87	0.383
Urban	32.85	<.0001	-13.72	<.0001	-35.25	<.0001
Income percentile 0-25	0.97	0.331	35.32	<.0001	12.91	<.0001
Income percentile 26-50	-23.72	<.0001	38.22	<.0001	33.35	<.0001
Income percentile 51-75	-3.25	0.001	-7.53	<.0001	-1.37	0.171
Income percentile 76-100	44.68	<.0001	-25.3	<.0001	-53.86	<.0001
Hospital System	543.32	<.0001	6.64	<.0001	-191.48	<.0001
Teaching hospital	495.66	<.0001	10.26	<.0001	-160.18	<.0001

Table 4.8. Two Sample T-Test for Trauma.

Condition = Stroke	Baltimore, Salisbury (N = 5,770)		Baltimore, Takoma Park (N = 10,267)		Salisbury, Takoma Park (N = 2,659)	
	t	***p***	***t***	***p***	***t***	***p***
Died during hospitalization	1.3	0.213	-0.27	0.787	-1.2	0.229
Age	-3	0.001	-1	0.141	2	0.111
Female	1.29	0.908	-2.92	0.003	-3.02	0.002
Admission day is a weekend	-0.05	0.956	-1.16	0.245	-0.71	0.476
Sepsis	1.27	0.202	-5.22	<.0001	-4.93	<.0001
Trauma	-1.26	0.207	2.09	0.037	2.37	<.0001
Stroke	.	.	.	<.0001	.	<.0001
Cardiac Arrest	0.03	0.98	-1.73	0.083	-1.29	0.198
STEMI	-1.07	0.284	0.1	0.923	1	0.317
Bed Size	18	<.0001	26	<.0001	2	0
Competition Index for all inpatient	-Infty	<.0001	-Infty	<.0001	-Infty	<.0001
Competition Index for inpatient from ED	-Infty	<.0001	-Infty	<.0001	-Infty	<.0001
Competition Index for Stroke	-Infty	<.0001	-Infty	<.0001	-Infty	<.0001
Elixhauser index	1.29	0.196	3.04	0.002	0.92	0
Charlson Index	0.88	0.378	2.722.72	0.006	1.06	0.288
White	-10.47	<.0001	20.36	<.0001	23.14	<.0001
Black	10.24	<.0001	-13.77	<.0001	-18.29	<.0001
Hispanic	-0.14	0.892	-6.59	<.0001	-5.25	<.0001
Asian	4.87	<.0001	-6.38	<.0001	-7.8	<.0001
Native American	0.32	0.747	-0.33	0.783	-0.5	0.618
Other	1.28	0.201	-2.77	0.005	-3.13	0.001
Medicare	-4.41	<.0001	1.3	0.194	4.51	<.0001
Medicaid	7.53	<.0001	0.69	0.492	-5.12	<.0001
Private	0.42	0.676	-2.97	0.003	-2.37	0.017
Other	1.67	0.09	5.4	<.0001	1.55	0.121
Urban	25.9	<.0001	-17.61	<.0001	-29.04	<.0001
Income percentile 0-25	-0.91	0.365	27.68	<.0001	12.18	<.0001
Income percentile 26-50	-20.2	<.0001	20.59	<.0001	27.07	<.0001
Income percentile 51-75	-1.27	0.203	-5.36	<.0001	-2.51	0.012
Income percentile 76-100	43.5	<.0001	-14.58	<.0001	-41	<.0001
Hospital System	306.32	<.0001	9.51	<.0001	-89.11	<.0001
Teaching hospital	256.11	<.0001	12.49	<.0001	-70.52	<.0001

Table 4.9. Two Sample T-Test for Acute Ischemic Stroke.

Condition = Cardiac Arrest	Baltimore, Salisbury (N = 1,780)		Baltimore, Takoma Park (N = 1,959)		Salisbury, Takoma Park (N = 511)	
	t	***p***	***t***	***p***	***t***	***p***
Died during hospitalization	1.46	0.144	0.59	0.556	-0.91	0.362
Age	0	0.69	-4	<.0001	-2	0.013
Female	0.76	0.445	-0.59	0.554	-1.03	0.303
Admission day is a weekend	-1.37	0.172	-0.1	0.917	1.1	0.273
Sepsis	0.5	0.614	-6.04	<.0001	-4.09	<.0001
Trauma	0.02	0.98	1.91	0.056	1.1	0.272
Stroke	-0.21	0.832	-1.53	0.126	-0.86	0.389
Cardiac Arrest	.	.	.	.	.	.
STEMI	-2.23	0.027	0.22	0.823	2.14	0.033
Bed Size	10	<.0001	14	<.0001	2	0.047
Competition Index for all inpatient	-Infty	<.0001	-Infty	<.0001	-Infty	<.0001
Competition Index for inpatient from ED	-Infty	<.0001	-Infty	<.0001	-Infty	<.0001
Competition Index for Cardiac Arrest	-Infty	<.0001	-Infty	<.0001	-Infty	<.0001
Elixhauser index	-1.31	0.19	-0.01	0.994	1.18	0.237
Charlson Index	-0.61	0.542	-0.9	0.371	-0.03	0.976
White	-3.25	0.001	10.85	<.0001	9.92	<.0001
Black	3.43	0.001	-6.75	<.0001	-7.44	<.0001
Hispanic	-1	0.316	-4.09	<.0001	-2.59	0.01
Asian	0.32	0.752	-2.64	0.001	-2.49	0.01
Native American	1.41	0.157	-1.09	0.276	-1.42	0.157
Other	0.15	0.876	-0.68	0.499	-0.6	0.552
Medicare	-1.33	0.184	-1.73	0.083	-0.07	0.942
Medicaid	5.25	<.0001	3.58	.0004	-1.71	0.088
Private	-1.6	0.109	-1.31	0.191	0.53	0.594
Other	-0.41	0.68	4.72	<.0001	1.74	0.083
Urban	11.35	<.0001	-3.64	.0003	-11.88	<.0001
Income percentile 0-25	2.83	0.005	13.82	<.0001	3.95	<.0001
Income percentile 26-50	-8.26	<.0001	10.55	<.0001	11.59	<.0001
Income percentile 51-75	-1.12	0.264	-4.85	<.0001	-2.14	0.033
Income percentile 76-100	12.57	<.0001	-6.96	<.0001	-11.65	<.0001
Hospital System	134.57	<.0001	2.76	<.0001	-46.7	<.0001
Teaching hospital	97.53	<.0001	2.81	<.0001	-35.8	<.0001

Table 4.10. Two Sample T-Test for Cardiac Arrest

Condition = STEMI	Baltimore, Salisbury (N = 2,420)		Baltimore, Takoma Park (N = 2,570)		Salisbury, Takoma Park (N = 644)	
	t	***p***	***t***	***p***	***t***	***p***
Died during hospitalization	-0.47	0.635	-1.66	0.098	-0.76	0.447
Age	0	0.905	0	0.843	0	0.971
Female	0.85	0.394	1.12	0.264	0.04	0.964
Admission day is a weekend	-1.08	0.28	-0.3	0.766	0.68	0.494
Sepsis	2.67	0.008	-3.58	.0004	-4.76	<.0001
Trauma	0.1	0.919	0.24	0.811	0.08	0.938
Stroke	-1.06	0.292	-0.22	0.829	0.77	0.439
Cardiac Arrest	-1.82	0.07	-0.62	0.535	1.19	0.235
STEMI	.	.	.	.	.	.
Bed Size	5	<.0001	8	<.0001	4	<.0001
Competition Index for all inpatient	-Infty	<.0001	-Infty	<.0001	-Infty	<.0001
Competition Index for inpatient from ED	-Infty	<.0001	-Infty	<.0001	-Infty	<.0001
Competition Index for STEMI	-Infty	<.0001	-Infty	<.0001	-Infty	<.0001
Elixhauser index	3.27	0.001	2.4	0.016	-0.92	0.358
Charlson Index	3.62	.0003	3.16	0.001	-0.66	0.51
White	-2.59	0.009	11.93	<.0001	10.57	<.0001
Black	4.09	<.0001	-7.13	<.0001	-8.58	<.0001
Hispanic	-1.34	0.182	-5.25	<.0001	-3.48	.0005
Asian	1.33	0.185	-3.45	.0006	-3.82	<.0001
Native American	2.65	0.008	-1.9	0.057	-2.47	0.014
Other	-1.35	0.719	2.17	0.03	2.25	0.025
Medicare	-0.36	0.719	0.47	0.64	0.61	0.541
Medicaid	3.63	.0003	1.49	0.135	-1.66	0.097
Private	-1.61	0.107	-1.93	0.054	0.01	0.99
Other	1.15	0.252	2.66	0.008	0.65	0.519
Urban	15.49	<.0001	-7.61	<.0001	-16.95	<.0001
Income percentile 0-25	-1.65	0.101	10.82	<.0001	6.09	<.0001
Income percentile 26-50	-8.7	<.0001	11.93	<.0001	12.54	<.0001
Income percentile 51-75	-0.97	0.333	-1.02	0.307	0.12	0.906
Income percentile 76-100	17.08	<.0001	-7.83	<.0001	-18.93	<.0001
Hospital System	154.15	<.0001	-1.13	0.261	-73.67	<.0001
Teaching hospital	138.16	<.0001	-0.24	0.811	-60.29	<.0001

. Table 4.11. Two Sample T-Test for STEMI.

The t-tests showed no significant differences for condition-specific mortality among the HRRs. There are significant demographic differences among the HRRs for all the conditions, especially for race, payer, and income quartile, indicating the need to control for these variables in the multivariable regression analyses.

Approximations of underlying patient severity, as assessed by the Elixhauser and Charlson Comorbidity Indices, were not significantly different among the HRRs, except for the trauma condition between Salisbury and Takoma Park. The t-test results also allow relative and conditional comparisons of one condition by another.

Hospital characteristics are significantly different in the all of the HRR and condition comparisons. The variables bed size, teaching status and hospital system affiliation vary among the HRRs, framing the premise for this study’s examination of hospital competition and outcomes.

4.5 Competition and Mortality Regressions

4.51 Initial Analysis of Binary Competition Variable and Mortality

The Chi-Square test and multivariable binary logistic regression for the binary competition variable, comparing the Salisbury HRR to the Baltimore and Takoma Park HRRs, and condition-associated mortality were not significant, implying that the next logical step would be to control for confounders. In Table 4.12, the Chi-Square Test results are outlined for the different conditions. None of the conditions showed a significant relationship between the regional competition and mortality.

Condition	χ^2	p
Sepsis	0.438	0.803
Trauma	4.013	0.134
Stroke	1.5	0.473
Cardiac Arrest	2.396	0.301
STEMI	3.201	0.201

Table 4.12. Chi-Square Test for HRR by Mortality.

For the basic logistic regression, the main independent variable was the binary competition variable that compared the Salisbury HRR's low level of competition, as the treatment group, to the Baltimore and Takoma Park HRRs' high levels of competition, as the reference group. This allowed for a regional comparison of varied levels of competition. The basic logistic regressions, without any controls, results for the different conditions are modeled in Table 4.14 through odds ratio point estimates with a 95% confidence interval and two-tailed statistical significance level, α, at 0.05. For the sepsis basic model, the odds ratio point estimate is 0.957 and for STEMI, the odds ratio point estimate is 0.952. Because these odds ratio estimates are below one, it indicates that there is a lower odds of sepsis and STEMI mortality in Salisbury compared to Baltimore and Takoma Park. However, the p-value for these regressions were >0.05, the relationship is therefore not significant.

In contrast to this, the other conditions have point estimates higher than one, suggesting that the odds of mortality for trauma, acute ischemic stroke, and cardiac arrest are all higher in Salisbury than Baltimore and Takoma Park. However, the p-values for these conditions' basic regression models are all >0.05 as well, indicating insignificant associations. The high p-values indicate that none of the basic, binary logistic regressions' results for the five conditions were significant.

Model	**OR**	**95% CI**	***df***	***p***
Basic	0.957	0.815, 1.123	2	0.631
Demographics	1.018	0.865, 1.198	10	0.727
Comorbidity	0.929	0.791, 1.091	4	0.414
Demographics+	1.311**	1.081, 1.591	18	0.006
Demographics+, Comorbidity	1.251*	1.031, 1.519	20	0.024
Facility	0.745**	0.619, 0.897	4	0.001
Facility+	0.911	0.636, 1.303		0.609
Demographics+, Comorbidity, Facility	0.982	0.788, 1.225	22	0.814

Note. *p<.05**p<0.01. All models include low competition binary variable.
Basic – only low competition binary
Demographics includes: age, age squared, gender binary, racial binary
Comorbidity includes: Elixhauser Comorbidity, Charlson Comorbidity Index
Demographics+ includes: demographics, payer binary, urban, income quartile binary
Demographics+, Comorbidity includes: demographics+, comorbidity
Facility includes: bed size, teaching status
Facility+ includes: hospital fixed effects
Demographics+, Comorbidity, Facility includes: demographics+, comorbidity, facility

Table 4.13. Results of Stepwise Regression Examining Effects of Competition on Sepsis Mortality, with Instrumental Variables Analysis for Hospital Competition.

Model	Sepsis	Trauma	Stroke	Cardiac Arrest	STEMI
Basic	0.957	1.284	1.241	1.264	0.952
Demographics	1.011	1.425*	1.281	1.221	0.922
Comorbidity	0.929	1.273	1.24	1.214	0.953
Demographics+	1.311**	1.581*	1.603*	1.308	1.074
Demographics+, Comorbidity	1.242**	1.535*	1.609*	1.227	1.108
Facility	0.737**	0.861	0.84	1.568*	1.424
Facility+	0.911	0.834	1.172	2.051	0.321
Demographics+, Comorbidity, Facility	0.974	0.985	1.073	1.578	1.85*

Note. **p*<.05 ***p*<0.01. All models include low competition binary variable.
Basic – only low competition binary
Demographics includes: age, age squared, gender binary, racial binary
Comorbidity includes: Elixhauser Comorbidity, Charlson Comorbidity Index
Demographics+ includes: demographics, payer binary, urban, income quartile binary
Demographics+, Comorbidity includes: demographics+, comorbidity
Facility includes: bed size, teaching status
Facility+ includes: hospital fixed effects
Demographics+, Comorbidity, Facility includes: demographics+, comorbidity, facility

Table 4.14 Results of Stepwise Regression Examining Effects of Competition on Mortality for All Conditions.

The stepwise regressions showed significant results for the demographics+ and demographics+, comorbidity model for sepsis, trauma, and stroke. Also, the significant results for the sepsis and cardiac arrest facility model suggest that the association of between hospital competition and mortality may vary by facility-level characteristics.

The odds of sepsis mortality were higher in a low competition region than the high competition regions for the demographics+ (1.311, p = 0.006) and demographics+, comorbidity models (1.251, p = 0.024). The sepsis facility model showed the opposite result (0.737, p = 0.001); the odds of sepsis mortality in a low competition region are lower than high competition regions. This is the only regression that suggests that the likelihood of mortality is lower in a low-competition region.

Similar to the sepsis demographics+ model, the trauma (1.581, p = 0.021) and acute ischemic stroke (1.585, p = 0.029) conditions show an association of higher mortality in the low competition region than high competition regions. Likewise, the demographics+, comorbidity model for sepsis (1.251, p = 0.024), trauma (1.535, p = 0.031) and acute ischemic stroke (1.591, p = 0.028) showed significantly likelihood of mortality in the low competition region. These results indicate that a HRR with lower levels of competition have a higher likelihood of mortality for these conditions, compared to regions with high levels of competition.

While the sepsis facility model suggests that there are lower odds of mortality in the low competition region, the cardiac arrest facility model (1.578, p = 0.024) shows otherwise and reiterates the other models’ significant results. Besides the sepsis facility model, the other significant multivariable regressions suggest that a region with lower competition has higher odds of mortality than high competition regions.

For the demographics+ and demographics+, comorbidity models, sepsis, trauma, and acute ischemic stroke all had significant results, with point estimates higher than one. Specifically, the point estimates for sepsis was 1.301 and 1.242. For trauma, the estimates were 1.59 and 1.537 for the two models. The trauma demographics model was also significant, with a point estimate of 1.425. For acute ischemic stroke, the point estimates for the demographics+ and demographics+, comorbidity models were 1.603 and 1.609. These odds ratio point estimates indicate that the odds of mortality are higher in a low competition HRR than a high competition HRR. While only some of the results indicated significant associations, the initial results from the multivariable binary logistic regressions suggest that higher competition may result in better outcomes, when controlling for confounding factors.

The final stepwise regression model included all demographics, comorbidity, and hospital characteristics as covariates, with the binary competition variable as the main independent variable and mortality as the dependent variable. There is a significantly higher likelihood of STEMI mortality (1.894, $p = 0.007$) in the low competition region than high competition region. Mortality did not vary significantly for sepsis, trauma, acute ischemic stroke, and cardiac arrest ($p > 0.05$) when considering all patient- and hospital-level covariates.

4.6 Two Stage Least Squares Estimation

The 2SLS estimation was conducted for all of the conditions of interest, but only sepsis and trauma showed significant associations. These conditions had significant, and reversed, results upon initially adding the hospital system affiliation covariate in the multivariable logistic regression. The OLS and 2SLS results for sepsis are highlighted in Table 22 and for trauma in Table 23. For sepsis, the OLS F-value was 111,143.6, an extremely high value, already indicating that the two estimates may not be comparable. A large F-statistic indicates that OLS is inconsistent, and that the variable may be endogenous. The intercept parameter was 0.336 with a t-value of 115.37, significant with a p-value of <.0001. The system binary parameter was -0.336, with a t-value of -105.56, significant with a p-value of <.0001. For the 2SLS, the F-value was 23.75, which is still higher than the proposed 10 to indicate the use of instrumental variable analysis. The intercept parameter estimate was 0.125, with a t-value of 57, and significant with a p-value of <.0001. For the competition binary variable, the parameter estimate was -0.079, with a t-value of -4.87, and significant with a p-value of <.0001. The differences in parameter estimates indicates that the two estimation models produce different results, indicating the need to test exogeneity.

4.6.1 Hausman Test of Endogeneity

The OLS and 2SLS parameter estimates are inputted in the Hausman Test equation:

$$H = \frac{\left(\hat{\theta} - \tilde{\theta}\right)^2}{(\tilde{s} - \hat{s})^2}$$

For sepsis, the Hausman Test Statistic was 92.16 and for trauma, the Hausman Test Statistic was 105.06. These are extraordinarily high values, leading to rejection of the null hypothesis that there is no difference between the two variables. This indicates that competition is endogenous, supporting the use of the instrumental variable analysis, treating competition as endogenous.

4.7 Binary Logistic Regressions with Instrumental Variable Method

The results of the binary logistic regressions with instrumental variable analysis for the different emergency care outcomes are in Table 4.15. The instrumental variables analysis for hospital system affiliation switched the odds ratio estimate, where higher hospital system competition in the HRR is associated with increased odds of mortality for sepsis and trauma.

Model	**OR**	**95% CI**	***df***	***p***
Basic	0.65**	0.53, 0.797	2	<.0001
Demographics	0.683**	0.556, 0.84	10	.0003
Comorbidity	0.624**	0.509, 0.766	4	<.0001
Demographics+	0.902	0.713, 1.142	18	0.392
Demographics+, Comorbidity	0.855	0.675, 1.083	20	0.194
Facility	0.615**	0.499, 0.758	4	<.0001
Demographics+, Comorbidity, Facility	0.811	0.636, 1.035	22	0.092
Demographics+, Comorbidity, Facility†	0.745**	0.6, 0.926	20	0.007

Note. *p<.05 **p<0.01. All models include low competition binary variable.
Basic – only low competition binary
Demographics includes: age, age squared, gender binary, racial binary
Comorbidity includes: Elixhauser Comorbidity, Charlson Comorbidity Index
Demographics+ includes: demographics, payer binary, urban, income quartile binary
Demographics+, Comorbidity includes: demographics+, comorbidity
Facility includes: bed size, teaching status
Facility+ includes: hospital fixed effects
Demographics+, Comorbidity, Facility includes: demographics+, comorbidity, facility

Table 4.15. Results of Stepwise Regression Examining Effects of Competition on Sepsis Mortality, with Instrumental Variables Analysis for Hospital Competition.

Sepsis	OR	OR§
Basic	0.957	0.65**
Demographics	1.018	0.683**
Comorbidity	0.929	0.624**
Demographics+	1.311**	0.902
Demographics+, Comorbidity	1.251*	0.855
Facility	0.745**	0.615**
Facility+	0.911	0.811
Demographics+, Comorbidity, Facility	0.982	0.745**

Note. § - with hospital system binary var., *_p_<.05, **_p_<.01

Basic – only low competition binary
Demographics includes: age, age squared, gender binary, racial binary
Comorbidity includes: Elixhauser Comorbidity, Charlson Comorbidity Index
Demographics+ includes: demographics, payer binary, urban, income quartile binary
Demographics+, Comorbidity includes: demographics+, comorbidity
Facility includes: bed size, teaching status
Facility+ includes: hospital fixed effects
Demographics+, Comorbidity, Facility includes: demographics+, comorbidity, facility

Table 4.16. Results of Stepwise Regression Examining Effects of Competition on Sepsis Mortality, with Instrumental Variables Analysis for Hospital System Affiliation.

Trauma	OR	OR§
Basic	1.284	0.566*
Demographics	1.425*	0.533*
Comorbidity	1.273	0.566*
Demographics+	1.59*	0.593
Demographics+, Comorbidity	1.537*	0.588
Facility	0.861	0.539*
Facility+	0.834	0.834
Demographics+, Comorbidity, Facility	0.985	0.549*

Note. § - with hospital system binary var., *p<.05, **p<.01
Basic – only low competition binary
Demographics includes: age, age squared, gender binary, racial binary
Comorbidity includes: Elixhauser Comorbidity, Charlson Comorbidity Index
Demographics+ includes: demographics, payer binary, urban, income quartile binary
Demographics+, Comorbidity includes: demographics+, comorbidity
Facility includes: bed size, teaching status
Facility+ includes: hospital fixed effects
Demographics+, Comorbidity, Facility includes: demographics+, comorbidity, facility

Table 4.17. Results of Stepwise Regression Examining Effects of Competition on Trauma Mortality, with Instrumental Variables Analysis for Hospital System Affiliation.

Stroke	OR	OR§
Basic	1.241	0.632
Demographics	1.281	0.618
Comorbidity	1.24	0.628
Demographics+	1.603*	0.754
Demographics+†	1.609*	0.754
Demographics+, Comorbidity	0.84	0.572
Facility	1.172	1.172
Facility+	1.073	0.668

Note. § - with hospital system binary var., **p*<.05, ***p*<.01

Basic – only low competition binary
Demographics includes: age, age squared, gender binary, racial binary
Comorbidity includes: Elixhauser Comorbidity, Charlson Comorbidity Index
Demographics+ includes: demographics, payer binary, urban, income quartile binary
Demographics+, Comorbidity includes: demographics+, comorbidity
Facility includes: bed size, teaching status
Facility+ includes: hospital fixed effects
Demographics+, Comorbidity, Facility includes: demographics+, comorbidity, facility

Table 4.18. Results of Stepwise Regression Examining Effects of Competition on Acute Ischemic Stroke Mortality, with Instrumental Variables Analysis for Hospital System Affiliation.

Cardiac Arrest	**OR**	**OR§**
Basic	1.264	1.376
Demographics	1.221	1.301
Comorbidity	1.214	1.359
Demographics+	1.308	1.473
Demographics+†	1.227	1.434
Demographics+, Comorbidity	1.568*	1.57
Facility	2.051	2.051
Facility+	1.578	1.618

Note. § - with hospital system binary var., ****p*<.05, *****p***<.01**

Basic – only low competition binary

Demographics includes: age, age squared, gender binary, racial binary

Comorbidity includes: Elixhauser Comorbidity, Charlson Comorbidity Index

Demographics+ includes: demographics, payer binary, urban, income quartile binary

Demographics+, Comorbidity includes: demographics+, comorbidity

Facility includes: bed size, teaching status

Facility+ includes: hospital fixed effects

Demographics+, Comorbidity, Facility includes: demographics+, comorbidity, facility

Table 4.19. Results of Stepwise Regression Examining Effects of Competition on Cardiac Arrest Mortality, with Instrumental Variables Analysis for Hospital System Affiliation.

STEMI	OR	OR§
Basic	0.952	0.831
Demographics	0.922	0.754
Comorbidity	0.953	0.826
Demographics+	1.074	0.902
Demographics+†	1.108	0.921
Demographics+, Comorbidity	1.424	1.004
Facility	0.321	0.321
Facility+	1.85*	1.262

**Note. § - with hospital system binary var., ****p*<.05, *****p*<.01

Basic – only low competition binary
Demographics includes: age, age squared, gender binary, racial binary
Comorbidity includes: Elixhauser Comorbidity, Charlson Comorbidity Index
Demographics+ includes: demographics, payer binary, urban, income quartile binary
Demographics+, Comorbidity includes: demographics+, comorbidity
Facility includes: bed size, teaching status
Facility+ includes: hospital fixed effects
Demographics+, Comorbidity, Facility includes: demographics+, comorbidity, facility

Table 4.20. Results of Stepwise Regression Examining Effects of Competition on STEMI Mortality, with Instrumental Variables Analysis for Hospital System Affiliation

Sepsis			Trauma		
p	OR	95% CI	*p*	OR	95% CI
0.0003	0.776	0.676, 0.890	0.0002	0.523	0.373, 0.733

Table 4.21. Results of Binary Logistic Regression Examining Effects of Competition on Sepsis and Trauma Mortality, with Instrumental Variables Analysis for Hospital System Affiliation, exclusion of Competition Binary Variable.

Note. *Uses Demographics+, Comorbidity, Facility Model includes: age, age squared, gender binary, racial binary, payer binary, urban, income quartile binary, Elixhauser Comorbidity, Charlson Comorbidity Index, bed size, teaching status, and hospital system affiliation as an instrumental variable.*

Sepsis One-Stage Least Square

Variable	Parameter Estimate	Standard Error	*t*	*p*
Intercept	0.0994	0.004	19.86	<.0001
System	0.0266	0.005	-105.56	<.0001

Note**.** F-statistic = 11,143.6

Sepsis Two-Stage Least Square

Variable	Parameter Estimate	Standard Error	*t*	*p*
Intercept	0.125	0.002	57	<.0001
System	-0.079	0.016	-4.87	<.0001

Note**.** F-statistic = 23.75
Hausman Test Statistic = 92.16 for sepsis

Table 4.23. Results of the Two-Stage Least Square Estimations for Sepsis.

Trauma One-Stage Least Square

Variable	Parameter Estimate	Standard Error	*t*	*p*
Intercept	0.016	0.002	5.98	<.0001
System	0.012	0.002	4.28	<.0001

Note**.** F-statistic = 18.31

Trauma Two-Stage Least Square

Variable	Parameter Estimate	Standard Error	*t*	*p*
Intercept	0.028	0.001	27.79	<.0001
System	-0.029	0.006	-4.28	<.0001

Note**.** F-statistic = 105.06
Hausman Test Statistic = 105.06 for trauma

Table 4.24. Results of the Two-Stage Least Square Estimations for Trauma.

The instrumental variables analysis reversed the original stepwise regression estimates, and became significant, for sepsis and trauma in the basic, demographics, comorbidity, facility, ‘demographics+, comorbidity, and facility’ models. The estimate for the original sepsis facility model (0.737, $p = 0.001$) was the only regression that showed a lower odds of mortality in a low competition region. The same model, with inclusion of the instrumental variable, amplifies this association with an even lower point estimate of 0.615 ($p <.0001$).

For sepsis, the ‘demographics+, comorbidity, facility’ model with all covariates became significant as well (0.745, $p = 0.007$), showing a significantly lower odds of sepsis mortality in a low competition region, compared to a high competition region when controlling for all patient- and hospital-covariates. The average estimates for sepsis in the basic, demographics, comorbidity, and demographics+ model was 0.643 ($p <.0001$). The odds of mortality is on average, 35 percent less in a low competition region compared to a region with high competition.

For trauma, the inclusion of instrumental variable analysis showed significant, and reversed, estimates for the same significant models as sepsis. The original estimate for the basic model switched from 1.284 to 0.566 ($p = 0.033$). This switch in estimate direction also occurs for the demographics (0.533, $p = 0.019$) and comorbidity model (0.566, $p = 0.033$) – justifying the need for instrumental variable analysis to produce more consistent and accurate parameter estimates. The estimates for the facility and ‘demographics+, comorbidity, facility’ models became significant with instrumental variables analysis, with estimates of 0.539 ($p = 0.027$) and 0.549 ($p = 0.047$), respectively. Because the point estimates are below one, this suggests that the odds of trauma mortality is almost half as less likely in a low competition region than a high competition region.

The demographics+ and demographics+, comorbidity models for sepsis and trauma became insignificant with the instrumental variables analysis. Inpatient mortality for acute ischemic stroke, cardiac arrest, and STEMI showed no significant changes after inclusion of the instrumental variable.

Upon removing the competition variable from the demographics+, comorbidity and facility model, the sepsis and trauma models were significant below <.01. In a low competition region, sepsis mortality is 32 percent lower (0.776, $p = 0.0003$) than a high competition region. The trauma condition heightens this protective effect of a low competition region – mortality in a low competition region is 0.53 less likely than a high competition region. In essence, the odds of trauma mortality is nearly cut in half in a low competition region.

4.8 Conclusion

While initial results suggest that an HRR with high levels of hospital competition improves outcomes for emergency conditions, these stepwise regressions did not consider the potential endogeneity of competition, possibly skewing the results. The stepwise regressions results without the instrumental variable method support previous studies' findings of competition improving outcomes. For sepsis, trauma, acute ischemic stroke, cardiac arrest, and STEMI, the odds of mortality were greater in a low competition region compared to a high competition region. This suggests that competition can improve quality, delivery of care, and thus, patient outcomes.

In the 2SLS estimations, competition was considered endogenous and the instrumental variable of hospital system affiliation was included. The direction reversal in estimates for sepsis and trauma suggest that the odds of mortality are lower in a region with low competition compared to a region with high competition.

The use of instrumental variable analysis was validated through the 2SLS estimation, yielding significantly different estimates from the OLS and the IV, and the Hausman Test for endogeneity. The instrumental variable results suggest that hospital system affiliation is highly correlated with competition, and potentially improved outcomes but only through the competition. Upon treating competition as an endogenous variable, the subsequent multivariable regressions reveal a positive relationship between competition and mortality for sepsis (0.776, p = 0.0003) and trauma (0.523, p = 0.0002).

5: Discussion

This study's findings suggest variability in inpatient hospital mortality for emergency care conditions and contrasting levels of regional competition. This study estimated the relationship between competition and emergency outcomes, by accounting for the presence of hospital systems in a region. Initial results using stepwise regression models, accounting for common patient- and hospital-covariates, were comparable to the findings from previous studies examining competition and patient outcomes (Gaynor & Town, 2012; Kessler & McClellan, 2000; Miller, 1996; Bloom et al., 2010; Sari, 2002). The odds of mortality for emergency care conditions were higher in a low competition region. However, with consideration to the possibility of inconsistent parameter estimates due to a possible endogenous regressor, the regressions with instrumental variable analysis, show that a region with low competition can have a protective effect on mortality for these conditions – the odds of mortality for sepsis (0.776) and trauma (0.53) were significantly lower for a low competition region compared to a regions with high competition. The differences in parameter estimates from the original logistic regressions and the subsequent regressions using instrumental variable analysis suggest that there may be an association between system-affiliation, volume, and thus impacting the level of competition.

These results suggest that lower levels of competition promotes better outcomes, refutes basic economic theory and previous findings that competition improves quality of care. While it is notoriously difficult to measure the effects of mergers (Gaynor, 2012), this study assesses variables related to hospital consolidation through the explanatory variable of varying regional competition levels and instrumental variable of hospital system affiliation. The instrumental variable analysis suggests that lower levels of competition are associated with better outcomes, as shown by decreased sepsis and trauma mortality. Additionally, these results underscore the need to discretely examine the outcomes of unplanned, critical illnesses.

The study developed a groundbreaking modified-HHI methodology and use of instrumental variable analysis to examine the impact of competition in unplanned, critical illness. Much of the quality and outcomes literature focuses chronic conditions and planned care at the individual hospital level, with little regard to care coordination factors. This study is the one of the first to provide estimates of the effect of competition on emergency care outcomes, linking instances of the delivery of high-quality emergency care problem in the context of health economics. The present findings offer support for the idea that competition may be aversive in instances of unplanned, critical illness – instead, coordinated hospital systems may be better suited to deliver timely, high-quality care for emergency care conditions.

The study's methodology and ability to exploit Maryland's natural experiment of regulated payments allows a unique study of competition and emergency care outcomes. SID is a large, state database used to estimate the effect of competition on mortality for emergency care conditions based on real-world data. The database is contained within the state of Maryland, which utilizes an all-payer model, naturally controlling for price. In essence, it allowed for a study of regional competition, attenuating the effect of price. Previous studies that attempted to study the effects of competition on patient outcomes are unable to differentiate between the impact of price and the number of providers on patient outcomes. Maryland's All-Payer Model is the only state in the nation that can provide an environment to purely measure competition, as the number of providers in the local healthcare market, on patient outcomes.

Most hospital consolidation opponents suggest that hospital consolidation increases insurance clout, and therefore price. On the other hand, those in favor of hospital consolidation cite improvements in quality and patient outcomes. This study provided a context to study these claims. Because hospitals cannot compete on price, the state of Maryland has created a level-paying field, allowing for studies of regulated payments and volume-based competition. As more states consider adopting a fixed-payment approach, or even capitation, this study's results can provide insight on the effects of a uniform payment system on emergency care outcomes.

Second, econometric methods of instrumental variables analysis were used to enable inference regarding the impact of a low competition HRR on mortality for emergency care conditions. This has implications for future studies of hospital system affiliation and quality. Despite the use of the Hasuman and 2-Stage Least Squares Estimations, further tests need to be conducted to validate this instrumental variable.

The study has certain limitations. The Dartmouth Atlas uses old data and arbitrary rules to determine boundaries for HRRs; these may not be reflective of actual health utilization patterns in the state. It is based on neurosurgical and cardiovascular surgery patterns, whereas this study is focused on unplanned, critical illnesses. The Dartmouth HRR guidelines can cross state lines. Therefore, the two other hospitals located in Delaware for the Salisbury HRR were not examined. Additionally, the state of Maryland is comprised of only three HRRs, signifying the more appropriate methodology of considering the competition index as binary, rather than continuous. For future studies that encompass more regions, the index could be considered continuous or use its log, to provide further insight of the effect of regional competition on emergency care outcomes.

The use of Maryland SID data has limitations as well. This study only examined Maryland hospitals, ignoring the neighboring effect of Virginia, Delaware and Washington, D.C. The Takoma Park HRR is located adjacent to the Washington, D.C. HRR, rendering the neighboring effect event more pronounced in the state and perhaps ignoring the outcomes of those patients that visit EDs in Washington, D.C. opposed to Takoma Park. Because Maryland is comprised of only three HRRs, limiting the competition measure methodology to be binary, opposed to continuous. A continuous HHI would be a more appropriate and valid measure of competition. Also, a study of more than three regions would allow for a more in-depth and comprehensive study of competition and sudden critical illness outcomes. For future studies that encompass a greater number of regions, the index could be considered continuous or use its log, to provide further insight of the effect of regional competition on emergency care outcomes.

This study only examined one year of data, preventing any longitudinal conclusions. Coding variability is a concern with discharge abstracts and administrative data. ICD-9 coding may have inaccuracies, without laboratory results or patient health status assessments to unobservable patient severity bias. Without prior patient history or functional outcomes, the severity of the diagnosis is unknown. Furthermore, sepsis coding is highly variable, indicating that the ICD-9 codes used may not contain the true incidence of sepsis within the state. This study only considered cases originating from the ED and excluded transfers. This may create bias in the results, because within-hospital transfers may alter outcomes. Health systems are more likely to transfer patients within the affiliated hospitals because of shared financial incentives. However, this study excludes this population because it only considered the ED-admitted population, rather than those admitted via interfacility transfer.

This state data did not consider geographical limitations. While the Salisbury HRR is largely isolated by the Chesapeake Bay, this study did not explicitly consider any other geographical barriers. Maryland’s topography includes a significant number of rivers and other waterways that may be creating geographic variations. Additionally, rates of diversion were not examined in this study.

Although this study considered instrumental variable analysis validity tests, more comprehensive tests could be performed with hospital-quality measures such as Hospital Compare data and other report cards. Intuitively, hospital system affiliation relates to mortality – larger, closed health systems boast improved health outcomes. This implies that hospital system affiliation and mortality may not be exogenous. Additionally, the Hausman Test requires two exogenous variables but this study only considered hospital system. Future studies can include multiple exogenous relationship to validate competition as an endogenous variable, and its association with hospital system affiliation and mortality. Additionally, the study could consider hospital system affiliation as a covariate, rather than an instrumental variable. While the instrumental variable was created as a logical process and an attempt to understand the association between competition and emergency care outcomes, it is not necessarily restricted to only an instrumental variable approach. The use of hospital system affiliation as a covariate could provide a more accurate statistical analysis, without the need for the instrumental variable validation.

Finally, this study only utilized inpatient onsite mortality measures as a quality indicators. To supplement the mortality variable, binary hospital variables were used to control for hospital-specific unobserved factors. However, the association between regional competition and mortality is nonlinear, indicating that the hospital-specific effects are not necessarily differenced away. Future studies may use additional health care quality measures, combining quantitative and qualitative data to provide better insight on this relationship.

5.1 Future Directions

Future studies can use longitudinal and more comprehensive datasets to characterize the role of competition in a rate-regulated state. With the implementation of the new All-Payer model, that includes quality-payment initiatives and global budgets, these reforms follow the model of capitation. This has significant implications for hospital competition, removing the volume-based component of competition. Therefore, longitudinal studies with future cohorts of Maryland SID data can seek causal inference between the global budget implementation and patient outcome.

Furthermore, the use of more comprehensive quality indicators for hospitals can provide better proxies for hospital quality. With the use of Hospital Compare data, future studies can use the structural and process measures that pertain to the ED to assess hospital quality. By identifying measures not related to competition, and controlling for these factors, the relationship between competition and hospital quality can be more definitive. Currently, the use of hospital controls may detract away from the real relationship of competition and quality. Additionally, in the state of Maryland, the range of quality may not be significantly different, prompting further studies in other states.

Additionally, condition-specific HHI calculations should be further investigated, especially for specialized sectors. Since emergency care is fundamentally different than planned care, the use of ED- and condition-specific HHIs revealed a more accurate assessment of the emergency care health market. The use of the modified-HHIs could be applied to claims data, to assess the relationship between reimbursement rates for different diseases and competition as well.

Ultimately, the Maryland-All Payer model is designed to control costs and improve quality through its new targets of reducing readmissions, hospital-acquired conditions, and improving population health measures (CMS, 2014). This state data could be compared with a similar state that does not use an All-Payer Model, to compare the effectiveness of the state's reforms.

5.2 Public Health Significance

The emergency care system is designed to optimize patient outcomes for day to day emergencies, while ultimately enhancing preparedness efforts for larger scale emergencies. Inherently, a more coordinated system is inherently a more prepared system. Some suggest that coordination can take place through consolidated hospital systems, and the study's findings and use of instrumental variable method for hospital system affiliation can attest to such claims. Emergency care provides unexpected care for individuals with acute care needs, and on a larger scale, provides care for catastrophes.

Despite the difficulty in ascertaining a state or region's level of preparedness, using day-to-day outcomes can provide insight on the level of effectiveness and functionality of the emergency care system. Theoretically, if trauma mortality rates are relatively low for everyday occurrences, the emergency care system is more prepared and will be able to effectively respond in times of a mass shooting or a large-scale disaster.

While the role of competition in emergency care has much to be discovered, an understanding of competition in a rate-regulated setting can provide insight on the relationship between competition and quality of care in the emergency care setting. Furthermore, an understanding of the role of competition in the emergency care sector can inform coordination initiatives among providers, to ultimately create an emergency care system that is patient-centered and integrated to provide high quality care and respond in times of emergency.

Appendices

Appendix A

Classification of Hospitals and Hospital Systems by HRRs.

Baltimore

Hospital	Health System
Baltimore Washington Medical Center	University of Maryland Medical System
Bon Secours Baltimore Health System	Bon Secours Health System, Inc.
Carroll Hospital Center	
University of Maryland Shore Medical Center at Chestertown	University of Maryland Medical System
MedStar Franklin Square Hospital Center	MedStar Health
MedStar Good Samaritan Hospital	MedStar Health
Greater Baltimore Medical Center	
MedStar Harbor Hospital	MedStar Health
Harford Memorial Hospital	Upper Chesapeake Health System
Howard County General Hospital	Johns Hopkins Health System
Johns Hopkins Bayview Medical Center	Johns Hopkins Health System
Johns Hopkins Hospital	Johns Hopkins Health System
University of Maryland Rehabilitation and Orthopedic Institute	University of Maryland Medical System
University of Maryland Medical Center Midtown Campus	University of Maryland Medical System
University of Maryland Shore Medical Center at Easton	University of Maryland Medical System
Mercy Medical Center	
Northwest Hospital	LifeBridge Health
Saint Agnes Hospital	Ascension Health
Sinai Hospital of Baltimore	LifeBridge Health
St. Joseph Medical Center	University of Maryland Medical System
MedStar Union Memorial Hospital	MedStar Health
University of Maryland Medical Center	University of Maryland Medical System
Upper Chesapeake Medical Center	University of Maryland Medical System

Salisbury

Hospital	Health System
Atlantic General Hospital	
McCready Foundation	
Peninsula Regional Medical Center	

Takoma Park

Hospital	Health System
Doctors Community Hospital	
Holy Cross Hospital	Trinity Health
Laurel Regional Hospital	Dimensions Healthcare System
MedStar Montgomery Medical Center	MedStar Health
Prince George's Hospital Center	Dimensions Healthcare System
Washington Adventist Hospital	Adventist HealthCare

Note. N=32. Blanks for health system indicate independent hospital, not belonging to a system

Appendix B

ICD-9 CM Codes for Sepsis.

ICD-9 CM Diagnosis Code	Condition
003.1	Salmonella Septicemia
020.2	Septicemia Plague
022.3	Anthrax Septicemia
036.2	Meningococcemia
036.3	Waterhouse-Friderichsen Syndrome
038.0	Streptococcal Septicemia
038.10	Staphylococcus Septicemia, Not Otherwise Specified
038.11	Staph Auerus Septicemia
038.12	MRSA Septicemia
038.19	Staphylococcal Septicemia, Not Elsewhere Classified
038.2	Pneumococcal Septicemia
038.3	Anaerobic Septicemia
038.40	Gram-Negative Septicemia, Not Otherwise Specified
038.41	H. Influenae Septicemia
038.42	E. Coli Septicemia
038.43	Pseudomonas Septicemia
038.44	Serratia Septicemia
038.49	Gram-Negative Septicemia, Not Elsewhere Classified
038.8	Septicemia, Not Elsewhere Classified
038.9	Septicemia, Not Otherwise Specified
054.5	Herpetic Septicemia
098.89	Gonococcemia
112.5	Systemic Candidiasis
449	Septic Arterial Embolism
785.52	Septic Shock
790.7	Bacteremia
995.92	Systemic Inflammatory Response Syndrome due to Organ Dysfunction

Appendix C

ICD-9 CM Codes for Trauma, Stroke, Cardiac Arrest, and STEMI

ICD-9 CM Diagnosis Code	**Condition**
800 – 904, 910 – 929, 940 - 957	Trauma
362.3, 433.x1, 434.x1, 436	Acute Ischemic Stroke
427.5	Cardiac Arrest
410.x, excluding 410.71	STEMI

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