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AN ASSESSMENT OF THE RELATIONSHIP BETWEEN HOSPITAL

REIMBURSEMENTS AND HOSPITAL-ACQUIRED INFECTIONS

By

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A DISSERTATION IN PRACTICE

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Abstract

Patients enter healthcare systems and hospitals to maintain their health, prevent disease, and receive care and treatment from injuries or illness, but no one expects to become more injured, nor sicker, while in the care of these health systems. To 'do no harm' is a foundational phrase to all healthcare providers, clinical staff, and administrative personnel, yet patients continue to suffer from preventable hospital-acquired infections. Efforts have been put in place by the Centers for Medicare and Medicaid (CMS) to negatively reinforce hospitals through reimbursement reductions that do not prevent these infections from occurring. This quantitative, retrospective study aimed to explore whether decreases in CMS reimbursements to hospitals from the HACRP policy have impacted the rates of hospital-acquired infections across the United States. The results of this study found significant differences from the pre-policy and post-policy review periods, validating the efficacy of the HACRP policy, and showing a reduction of overall hospital-acquired infections in the post-policy period. The most significant finding was that the hospitals who would have received a payment reduction from HACRP scores in 2013 (pre-policy), showed the most improvements in reducing hospital-acquired infections in the post-policy period of 2019. Based on these findings, CMS and its beneficiaries could benefit even more by incorporating the same payment reduction methodology against the many other hospital-acquired conditions not included in the HACRP. Additionally, private health insurers may also find benefit in applying the same methodology to seek reductions in costs, and put the onus on the hospitals to keep their patients safe and free, from hospital-acquired infections.

Keywords: CMS, HACRP, hospital-acquired infections, reimbursement

Dedication

I would like to dedicate this dissertation, and the completion of my doctoral degree, to all of my previous leaders and mentors who believed in me and motivated me to pursue, and complete, my terminal degree. Without their encouragement for me to apply for a doctoral degree, I would never have gone on this amazing journey. Thank you all again for believing in me and helping me to see that I could believe in myself to reach such an amazing accomplishment in my life.

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Table of Contents

List of Tables

List of Figures

Page

CHAPTER ONE: INTRODUCTION

Patients deserve dignity, respect, and not to be further harmed by the healthcare system meant to heal and cure individuals. Hospital-acquired infections are an example of patient safety events that continue to cause harm to patients. In efforts to decrease hospital-acquired infections, the Centers for Medicare and Medicaid established a policy to reduce reimbursements to hospitals that have the worst hospital-acquired infection rates across the U.S. (McClung et al., 2017). This policy has been ongoing for several years, providing sufficient data to determine if the negative reinforcement of decreased revenue has effectively reduced harm to patients and lowered the incidence of preventable infections.

Statement of the Problem

Under the age-old premise of nonmaleficence, more commonly known as *to do no harm*, physicians, nurses, allied health providers, and hospital systems have strived to heal and cure patients of their sicknesses, diseases, and injuries (NWABR, 2022). While this should be expected for each and every patient who has a healthcare encounter, this, unfortunately, is not always the case. Patients continue to suffer from harm due to patient safety events that should have, and could have, been prevented. Makary and Daniel (2016) noted from their research that medical errors were ranked as the third leading cause of death, and calculate that an average of 251,454 patients die every year in the United States from these medical errors. Although efforts have been made through the years, patient safety events such as medication errors, surgical errors, and hospital-acquired infections (HAI), continue to occur and cause harm during their healthcare treatments (WHO, 2019). No patient wants to be injured or become sicker during their hospital stay. Likewise, health insurance companies may not like paying for treatments needed because a hospital harmed a patient. But if harm is such an issue within healthcare systems that it affects the receiver of services (patients) and the payer of services (insurers), why is not more being done to prevent such events from occurring while performing the services (hospitals)?

In efforts to respond to this, through the Deficit Reduction Act of 2005, the Secretary of Health and Human Service, with oversight of the Centers for Medicare and Medicaid Services (CMS), established a policy regarding hospital-acquired conditions (HAC) that evaluated payments for conditions that realistically could have been prevented by the hospital (CMS, 2021). As the largest health insurer and payer in the United States, this policy enabled CMS to seek to control the costs of government expenditures on healthcare payments for covered entities and lead by example by implementing value-based purchasing models through focusing on Medicare beneficiaries. Through this effort, the 'value' of healthcare service becomes an essential function of healthcare services as more efforts were placed on strengthening the relationship between the quality of care provided and the costs consumed for providing those services (Nash et al., 2019). Then, after years of evaluation, in 2014, the HAC policy later evolved into the Hospital-Acquired Condition Reduction Program (HACRP), which sought to reduce reimbursements to hospitals that cause injury or harm to patients from preventable hospital-acquired infections (CMS, 2020b). The HAIs that CMS began to track for this potential reduction in reimbursements included CLABSI (Central Line-Associated Bloodstream Infection), CAUTI (Catheter-Associated Urinary Tract Infection), SSI (Surgical Site Infection for Abdominal Hysterectomy and Colon

Procedures), MRSA (Methicillin-resistant Staphylococcus aureus) bacteremia, and CDI (Clostridium difficile Infection) (CMS, 2022a). Additionally, PSI (Patient Safety Indicator) 90 scores were also added to HACRP policy, and its values are included in the production of the overall composite scoring.

Although patients may still become infected with other microorganisms and diseases during their healthcare endeavor, the five infections that CMS has chosen to focus on are some of the most complex organisms to treat and cure (Lawton et al., 2020). Thus, efforts should be in place within each hospital or hospital system to improve the quality of care provided and prevent those listed infections. Although CMS has instituted a policy strictly focused on reducing these infections, what remains unknown is whether this reduction in reimbursements over the past couple of years has improved the quality of care within hospitals with a safer, healthier environment through the reduction of the overall number of hospital-acquired infections across the country. Currently, one out of every 25 patients who enter the U.S. healthcare system acquires an infection during their care, leading to around 90,000 annual deaths (Lagasse, 2018). Additionally, by not preventing these infections from occurring, the cost of treating these infections ranges from about $1,000-$50,000 per incident, depending on the type of infection and when it is caught in the disease process (The Leapfrog Group, 2018). As these dollar figures are multiplied by the number of patients with HAIs, billions of dollars continue to be wasted annually to treat these infections when they could have been prevented (Lagasse, 2018).

Purpose of the Study

The purpose of this study is to explore whether decreases in CMS reimbursements to hospitals from the HACRP policy have impacted hospital-acquired infections across the United States.

Research Question

What is the relationship between CMS' reductions in reimbursements from the Hospital-Acquired Conditions Reduction Program (HACRP) policy and hospital-acquired infections across the United States?

Research Hypothesis: The existence of the financial disincentive from the HACRP policy has lowered the incidence of HAIs.

Aim of the Study

The aim of this dissertation in practice is to better understand how negative reinforcement of reduced reimbursements to hospitals from CMS has impacted hospital-acquired infections. Since implementing the HACRP policy, many hospitals have been directly impacted by reductions in reimbursements, while the remaining hospitals have been indirectly affected by the potential threat of losing reimbursements should they not maintain or improve their HAI ratings. Ultimately, no hospital accepting CMS reimbursement is immune to this policy. Thus, with this CMS oversight and its effects on hospital revenue, hospitals may have been motivated to increase their infection prevention efforts. The significance of the study is to further understand if the reduction of reimbursements may have led to decreasing the overall number of hospital-acquired infections.

Whether correlations or significant differences were found in the study or not, the results may provide valuable insight into whether negative reinforcement may have influenced positive outcomes (a decrease in HAIs). These results could help hospital systems, insurers, and policymakers determine if the current HACRP policy practice is effective or if changes and updates need to be made in order to meet the policy's goals. If no relationships were found within the study, it could signal that negative reinforcement through monetary loss in revenue may not be an effective methodology to decrease HAIs. Thus, questions would need to be asked as to whether the HACRP should be discontinued, or financial disincentives be modified. Likewise, if significant differences in HAI rates are found between the pre-HACRP years and the post-HACRP years, that could signal that the policy may be effective and should be maintained. Additionally, these results could help hospital systems, insurers, and policymakers decide whether negative reinforcements through a reduction in reimbursements could be applied to other practices to improve the overall safety and quality of care provided to patients.

Definition of Relevant Terms

The following terms were used operationally within this study.

Reimbursement: describes the payment to a hospital, healthcare provider, diagnostic facility, or other healthcare providers for providing care to a covered health insurance beneficiary (Torrey, 2020).

Hospital-acquired infection: infections not present on admission to a hospital that a patient acquires while receiving treatment in a healthcare facility (Rhode Island Department of Health, n.d.).

Negative reinforcement: a method of motivation that can be used to modify specific behaviors (Marcin, 2017).

Revenue cycle: comprised of "all the activities that lead to payment for services provided, from patient registration to verification of benefits to care delivery, to claim submission and reimbursement" (Williams, 2022, para. 2).

CMS Patient Safety and Adverse Events Composite (PSI 90): "summarizes patient safety across multiple indicators, monitors performance over time, and facilitates comparative reporting and quality improvement at the hospital level" (Innovation, 2019, para. 3).

Methodology Overview

To conduct this quantitative, non-experimental study, retrospective data was acquired from the CMS website. The data on the CMS website is publicly available and will provide the data and values for the variables to be evaluated. The data consists of annual information on the HAI score ratings for each of the five hospital-acquired infections that CMS chose to focus on, the PSI-90 scores, as well as the composite HACRP score ratings at the hospital level. The composite HACRP score ratings are the values that CMS uses to apply its reduction in reimbursements (CMS, 2020a). The annual data available consists of HACRP results from data ending in 2013 to 2019 (see Appendix A); 2019 data is the most recent data available as CMS did not collect this data during the COVID-19 pandemic.

Every year, CMS analyzes the coded data for insurance claims seeking reimbursement and notes whether any of the five HAIs were found in the claims documentation and surveillance data (CMS, 2020a). For the first three years evaluated in this study, CMS produced scores (1-10) for the five HAIs, the PSI-90 score, and the composite score. However, for the remainder of the years in the study, 2016-2019, CMS changed its methodology for analysis of the HACRP policy to producing only Winsorized z-scores for each given measure (CMS, 2022a). From these z-scores, CMS was better able to visualize the distribution and more effectively place hospitals into their associated quartiles (CMS, 2022a). Hospitals that fall within the first three quartiles would not have any reductions in reimbursement assessed; however, hospitals in the fourth quartile would have payment reductions.

CMS (2022a) considers hospitals that fall into the fourth quartile (75th percentile) to be in the worst-performing quartile. Although there is no specific titling to the hospitals that fall within the first three quartiles (sometimes referred to as well-performing), being labeled as a hospital in the worst-performing quartile will lead CMS to negatively reinforce, through monetary means, those hospitals to provide safer, quality patient care. To do so, those hospitals in the fourth quartile are subject to a 1% payment reduction over the next year of CMS reimbursements (CMS, 2022a). Therefore, for every $100 a hospital seeks to be reimbursed for providing care to a Medicare beneficiary, the hospital has the potential to only receive up to $99. Although the 1% reduction may appear to be negligible, Definitive Healthcare (2019) found that the hospitals that fell within the fourth quartile in 2018 suffered a loss in revenue ranging from $1.2 million to $2.8 million just that year. Additionally, with the mean operating margins of hospitals at around 4.6%, Shryock (2022) notes that nearly one-third of hospitals are operating in the red. This would then imply that the 1% reduction in reimbursements could reduce marginal profits for two-thirds of the hospitals, but further adds to the deficit in operating costs for the other one-third.

Delimitations, Limitations, and Personal Biases

Several different delimitations were considered in planning for this dissertation in practice to decide on a path forward to conduct the study. Although many healthcare insurers may have the same methodology in reducing reimbursements when patient events occur, using CMS data provides a structured approach to consistent measurement since the HACRP inception. Thus, hospitals that do not receive CMS reimbursements will not be tracked within this study. Additionally, CMS tracks and measures other types of hospital-acquired conditions (retained foreign objects, pressure ulcers, etc.); however, this study will focus only on hospital-acquired infections. Time was another factor for consideration as the annual data covers only time periods ending in 2013 through 2019; The data from 2019 is the most recent data available to analyze as CMS has not reported any newer data due to its focus of the COVID-19 pandemic since early 2020.

Due to the nature of acquiring secondary data from a centralized database from which raw data cannot be queried, there will be limitations with claiming causation between the assessed variables in the study. Also, the acquired data will not contain information about whether hospitals actually invested money into preventing HAIs. However, the data will provide information for analysis on whether HAIs have increased or decreased over time based on initially being noted as a well-performing hospital or a worst-performing hospital using pre-policy data from 2013. Additionally, although CMS is the largest health insurance provider, other health insurance companies likely pay more for healthcare for their covered beneficiaries. Thus, applying this study's results across all health insurers may not be generalizable because every hospital has multiple payers (insurers) and different payment (reimbursement) structures from each insurer.

Although efforts at improving patient safety is a primary premise of what the researcher seeks to inform, implement, and educate others on, it is a noted bias that the researcher has in conducting this study. The researcher believes that no patient should be injured or harmed while receiving care meant to heal or cure. Due to this, there is a noted bias toward hospitals doing everything they can to prevent patient events from occurring. Likewise, as an administrator and educator on healthcare, the researcher also understands that healthcare is a complex industry with many facets that must be managed and led appropriately to lead to a successful business. Bottom line, healthcare is a business, and needs to run like a business in order to maintain its ability to provide care. However, the balance of providing safe, quality patient care and maintaining costs throughout the revenue cycle, can sometimes become unbalanced due to healthcare's complexity. Thus, in reflecting and maintaining awareness of these two, sometimes opposing, viewpoints of healthcare, the researcher will continuously monitor for subjectivity and only perform analysis and production of results through objective means.

Reflections of the Scholar-Practitioner

From taking care of patients at the bedside, to managing and leading in hospitals, I have seen firsthand the effects of hospital-acquired infections. When patients acquire these infections, they stay longer in the hospital, are inundated with medications that potentially have secondary effects due to the potency of the medications, and some even die. More often than not, many of the HAIs I have helped treat or performed root cause analyses (RCA) on, were related to improper or incomplete policies. Although these events usually involved highly skilled and competent practitioners operating at the last possible point of prevention, many of the current policies in place allowed for patient safety events like HAIs to pass through safeguards meant to catch and prevent events earlier in the process. It is of note that some cases where HAIs occurred were related to willful disregard of hand hygiene or maintaining sterile operational fields; however, most cases were due to larger-level hospital decisions and policies.

Often, the question of HAI prevention is met with the response of, "is the bang worth the buck"? Investing in HAI prevention can be an expensive mission, especially if an organization has previously lacked in its efforts (Dick et al., 2015). With that, I believe most individuals in healthcare would likely agree that, morally and ethically, preventing HAIs would be the right thing to do. However, when it comes down to investing the money needed to improve efforts to decreasing HAIs, many hospitals may be less likely to pursue a prevention endeavor if they have a higher payer mix of private insurers (Johns Hopkins Medicine, 2013). Unlike CMS, private payers are more likely to fully reimburse hospitals even when HAIs occur (Johns Hopkins Medicine, 2013). Healthcare costs in the United States are high, and hospitals are under numerous financial and budgetary pressures. Then, couple these costs to investing in preventing HAIs with additionally losing revenue from reimbursements from policy initiatives like HACRP, there is a lot of money, or lack thereof, to figure out. This could ultimately lead hospitals to a crossroads in deciding whether HAIs are just an acceptable, normal result of business for which the reduction penalty may not even be higher enough to matter, or, whether to put their focus on efforts on doing what is right to invest downstream in the prevention of the HAIs, which may essentially save the hospitals money in the long run.

Summary

Efforts to prevent HAIs from occurring is a significant and important aspect to most, if not all, hospitals and healthcare systems. Due to the lack of these efforts over previous decades, CMS moved forward in 2014 with the HACRP policy to penalize hospitals considered worst-performing by CMS's methodology of assessing HAIs. Every year since then, many hospitals continue to miss out on reimbursable revenue due to their high HAI score ratings, which affects the hospital's bottom line and, ultimately, the patients they treat. The literature review will provide further background on the development of HACRP into official policy and the evolution of hospital HAI preventive care over time.

CHAPTER TWO: LITERATURE REVIEW

To realign value with services provided in healthcare delivery, the Centers for Medicare & Medicaid Services (CMS) changed their methodology for reimbursements, which has led to financial and policy impacts from its creation. Although the hospital-acquired conditions (HAC) policy was created through the implementation of the Deficit Reduction Act of 2005, the HAC policy later evolved into the Hospital-Acquired Condition Reduction Program (HACRP) in 2014 to reduce reimbursements to hospitals that cause injury or harm to the patients from preventable hospital-acquired infections (CMS, 2020b). The purposes behind these policies were to reduce hospital-acquired conditions, which include hospital-acquired infections, through penalizing hospitals for when Medicare patients acquired such preventable conditions, and to inspire hospitals to provide better quality of care by minimizing the rates of preventable conditions (Peasah et al., 2013; Stone et al., 2010). The following literature review will first provide an overview of the five HAIs included in the HACRP policy and their ability to be transmitted to patients while in the care of hospital systems. Next, this will be followed by research supporting efforts to reduce and prevent these HAIs. The literature review will conclude by reviewing both the financial and policy impacts of implementing a value-based purchasing program like the HACRP policy.

Hospital-Acquired Infections

Infections, Organisms, and Safety

Although the 2008 HAC policy includes eight hospital-acquired conditions, only two of these conditions were directly related to HAIs (Clancy, 2009). One of the conditions was explicitly associated with a patient acquiring catheter-associated urinary tract infections (CAUTI) and the other condition was related to a central line-associated bloodstream infections (CLABSI) (Clancy, 2009). Although the catheter types that are associated with each of these infections are physically different (size, shape, length, etc.) and inserted via different routes, both catheters enter the human body to allow for the passage of fluid (medications, urine, etc.) either internally or externally, depending on the intended purpose (Desra et al., 2016). Additionally, the placement of these catheters is considered a minimally invasive procedure. However, as these catheters remain inside the human body for days or weeks at a time, this potentially enables the introduction of infections and organisms into the body when not maintaining sterile technique while inserting the catheters or not maintaining the cleanliness and aseptic protocols to maintain the catheters in place (Desra et al., 2016).

After focusing on CAUTI and CLABSI, three other hospital-acquired infections were later added to the list for the implementation of the HACRP policy. Like the previously mentioned HAIs, surgical site infections (SSI) also enable the introduction of infections and organisms into the human body, however, through more invasive means (Mauzey, 2012). In a study performed by Mauzey (2012), it was found that sterile technique and cleanliness of the operative site intraoperatively, postoperatively, and with a structured antibiotic regimen, help decrease SSI rates. Likewise, through the introduction of catheters or abdominal incisions, Methicillin-resistant Staphylococcus aureus (MRSA) can be passed and introduced into a patient when sterile and aseptic techniques are not followed (Rocha et al., 2020). MRSA bacteria becomes resistant to much of the antibiotics frequently used to treat ordinary staph infections, which further extends the treatment and recovery time periods from such an infection (Mayo Clinic, n.d.b). However, unlike the previous HAIs discussed, Clostridium difficile infection (CDI) is the easiest infection to spread to any patient, whether they have had surgery, a catheter placed in their body, or are just a patient being monitored in a hospital bed. CDI is easily spread by providers and staff coming into contact with patients or patients coming into contact with contaminated objects or surfaces (Drozd et al., 2015). CDI affects the large intestine and may cause severe diarrhea and potentially lead to permanent harm to the colon (Mayo Clinic, n.d.a).

To assess how often these conditions are found in coding and billing data, Meddings et al. (2010) conducted a study through a retrospective medical record review to verify the accuracy and documentation of properly coding for these conditions through validation with a physician abstractor. The physician abstractor was chosen to relook at the documentation on a patient, as if they coded and billed for services provided to the patient. Meddings et al. (2010) further noted that only secondary diagnosis codes would be reviewed. If a patient had either condition as a primary diagnostic code, the condition would not be hospital-acquired. From their study, Meddings et al. (2010) found that the physician abstractor discovered 50% more patients who should have been coded with hospital-acquired infections than noted in the original documentation. Conversely, the authors noted that some of the patients initially classified as HAIs, were actually infections present upon admission; thus, accuracy in the coding and billing process was found to be problematic with hospital coders (Meddings et al., 2010).

Likewise, in response to findings like these, hospitals questioned how to better assess for these HAIs. McHugh et al. (2011b) found that several hospitals conducted routine urine cultures to evaluate for a CAUTI, which may have increased the incidence of CAUTI, but may also have led to false positives. Although proactively finding out which patients had a CAUTI and needed to be treated with antibiotics is good for the both the patient and the hospital, false positives could have occurred due to the lack of sterile or aseptic technique of acquiring the specimen, which may in turn have lead to the incorrect diagnoses and usage of antibiotics when not truly warranted. Additionally, usage of antibiotics when not needed, or even over usage of antibiotics, may potentially lead to increased antibiotic resistance amongst patients (McHugh et al., 2011b). Meddings et al. (2012) added that the false positives further negatively impacted the costs associated with increased laboratory tests and increased antibiotic usage when there was already going to be a financial deficit in reimbursements when a hospital infection occurred. Kavanagh (2014) also noted that although some hospitals tried to get ahead of diagnosing HAIs, some of these infections may not show up until after a patient is discharged, which may lead patients to be readmitted to the hospital in order to treat the HAI.

To focus on patient safety within the HACRP policy, CMS chose to adopt the Agency for Healthcare Research and Quality's (AHRQ) PSI 90 composite scoring methodology to add those scores into the overall HACRP composite scoring. Although originally titled 'Patient Safety of Selected Indicators Composite' in its inception, the title for the PSI 90 composite scoring changed to 'Patient Safety and Adverse Events Composite' to better capture the notion of patient safety events resulting in harm being included in its data (AHRQ, 2016). The PSI 90 composite score was established to provide a primary metric that could be evaluated equally across all hospitals to better understand, communicate, and track patient safety (Zrelak, 2022). To calculate the PSI 90 composite score, each hospital is measured against the rates of ten patient safety indicators, which are then calculated through a weighted average to produce the overall PSI 90 composite score (Innovation, 2019). The included patient safety indicator events encompass six different pre and post-operative events, pressure ulcers, pneumothorax, accidental puncture/laceration, and hip fractures that occurred during a patient’s hospital stay. Overall, the purpose of CMS choosing to adopt the PSI 90 composite measure was to appropriately “reflect the safety climate of a hospital by providing a marker of patient safety during the delivery of care” (Innovation, 2019, p. 1).

Prevention Efforts

Due to the focus on these HAIs, several hospitals found benefit in playing an active role in preventing these conditions. Wald et al. (2012) found that the hospitals studied showed improvement in their nursing protocols related to inserting, maintaining, and removing indwelling urinary catheters after the establishment of the HAC policy. The authors also noted decreased rates of HAIs like CAUTI through increased availability of resources like bladder scanners and active surveillance practices. Additionally, McHugh (2011a) noted that staffing skill types, design or architectural layout of a nursing unit, and overall culture may also impact hospitals' prevention efforts. The authors also found that different levels of skill types, and individuals’ different levels of experience, in part with working as a cohesive unit, impact the ability of hospitals to prevent, or at least reduce, their HAI rates. Moreover, to assess these differences and variations, Andrews and Wessels (2009) noted that hospital leaders need to maintain awareness of these prevention efforts through the usage of practical analytical tools and technologies to be successful in their prevention endeavors.

Likewise, Clancy (2009) noted that in an effort to decrease the rates of HAIs, the focus on awareness and usage of evidence-based approaches is foundational in accomplishing these interventions. McHugh et al. (2011b) add from their qualitative study, that the HAC policy created “a heightened awareness, a stronger hospital-wide focus on the conditions, and or provided an extra incentive for the hospital to reduce HACs" (p. 674). Additionally, the authors found that most of their respondents noted that eradicating or reducing HAIs became more of a priority after the HAC policy was created, especially when other organizations and accrediting bodies, like the Joint Commission, pushed for more focus on HAIs as well. Moreover, patients themselves may not always understand their part in reducing HAIs (handwashing, cleanliness, etc.), so increasing their awareness may improve overall outcomes, safety, and quality within a hospital (Mo & Tambyah, 2015). Additionally, by preventing HAIs, it not only helps the organization financially, but patients receive the care intended and limit any extra care needed that may affect a patient financially due to loss of income from extended hospital stays and recovery periods.

CMS Reimbursements

Financial Impacts

As efforts to prevent and address HAIs take time and funding, assessing the financial impacts to hospitals of reducing CMS reimbursements from HAIs is crucial. McHugh et al. (2011b) noted that their respondents had seen a loss in revenue from increased testing and administrative procedures like coding. Additionally, respondents indicated that even though HAIs may not be something that occurs frequently, they cost a hospital more to treat those associated infections. Furthermore, annual losses may range from hundreds of thousands to potentially millions of dollars lost without reimbursement for this care. Cohen et al. (2018) found that, on average, each patient with an HAI costs an organization between $6000 and $50,000 in direct care costs. Conversely, although these decreased reimbursements may significantly affect hospitals systems with high Medicare or Medicaid patient loads, hospitals systems that care for patients with private insurers may have agreements for higher markup costs, which may lead them to feel less encumbered by policies like the HAC (Cohen et al., 2018). Likewise, organizations that can maintain their financial performance by not being burdened by payment reduction initiatives from value-based purchasing programs, may allow hospitals to better invest in HAI prevention initiatives (Turner et al., 2015).

Another secondary financial issue is that of organizational liability from an HAI. Even with using and applying best practices for reducing or preventing HAIs, hospitals may still be held liable for the negligence or omittance of actions performed by their employees (McQuoid-Mason, 2012). Moreover, "hospitals may be liable to patients who acquire hospital infections through the negligent or intentional conduct of their employees acting in the course and scope of their employment" (McQuoid-Mason, 2012, p. 364). Additionally, Bolcato et al. (2020) found, from conducting their meta-analysis case report, that professional liability may be directly related to a lack of infection prevention. The authors further discuss that not only are hospitals held accountable for the lack of prevention measures or diagnostic activities, but potentially even manufacturers of systems, devices, or equipment that led to the HAI, may also be held accountable. Thus, Bolcato et al. (2020) add that organizations need to play an active role in limiting liability and maximizing reimbursements to limit financial impacts from hospital-acquired infections.

Policy Impacts

In relation to the differences between hospitals across the U.S. healthcare system, some hospitals may be minimally impacted by the HAC policy, while others may become heavily burdened by it. Safety net hospitals, usually public hospitals or those with high numbers of Medicare and Medicaid patients and generally serve vulnerable populations, commonly lack the finances and resources to actively pursue decreasing HAIs (McHugh et al., 2011b). Additionally, lost revenue from any HAI significantly impacts these organizations, which in turn, may lead to further reductions in services and care for their patient population (McHugh et al., 2011b). Compared to other hospitals that care for CMS-insured patients, safety-net hospitals were found to have an almost 20% higher chance of acquiring an infection while being treated (McHugh et al., 2011a). Lee et al. (2015) noted that in their review of hospitals that fall within the lowest quartile of CMS' policy, safety-net hospitals and teaching hospitals were the most significant percentage of hospitals in that quartile. Additionally, although these hospitals had shown improvement in their HAIs from pre-to-post policy periods, they continue to fall in the lowest quartile (Lee et al., 2015).

Likewise, Sarrami and Hollier (2021) found that hospitals that provided care to a more significant number of patients from minority groups also experienced disproportionate payment penalties from their inability to reduce or prevent HAIs. The secondary impacts of these financial reductions from the HAC policy at these hospitals may have reduced or worsened health disparities for patients seeking care at these hospitals (Sarrami & Hollier, 2021). Zogg et al. (2020) noted that this vulnerable population falls within the parameters of unintended consequences in that hospitals that care for these patients have a less likely chance of improving their care by reducing HAIs. In turn, these hospitals will be unable to operate outside of a deficit financially, and patients will likely continue to have increased chances of acquiring a hospital infection during their hospital stay (Zogg et al., 2020). Ultimately, through the HAC policy and its unintended consequences, hospitals with the least means and greatest need are punished for having worse outcomes, leaving them with even fewer means to invest in quality improvement initiatives to decrease HAIs (Zogg et al., 2020).

In reviewing previous literature on the effect of CMS implementing the Hospital-Acquired Condition policy in 2008 (the precursor to the HACRP policy), several different findings have been produced through the years. Waters et al. (2015) concluded that there were improvements in both CLABSI and CAUTI rates since the HAC policy was implemented. Peasah et al. (2012) additionally noted in their findings that they found an association between the reduction in CLABSI rates with the HAC policy. However, the researchers also noted that due to ongoing infection control improvements at the hospitals evaluated, the association could be overvalued as reductions in infections could be due to other variables (Peasah et al., 2012). Conversely, Lee et al. (2012) found in their study that there was "no evidence that the 2008 CMS policy to reduce payments for central catheter–associated bloodstream infections and catheter–associated urinary tract infections had any measurable effect on infection rates in U.S. hospitals" (p. 1428). As these three different studies took place before the HACRP policy implementation, similarities and differences may be found with updated studies.

Summary

No patient should be injured or acquire an infection from their care in a hospital. By introducing the initial HAC policy, CMS began to focus on affecting and more directly responding to these preventable conditions by reducing the money that hospitals are reimbursed for not preventing these patients' conditions. Then, with the advancement of the HACRP policy, HAIs were brought to the forefront of holding hospital organizations accountable for their inability to reduce or prevent HAIs through the value-based purchasing efforts of decreasing reimbursements. The five HAIs selected by CMS to hold hospitals accountable through the HACRP policy lead to increased costs for hospital systems and ultimately hurt, injure, and potentially lead to patients' demise. However, based on the literature reviewed, many hospitals are negatively impacted financially due to their high HAI rates, which may secondarily lead to an inability to invest in prevention efforts to better care for and treat their patients.

Strengths of the literature reviewed include information and studies on how low-cost prevention practices could help hospital organizations avoid reductions in reimbursements. Additionally, the review supports the reasoning for how preventing HAIs from occurring may help hospitals financially and ultimately help patients from being harmed by preventable infections. However, the limitations of the review are mainly focused on the years the studies had been conducted. Many studies and research focused early on the HACRP implementation, but not much has been conducted over the years to gain more timely and relevant supporting literature. Overall, creating the HAC policy to reduce HAIs was intended to lead to hospitals reducing HAI rates through prevention efforts, but the secondary effects of the policy may have further hurt hospitals in their efforts to reduce HAIs. Thus, the importance for organizations to implement evidence-based prevention practices and invest in organizational resources, continues to be an essential driver in improving the rates of HAIs nationwide. To review the effects of the HACRP policy further from its inception to more current times, the next chapter will work through the methodology for this dissertation in practice.

CHAPTER THREE: METHODOLOGY

Building upon the research question, this chapter will provide an overview of how the study was to be conducted. By reviewing the universe of hospitals, those that were penalized and non-penalized under the HACRP policy, the data was collected, cleaned, and analyzed. All hospital data that contained the inclusion criteria, were incorporated in the study. As per the IRB approval, the data was be pulled directly from the source websites (CMS and Definitive Health), merged, and analyzed through linear regression and difference in difference analysis. Upon merger of the data sets, hospital names, city, and states were removed from the primary data set to limit any bias in analyzing the data; the CMS regions were the lowest level of analysis for geographical areas.

Research Question

What is the relationship between CMS' reductions in reimbursements from the Hospital-Acquired Conditions Reduction Program (HACRP) policy and hospital-acquired infections across the United States?

Research Hypothesis: The existence of the financial disincentive from the HACRP policy has lowered the incidence of HAIs.

Method

Research Design Overview

To answer the research question, a non-experimental, quantitative study was planned to evaluate hospital-acquired infections (HAIs) and their relationships to whether hospitals received decreased reimbursements from CMS. This non-experimental research design fits appropriately to this study as the data to be evaluated is retrospective and publicly available. Additionally, the hospitals were not randomly assigned as the placement of the hospitals into the two groups was solely based on their HACRP composite scores noting whether they were well-performing or worst-performing. By applying quantitative analysis to this set of data, this study had the opportunity to assess for correlations and trends, and note any significant findings when discovered.

Three independent variables where analyzed within the study. The first is the CMS reimbursement penalty (yes/no) which is based on the composite score, and is defined by the nominal variables of worst-performing hospitals (those that receive reductions reimbursements) and well-performing hospitals (those that do not receive a reduction in reimbursements). Of note, CMS did not produce values for which hospital in the pre-policy year of 2013 were considered to be well or worst-performing, the researcher applied the methodology of z-scoring the hospital composite scores for that year and associated those hospitals in the fourth quartile to be theoretically, worst-performing. Every hospital in this study was then reassessed annually for whether they fall into one category or another based on that calendar year's composite scores. The second independent variable accounts for the years in the study (2013-2019). The third independent variable is the primary independent variable is the product of the other two independent variables to create an interaction term used for the regression analysis.

The primary dependent variables for the study are the of individual HAI scores, PSI-90 scores, and composite scores and all were assessed as a scale variable ranging from 1-10. These dependent variables are defined as the score ratings of preventable infections that patients acquired while being in the care of a hospital (CAUTI, CDI, CLABSI, MRSA, SSI), patient safety and adverse events scores (PSI 90), and the composite scores of those combined variables. The composite scores are what designates whether a hospital received a reduction in CMS reimbursements or not. Control variables were also included in the study, see the variable table list (Appendix B) for more information. The unit of analysis in the study were the approximately 3,000 hospitals associated with the study.

Participants

The overall number of hospitals that the CMS tracks for the HACRP policy is over 3,000 hospitals. Of those, approximately 25% are labeled as the worst-performing hospitals due to falling in the fourth quartile by having the highest infection rates. The remaining 75% of hospitals fall into the well-performing hospital category. The HACRP data is publicly available CMS data from 2013 - 2019, with hospital-acquired infection (HAI) composite data. For each evaluation of a year (example: 2013) in this study, it is noted that the values and scores produced by CMS account for two years' worth of scoring in each year's value (example: 2013 data = 01JAN12 – 31DEC13). However, the only analyzed year (2019+) that did not have two years' worth of data associated with the year, was due to the beginning of the COVID-19 pandemic. Secondary to the pandemic, data ending in 2019 was the most recent data available to be analyzed for this study. The data includes the values of the composite HACRP scores, the individual HAI scores (CLABSI, CAUTI, SSI, MRSA, & CDI), and the PSI-90 scores for each hospital analyzed. Moreover, as the data is publicly available with no attempts to limit transparency, hospitals are listed by name and state with each of their levels of HAIs. However, each hospital is also represented by a 'Provider ID' number which was used to help provide some level of anonymity to the hospitals evaluated.

Data Collection

Data Collection Sources

The primary data source for the study's analysis was acquired from CMS.gov, and provided data for the independent and dependent variables. At its initial access (splash page) level, the CMS website provides information for medical services Medicare and Medicaid eligible patients. However, the website additionally houses healthcare data at the hospital level that can be queried for analysis and research. The source of the data within the CMS system comes from claims data related to healthcare reimbursements or payment information (CMS, 2022b). The secondary data source, which provided the control variable data, was definitivehc.com (Definitive Healthcare website). As Definitive Healthcare provides a centralized database of health system data, the website collects its data from publicly available data (state, federal, agency) and data from licensed companies (Definitive Healthcare, 2019). The purpose of the website, and mission of the organization, it to help provide healthcare commercial intelligence to help organizations navigate the complexity of the healthcare environment (Definitive Healthcare, 2019).

Data Collection Procedures

The initial starting point was directly accessing the CMS website focused on the HACRP, which provided the most recent annual evaluation for the program (CMS, 2022b). This data was publicly available data. To access the available years of data, these annual data sets were located in the Hospital Data Archive section of CMS (2022c), which were then converted and downloaded in CSV files. This overall data collection from CMS was primarily based on selecting the correct files and saving the files accordingly. Additionally, to account for the control variables (size of hospital, geographic region, etc.) in the study, data was downloaded from the Definitive Health – Healthcare Analytics website. Once all data sets from CMS and Definitive Healthcare were downloaded, the files were then merged to provide a comprehensive data set.

Data Collection Tools

To proceed further into the steps and tools taken for data collection, it is noted that all of the CMS files were stored as zip files by annual file year, and were all labeled as 'hos_revised_flatfiles_archive_(date).' These files were downloaded and saved as un-zipped files. Within the many stored files located in the initial annual zip files download, mainly due to CMS placing all of their yearly data for 'all' metrics into the zip files, the named files that explicitly held the HACRP data were titled ‘hospital_quarterly _hac_domain_hospital’ within each unzipped file. Of note, although the files were labeled as 'quarterly,' the files themselves do not have quarterly data, only annual for the HACRP data used in this study. Additionally, as these files had already been converted to CSV upon unzipping the initial zipped files, no further file conversions needed to occur. The files were then retitled and saved to account for each of the years of data to accurately keep the files clean and separated before moving to the next stage of the study.

Data Analysis

With all of the years of data stored in separate files, Excel’s VLOOKUP functionality was applied to combine all of the data into one primary file for analysis. This ultimately created a base file, without any manipulations, in case of the need to refer back to the base files at any point in time. Additionally, data was then cleaned and organized in a new primary file, and variables and information not needed for the study were deleted. Upon review of the overall data set, it was noted that several lines of data had the same hospital ID number, but different hospital names, which came about because hospitals changed their names over the years of the study. In understanding this, upon deleting the variables of hospital names, city, and states, I then removed duplicate rows from the data, reducing from what appeared to be 3,818 hospitals, was actually 3,436 individual hospitals. Then, the data set was reviewed and analyzed for any incomplete or missing data that would limit the ability to properly analyze the difference in means across the years of the study. For inclusion criteria, HACRP composite scores had to be available in both the 2013 and 2019+ data years for each hospital. Thus, any lines of data that did not have a composite HAI score in both years were removed, leading to a final sample of 2896. Once the data was organized appropriately for analysis, the data set was then uploaded into SPSS for processing.

Upon reviewing the specific data produced from the CMS files, it was noted that the first two study years (2013 & 2014), had actual scores associated with those years for each of the variables but the remaining years did not. The data that housed the 2015-2019 only produced Winsorized z-scores for every variable; thus, leading to a difficulty to assess differences in what should be comparison data. Due to this, the researcher chose to reverse the functions to produce a z-score in order to convert to an actual score for comparative analysis. Although this method notably has some limitations, the researcher chose to use the 2013 and 2014 data to produce means and standard deviations to be used in the conversion because no data was available for the remaining years to produce such values. From this, each variable (CAUTI, CDI, Composite, etc.) had to be recoded using the means and standard deviations from previous years of each variable. Upon completing this recoding, it was noted that several hospitals now had converted scores that were outside the normal score range for these variables. Due to this, the researcher cleaned the data updating values over the value of 10, to 10.0, and every value less than 1, to 1.0.

The initial statistical analysis performed in the study was a paired-samples *t*-test. With the establishment of the study's independent variable as nominal (yes or no theoretical payment reduction) that have scale (infection scores) dependent variable data, this initial, unadjusted analysis evaluated and compared the main differences between two data points in the years evaluated to assess for any significant differences (Field, 2012). To accomplish this analysis, the composite means of the initial year in the study (2013) were compared against the composite means in the 2019+ data. With the first year of HACRP occurring in 2014, evaluating 2013 data as the pre-policy year provided an overall review of pre-policy and post-policy periods. Also, with the availability of annual data, trends were assessed over the years to see where some of those differences occurred. Additionally, to further assess the primary two groups (worst-performing and well-performing), analysis was conducted by separating the two groups and assessing the trends across the years with each group. Of note, CMS did not specify for the pre-policy year of 2013 whether the hospitals would have or would not have received a reduction in reimbursements. Due to this, I performed my own analysis of converting composite scoring to z-scores, to provide information on where each hospital would have stood theoretically (worst-performing or well-performing) had the policy been in place. This helped to provide some perspective on the effectiveness of the HACRP policy since its inception.

As the paired samples *t*-test falls within parametric testing, several assumptions were made with the data. The first foundational element of parametric tests is that it was based on normal distribution (Field, 2012). From this normal distribution, there was an assumption of normality and linearity in which the outcome variables are related to predictors (Field, 2012). Another assumption to be made is that of the homoscedasticity of variance in that the residuals/results had similar variances (Field, 2012). One other assumption to note is that of independence which assumes that one data point did not influence another (Field, 2012). Independence implies that the behavior of one group did not impact the behavior of another group (Field, 2012). However, a violation of this assumption of independence on your *t*-test results is that it used repeated measures for which each hospital has multiple rows of data since infection rates are tracked over time. Due to this, further analysis was conducted through applying a mixed effects, linear regression model.

These multiple linear regressions with random effects models were produced to perform the difference in differences analysis for each HAI, the PSI 90, and the Composite scores. The original model was created using the overall Composite scores, and then the regressions were applied for each remaining variable to produce new models from that data. Before running the regression, an interaction term was created to evaluate the main effect from the product of the two predictors for whether or not a hospital would have theoretically been penalized in 2013, and the number of years in the study. This interaction term was created to help reduce the correlation between the two predictors, avoid problems of multicollinearity, and increase the accuracy and consistency of the regression coefficients to improve the explanation of the model (UCLA, n.d.). Moreover, this multiple linear regression model, assumed there was a linear relationship between the independent variables and the dependent variable. Also, the model is only valid for the range of data collected and used to calculate the coefficients (Sullivan, 2012). In total, seven models were produced in this study.

Methodological Integrity

To maintain security of the data, the data files were stored on the researcher's Dropbox application which was only accessible with the appropriate login and password. Although the data did not contain any PHI, the login and password access limited access to the data outside of the research team to confidentially maintain data assurance throughout the study. Ultimately, the data files, results, and findings were stored under the same login and password within the Dropbox application. Additionally, the researcher had no associations or relationships with the hospitals reviewed in the study that would have limited the integrity of the study.

Ethical Considerations

As the data was already publicly available and listed by hospital name, leaving the names of the hospitals in the study would have no more removed anonymity than what CMS had already provided on their website. However, to bring some anonymity back in this study, and reduce the potential risk of harm from public perception of the hospitals studied, the hospitals' unique ID numbers for the analysis were used should any further results need to show hospital-level data. Although individuals familiar with the data could still link those ID numbers back to the individual hospitals, it provides at least one level of anonymity for the already publicly available data. Also, using the unique ID numbers instead of hospital names may similarly help the researcher limit any potential bias that may occur during the analysis from knowing the location or name of each hospital. Additionally, regarding IRB approval to conduct the study, based on the already public availability of the data, this study met the criteria for exemption. Therefore, an exemption application was sent to the IRB and was approved two months later allowing the study to proceed with collecting and analyzing the data.

Summary

To evaluate the research question, retrospective data was be pulled directly from the CMS website and associated webpages. The data will be downloaded from zip files and converted into CSV files for initial review through the use of Excel. After combining the individually downloaded files and cleaning up the data elements, the data was then inputed into SPSS for analytic processing of a paired samples *t*-test. After conducting the initial *t*-tests, further definitive analysis was conducted through applying multiple linear regressions with random effects models. Efforts to maintain data integrity, limiting bias, and applying ethical research practice were preserved throughout the study. In the next chapter, the elements of this chapter were applied and the results of performing the statistical analysis will be discussed.

CHAPTER FOUR: RESULTS AND FINDINGS

In applying the methodology discussed in Chapter 3, this chapter will focus on analyzing the HACRP data, and produce results and findings from the analysis. The purpose of this study was to explore whether decreases in CMS reimbursements to hospitals from the HACRP policy have impacted hospital-acquired infections across the United States. To assess this, the following research question was developed: What is the relationship between CMS' reductions in reimbursements from the Hospital-Acquired Conditions Reduction Program (HACRP) policy and hospital-acquired infections across the United States? From this, the following research hypothesis was developed: The existence of the financial disincentive from the HACRP policy has lowered the incidence of HAIs for hospitals subject to penalty. Overall, this chapter will provide more insight into the effectiveness of implementing financial disincentives through the HACRP policy.

Results

To review the results of the study, a methodological approach was taken by first performing *t-tests* initially to assess for difference in composite means of the population of hospitals in the study. Additionally, *t-tests* were also performed by separating out the two groups of the independent variable: hospitals that would have been penalized and those that would not have been penalized. To further analyze and substantiate the findings from the *t-tests,* a multiple linear regression analysis with random effects was performed to create models for each of the HAIs, PSI 90, and composite variables. Within the regression models created, control variables were applied to reduce the possibility of compounding effects between the hospitals (see Table 1).

Table 1

Descriptive Statistics of Control Variables Separated by Hospitals Penalized and Not-penalized in the Pre- and Post-policy Periods

	Total (2896)	2013 No (2171)		2013 Yes (725)		2019 No (2171)		2019 Yes (725)	
	Mean/%	Mean/%	SD	Mean/%	SD	Mean/%	SD	Mean/%	SD
Average Length of Stay	4.80	4.60	1.10	5.00	1.40	4.60	1.20	5.00	1.20
Total Performance Score	29.06	30.41	15.35	27.85	14.87	30.55	15.99	27.43	12.63
Bed Utilization Rate	52.54%	49.93%	20.52%	55.49%	22.06%	50.26%	21.39%	54.48%	19.74%
CC/MCC Rate	64.25%	0.64	0.13	0.64	0.13	0.63	0.14	0.66	0.09
# of Licensed Beds	244	208	193	287	262	215	203	266	245
Case Mix Index	1.75	1.72	0.38	1.80	0.43	1.74	0.41	1.75	0.35
Market Concentration Index	0.32	0.33	0.33	0.29	0.31	0.32	0.32	0.33	0.34
Payor Mix: Medicaid Days	8.83%	8.17%	8.83%	9.59%	9.86%	8.27%	9.20%	9.28%	8.86%
Hospital Compare Rating									
0	9.70%	6.70%	-	3.00%	-	8.87%	-	0.83%	-
1	5.94%	3.80%	-	2.14%	-	1.97%	-	3.97%	-
2	20.23%	15.26%	-	4.97%	-	12.05%	-	8.18%	-
3	26.24%	20.10%	-	6.15%	-	19.99%	-	6.25%	-
4	25.28%	18.89%	-	6.39%	-	20.68%	-	4.59%	-
5	12.60%	10.22%	-	2.38%	-	11.29%	-	1.31%	-
Academic Medical Center									
No	93.89%	72.34%	-	21.55%	-	71.44%	-	22.44%	-
Yes	6.11%	2.62%	-	3.49%	-	3.42%	-	2.69%	-
HCAHPS Summary Star									
0	9.19%	6.66%	-	2.52%	-	8.08%	-	1.10%	-
1	2.21%	1.69%	-	0.52%	-	1.52%	-	0.69%	-
2	16.99%	12.26%	-	4.73%	-	11.53%	-	5.46%	-
3	45.75%	33.81%	-	11.95%	-	33.91%	-	11.84%	-

4	22.13%	17.44%	-	4.70%	-	16.47%	-	5.66%	-
5	3.73%	3.11%	-	0.62%	-	3.35%	-	0.38%	-
Geographic Classification									
Rural	10.57%	8.22%	-	2.35%	-	8.53%	-	2.04%	-
Urban	89.43%	66.75%	-	22.69%	-	66.33%	-	23.10%	-
Sole Community Hospital									
No	83.70%	61.57%	-	22.13%	-	62.60%	-	21.10%	-
Yes	16.30%	13.40%	-	2.90%	-	12.26%	-	4.04%	-
Ownership									
Gov - City/State	12.88%	9.08%	-	3.80%	-	8.70%	-	4.18%	-
Gov - Federal	0.83%	0.38%	-	0.45%	-	0.59%	-	0.24%	-
Gov - Other	1.45%	0.73%	-	0.73%	-	0.97%	-	0.48%	-
Proprietary	22.76%	17.96%	-	4.80%	-	18.85%	-	3.90%	-
Vol NFP - Church	13.43%	10.46%	-	2.97%	-	10.29%	-	3.14%	-
Vol NFP - Other	48.65%	36.36%	-	12.29%	-	35.46%	-	13.19%	-
Accreditation Agency									
Joint Commission	83.56%	64.16%	-	19.41%	-	62.47%	-	21.10%	-
Healthcare Facilities	3.69%	3.25%	-	0.45%	-	2.66%	-	1.04%	-
Det Norske Veritas HC	12.74%	9.53%	-	3.21%	-	9.74%	-	3.00%	-
Region									
Midwest	24.07%	18.40%	-	5.66%	-	18.16%	-	5.90%	-
Northeast	15.81%	10.81%	-	5.01%	-	10.50%	-	5.32%	-
Southeast	29.97%	23.52%	-	6.46%	-	22.48%	-	7.49%	-
Southwest	13.23%	10.67%	-	2.56%	-	10.88%	-	2.35%	-
West	16.92%	11.57%	-	5.35%	-	12.85%	-	4.07%	-

Note: These are the descriptive statistics for the 2,896 hospitals included in the study based on whether they were penalized or not in the pre-and post-policy periods of 2013 and 2019.

Hypothesis Testing

To test the hypothesis, an initial analysis of this study, a paired samples *t*-test was performed. This paired samples *t*-test allowed for the assessment of pre-policy HACRP composite scores in 2013 versus the post-policy analysis with HACRP composite score data ending in 2019 (2019+ data). The key point of this unadjusted analysis is that a lower mean score would signify that improvements have been made in preventing HAIs from the pre- to post-policy periods (scoring: lower is better). In comparing the same 2,896 hospitals from their pre-policy HACRP scores against their post-policy HACRP scores, the paired samples *t*-test (see Table 2) found significance in the mean differences of the composite scores pre-policy (M= 5.412, SD=2.036) and post-policy (M=5.280, SD=1.116); $t(2895) = 3.201$, $p = .001$, 95% CI [0.051, 2.12]. This significance in the difference of means notes that scores improved (lowered) from the pre-policy to post-policy time periods.

Table 2

Paired Samples t-test Composite Scores Pre-Policy and Post-Policy

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Dev	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	2013 Comp - 2019+ Comp	.131	2.205	.041	.051	.212	3.201	2895	.001

Note: This paired samples t-test assessed for differences between 2,896 hospitals from their composite HACRP scores from the 2013 to 2019+ data years. Significance was found $t(2895) = 3.201$, $p = .001$.

Additionally, although significance was discovered, the effect size of this analysis, through evaluation of Cohen's *d* (see Table 3), is noted to be small (.059).

However, although there is small effect size, due to the significance found in this *t*-test, the null hypothesis that there would be no difference between the pre-policy and post-policy time periods is rejected.

Table 3

Paired Samples Effect Sizes

			Standardizer[a]	Point Estimate	95% Confidence Interval	
					Lower	Upper
Pair 1	2013 Comp - 2019+ Comp	Cohen's d	2.205	.059	.023	.096
		Hedges' correction	2.205	.059	.023	.096

Note: The effect size of this *t*-test produced a value of d = .059, which notes a small effect size between the two points in time.

To more specifically address the components of the independent variable (theoretical payment reduction: ‘yes’ or ‘no’), the two groups of hospitals based on the independent variable group were assessed separately to evaluate differences within each group to see if one group had greater differences than the other. Continuing with the previous methodology, a paired samples *t*-test was performed to assess only hospitals that would have been penalized (‘yes’) in the pre-policy period of 2013 and were evaluated by their pre-policy HACRP scores against their post-policy HACRP scores. In comparing these hospitals that would have been penalized (‘yes’) in the pre-policy period, this paired samples t-test (see Table 4) included 725 hospitals and found significance in the mean differences of the composite scores pre-policy (M=7.966, SD=.8098) and post-policy (M=5.452, SD=1.079); $t(725) = 52.273$, $p = <.001$, 95% CI [2.419, 2.608]. This significance in the difference of means, notes that scores improved (lowered) from pre-policy to post-policy time periods of the hospitals that would have had payment reductions in the pre-policy period.

Table 4

Paired Samples t-test of HACRP Composite Scores Pre-Policy and Post-Policy (only hospitals that would have received payment reduction in the pre-policy period of 2013)

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Dev	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	2013 Comp - 2019+ Comp	2.513	1.294	.048	2.419	2.608	52.273	724	<.001

Note: This paired samples t-test assessed for differences between 725 hospitals (theoretically penalized pre-policy) from their composite HACRP scores from the 2013 to 2019+ data years. Significance was found $t(1448) = 52.273$, $p = <.001$

In addition to finding significance with this analysis, the effect size, through evaluation of Cohen's *d* (see Table 5), was noted to have a large effect between the two time periods evaluated for this specific population of hospitals: $d = 1.941$.

Table 5

Paired Samples Effect Sizes of HACRP Composite Scores that would have Received Payment Reductions in 2013 (pre-policy period)

			Standardizer[a]	Point Estimate	95% Confidence Interval	
					Lower	Upper
Pair 1	2013 Comp - 2019+ Comp	Cohen's d	1.294	1.941	1.817	2.065
		Hedges' correction	1.295	1.940	1.817	2.064

Note: The effect size of this *t*-test produced a value of $d = 1.941$, which notes a large effect size between the two points in time.

Similarly, to the previous paired samples t-test, another t-test was conducted to assess only the hospitals that would 'not' have been penalized in the pre-policy period of

2013 and were evaluated by applying their pre-policy HACRP scores against their post-policy HACRP scores. In comparing these hospitals that would 'not' have been penalized in the pre-policy period, this paired samples t-test (see Table 6) included 2,171 hospitals and also found significance in the mean differences of the composite scores pre-policy (M=4.560, SD=1.551) and post-policy (M=5.224, SD=1.122); $t(2171) = -16.793$, $p = <.001$, 95% CI [-.742, -586]. However, unlike the previous evaluation of payment reduction 'yes' hospitals that saw an improvement (decrease) in their composite scores, this evaluation of hospitals who would 'not' have received a payment reduction showed worsening (increase) in the composite scores in the post-policy period.

Table 6

Paired Samples t-test of Composite Scores Pre-Policy and Post-Policy (only hospitals that would 'not' have received payment reduction in the pre-policy period of 2013)

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Dev	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	2013 Comp - 2019+ Comp	-.665	1.843	.039	-.742	-.586	-16.793	2170	<.001

Note: This paired samples t-test assessed for differences between 2171 hospitals (not theoretically penalized pre-policy) from their composite HACRP scores from the 2013 to 2019+ data years. Significance was found $t(4340) = -16.793$, $p = <.001$.

In addition to finding significance with this analysis, the effect size (see Table 7) through evaluation of Cohen's *d* was noted to have a small, negative effect due to the increase (worsening) of composite scores from the pre-policy to the post-policy time periods evaluated for this specific population of hospitals; $d = -.360$.

Table 7

Paired Samples Effect Sizes of HACRP Composite Scores that would have 'not' Received Payment Reductions in 2013 (pre-policy period)

				Point	95% Confidence Interval	
			Standardizer[a]	Estimate	Lower	Upper
Pair 1	2013 Comp - 2019+ Comp	Cohen's d	1.843	-.360	-.404	-.317
		Hedges' correction	1.843	-.360	-.404	-.317

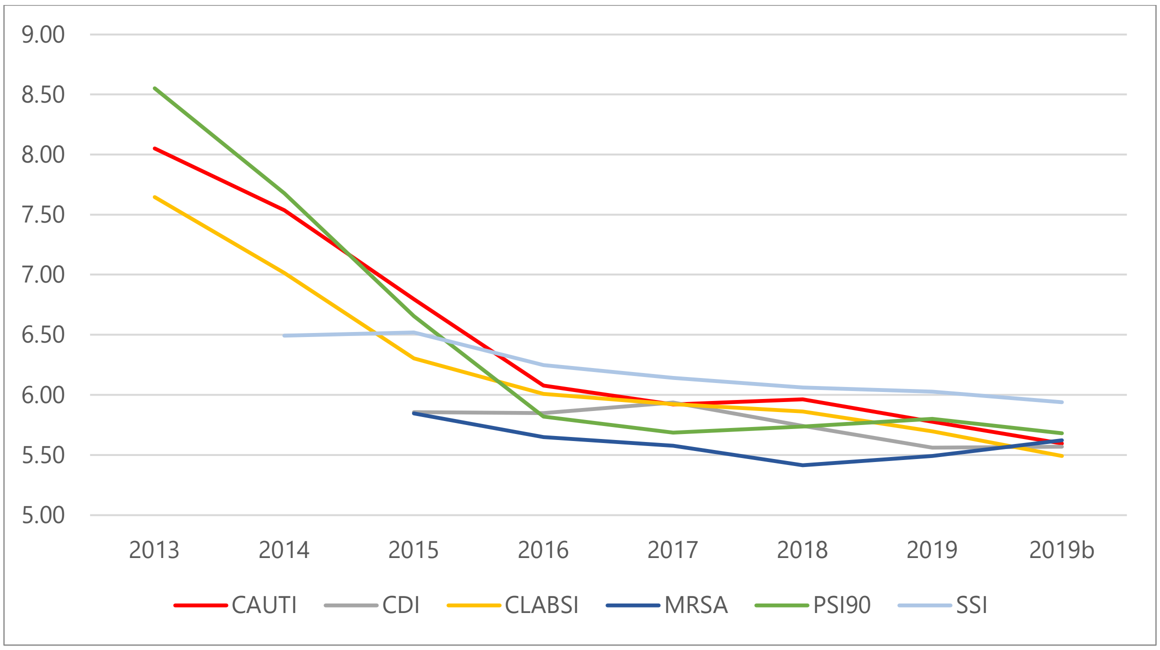
Note: The effect size of this t-test produced a value of d = -.360, which notes a negative, small effect size between the two points in time.

To more specifically address where some of these differences occurred within the overall composite scoring, each HAI and PSI 90 scores (by mean scores) was evaluated over the years of the study. This assessment allowed for the evaluation of annual trends across independent variable of the study: whether hospitals would have theoretically been penalized ('yes') or not penalized ('no') in the pre-policy period of 2013. For those hospitals that would have theoretically been penalized, a marked decrease (improvement) in HAI scores was noted through the years included in the study (Figure 1). Although only three categories (CAUTI, CLABSI, and PSI 90) were included in the initial 2013 composite scoring, when the remainder categories began to be included in the composite scoring (SSI in 2014, CDI & MRSA in 2015), those HAIs already started with lower scores. These lower initial scores could potentially imply that efforts to improve the reduction of HAI's had already been initiated due to the higher scores received in 2013.

Additionally, even after a steady decrease in scores from 2013 to 2016, scores continued to slowly decline for most HAIs across the remainder of the study years.

Figure 1

Mean HAI Scores: Scores Based on Pre-Policy Standings (only payment reduction 'yes')

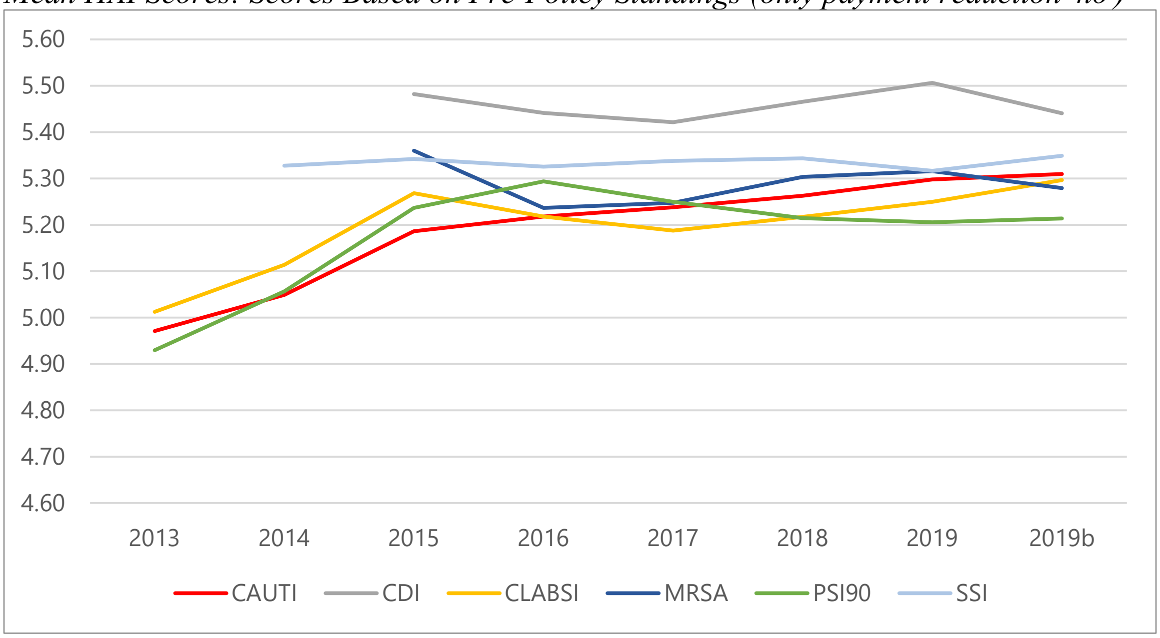


Note: Changes in mean HAI and PSI 90 scores over the period of study for only those hospitals that would have been penalized (yes) in the pre-policy period.

Conversely, when reviewing the HAI means of only those hospitals that would have theoretically 'not' received a payment reduction in their reimbursements based on the 2013 composite scores, these HAI scores increased (worsened) over the years (Figure 2). As with the previous figure's description, delayed entry of three HAI's was similarly as well. However, the scores of those later added HAIs initially started higher than the initial evaluated scores of the original HAI's, which could have skewed the composite scoring over those years. One key point with the following figure is that the scale is notably different than the previous, mainly due to the high HAI scores in 2013 and 2014 in the payment reduction previous ‘yes’ figure (Figure 1). Due to this, although increased scores occurred over the years for the payment reduction ‘no’ hospitals, these small increments of scores had no effect on the overall composite differences pre-policy to post-policy that were heavily improved upon by the payment reduction ‘yes’ hospitals.

Figure 2

Mean HAI Scores: Scores Based on Pre-Policy Standings (only payment reduction 'no')



Note: Changes in mean HAI and PSI 90 scores over the period of study for only those hospitals that would not have been penalized (no) in the pre-policy period.

Regression Analysis

Further analysis was then conducted on the data through creating a multiple linear regression model with random effects for the composite scores, each of the HAI scores, and the PSI 90 scores. In applying the control variables, each coefficient produced represents the impact of that variable on the predicted value of *y*, while holding all other independent variables constant (Sullivan, 2012). Additionally, in building the primary linear regression model, the composite scoring was modeled first as it was the primary factor analyzed with the *t*-test. Given this, the regression model created an intercept of 3.359 (p = <.001), with two primary predictor variables, b_1 and b_2 (see Table 8).

The estimate value for b_1 (PrePolicy_Pymt_Reduc) notes that by increasing b_1 by one unit, would increase the predicted value of y by 2.570 units (p = <.001). Additionally, increasing b_2 (Year) by one unit would also increase the predicted value of y by 0.077 units (p = <.001). These values prove valid as those who would have been theoretically penalized in the pre-policy period, would have started out at higher composite scores than those that did not, and then only increased further by 0.077 units for every year evaluated. However, the interaction term's estimate (b_3) produced an estimate value of -0.395 (p = <.001), which notes an overall decrease in the predictive value by 0.395, by each year of the Composite scoring. Thus, this regression model further validates the previous t-test results in that there was a difference in composite scoring from the pre-policy to post-policy periods, which further substantiates that scores improved (decreased) within that time period; accordingly supporting the notion to reject the null hypothesis.

To further review the regression model, when evaluating the control variables for their coefficient estimates within the model, fourteen of the twenty-four evaluated coefficients produced significant findings ($p < .05$). Additionally, to evaluate for whether multicollinearity was a problem with this regression, the variance inflation factors (VIF) were included in the table. Of those control variables, the range of variance inflation factors was 1.191 – 30.592. The majority of the coefficients produced VIF values less than 2.188, which indicated a low correlation of those predictors with other predictors

(EasyStats, n.d.). In assessing the VIF values over 3.000, the independent variable (b_1, VIF 4.950) and the interactive term (b_3, VIF 5.205) indicated a moderate correlation of those predictors with other predictors. Additionally, with an interaction term present in the model, it is noted that high VIF values are expected because this portion of multicollinearity among the component terms usually leads to inflated VIF values (EasyStats, n.d.). As for the remaining coefficients with moderate to high VIF values, although these variables would have likely been removed had they been evaluated as continuous variables, due to those values falling within a categorical variable, they remained in the model.

In seeking to assess for random effects model within the multiple linear regression, the variable of Hospital ID was used for the analysis as it has no direct value within the data set. Although the Hospital IDs were numbers, the increased number of a Hospital ID has no relation to a categorical or ranked variable. Additionally, the rationale for using the random effects model was that the variation across the Hospital IDs was assumed to be random and uncorrelated with the predictor and independent variables included in the model (Torrres-Reyna, 2007). Although random effects were expected by running this linear regression model, the random effect was found to not be significant as the estimate of the variance parameter for it was essentially 0.00 (see Table 9). However, a reasoning for why this estimate of the variance parameter produced a 0.00 value may be due to the fixed portion of the model explaining all of the variability. These random effects were assessed with each of the models produced to see if there were any differences with applying the HAI and PSI 90 scores. See Table 10 for the complete multiple linear regression model with random effects with Composite scores as the outcome variable.

Table 8

Multiple Linear Regression Model (Composite Scores)

Term	*b*	Estimate	Prob>|t|	VIF
Intercept		3.359	<.001	.
PrePolicy_Pymt_Reduc	b_1	2.570	<.001	4.950
Year	b_2	0.077	<.001	1.339
PrePolicyPymtReduc_Year_INTERACTION	b_3	-0.395	<.001	5.205
CC/MCC Rate	b_4	1.661	<.001	1.386
Bed Utilization Rate	b_5	0.008	<.001	1.794
Hospital Compare Overall Rating	b_6	-0.115	<.001	1.817
# of Licensed Beds	b_7	0.001	<.001	1.899
Average Length of Stay	b_8	0.073	<.001	1.699
Academic Medical Center	b_9	0.207	<.001	1.392
Case Mix Index	b_{10}	0.006	0.844	1.663
Total Performance Score	b_{11}	-0.004	<.001	1.854
Market Concentration Index	b_{12}	-0.084	0.097	1.391
Sole Community Hospital	b_{13}	-0.063	0.033	1.384
Payor Mix: Medicaid Days	b_{14}	0.001	0.406	1.245
Geographic Classification	b_{15}	0.038	0.258	1.191
Pt Survey (HCAHPS) Star Rating	b_{16}	-0.012	0.237	1.498
Region [Midwest]	b_{17}	0.016	0.395	1.761
Region [Northeast]	b_{18}	0.183	<.001	1.890
Region [Southeast]	b_{19}	-0.063	0.002	1.682
Region [Southwest]	b_{20}	-0.194	<.001	2.009
Ownership [Gov - City/State]	b_{21}	-0.089	0.061	6.066
Ownership [Gov - Federal]	b_{22}	0.484	<.001	30.592
Ownership [Gov - Other]	b_{23}	0.076	0.264	16.108
Ownership [Proprietary]	b_{24}	-0.213	<.001	7.029
Ownership [Voluntary Nonprofit - Church]	b_{25}	-0.154	<.001	6.776
Acred Agency [Joint Commission]	b_{26}	0.010	0.605	2.130
Acred Agency [HC Facilities Acred Pgm]	b_{27}	0.024	0.453	2.188

Table 9

Multiple Linear Regression Model – Random Effects (Composite Scores)

Random Effect	Var Ratio	Var Comp	Std Error	95% Lower	95% Upper	Wald p-Value	Pct of Total
Provider ID	0	0	1.556e-15	-3.050e-15	3.049e-15	1.000	0.000
Residual		1.681	0.016	1.649	1.713		100.0
Total		1.681	0.016	1.649	1.713		100.0

Table 10

Multiple Linear Regression Model – Random Effects ($\hat{y}$ = Composite Scores)

$$\begin{aligned}\hat{y} = 3.359 + 2.570b_1 + 0.077b_2 - 0.395b_3 + 1.661b_4 + 0.008b_5 - 0.115b_6 + 0.001b_7 \\ + 0.073b_8 + 0.207b_9 + 0.006b_{10} - 0.004b_{11} - 0.084b_{12} - 0.063b_{13} \\ + 0.001b_{14} + 0.038b_{15} - 0.012b_{16} + 0.016b_{17} + 0.183b_{18} - 0.063b_{19} \\ - 0.194b_{20} - 0.089b_{21} + 0.484b_{22} + 0.076b_{23} - 0.213b_{24} - 0.154b_{25} \\ + 0.010b_{26} + 0.024b_{27}\end{aligned}$$

In applying the same methodology as primary multiple linear regression with random effects model, the CAUTI scores were analyzed next as the outcome variable (see Table 11). Given this, the CAUTI regression model created an intercept of 3.811 (p = <.001). The estimate value for b_1 (PrePolicy_Pymt_Reduc) notes that increasing b_1 by one unit, would increase the predicted value of y by 2.556 units (p = <.001). Additionally, increasing b_2 (Year) by one unit would also increase the predicted value of y by 0.069 units (p = <.001). These values prove valid as those who would have been theoretically penalized in the pre-policy period, would have started out with higher CAUTI scores (leading to higher Composite scores) than those that did not, and then only increased further by 0.077 units for every year evaluated. However, the interaction term's estimate (b_3) produced an estimate value of -0.376 (p = <.001), which notes an overall decrease (improvement) in the predictive value by 0.376, by each year of the CAUTI scoring. Additionally, in reviewing the VIF values, the independent variable and the interaction term both remained with a moderate correlation, and variables within categorical variables remained continued to produce high VIF values noting a high correlation with those predictors (see Table 12). Moreover, no changes were noted within the random effects analysis as the estimate of the variance parameter produced the same value as the Composite analysis (0). See Table 13 for the complete multiple linear regression model with random effects with CAUTI scores as the outcome variable.

Table 11

Multiple Linear Regression Model (CAUTI Scores)

Term	*b*	Estimate	Prob>|t|	VIF
Intercept		3.811	<.001	.
PrePolicy_Pymt_Reduc	b_1	2.556	<.001	4.943
Year	b_2	0.069	<.001	1.342
PrePolicyPymtReduc_Year_INTERACTION	b_3	-0.376	<.001	5.190
CC/MCC Rate	b_4	0.425	0.036	1.362
Bed Utilization Rate	b_5	0.015	<.001	1.744
Hospital Compare Overall Rating	b_6	-0.119	<.001	1.800
# of Licensed Beds	b_7	0.001	<.001	1.911
Average Length of Stay	b_8	0.009	0.671	1.673
Academic Medical Center	b_9	-0.154	0.078	1.403
Case Mix Index	b_{10}	0.375	<.001	1.725
Total Performance Score	b_{11}	-0.012	<.001	1.857
Market Concentration Index	b_{12}	-0.126	0.063	1.402
Sole Community Hospital	b_{13}	-0.075	0.226	1.391
Payor Mix: Medicaid Days	b_{14}	-0.002	0.366	1.179
Geographic Classification	b_{15}	-0.007	0.925	1.157
Pt Survey (HCAHPS) Star Rating	b_{16}	0.060	0.008	1.547
Region [Midwest]	b_{17}	0.055	0.153	1.777
Region [Northeast]	b_{18}	0.309	<.001	1.916
Region [Southeast]	b_{19}	-0.149	<.001	1.689
Region [Southwest]	b_{20}	-0.564	<.001	2.025
Ownership [Gov - City/State]	b_{21}	-0.068	0.350	7.155
Ownership [Gov - Federal]	b_{22}	0.833	0.001	45.105

Term	*b*	Estimate	Prob>|t|	VIF
Ownership [Gov - Other]	b_{23}	-0.070	0.623	16.508
Ownership [Proprietary]	b_{24}	-0.445	<.001	8.451
Ownership [Voluntary Nonprofit - Church]	b_{25}	-0.158	0.030	8.021
Acred Agency [Joint Commission]	b_{26}	-0.001	0.996	2.131
Acred Agency [HC Facilities Acred Pgm]	b_{27}	-0.141	0.033	2.189

Table 12

Multiple Linear Regression Model – Random Effects (CAUTI Scores)

Random Effect	Var Ratio	Var Comp	Std Error	95% Lower	95% Upper	Wald p-Value	Pct of Total
Provider ID	0	0	1.159e-14	-3.070e-14	3.074e-14	1.000	0.000
Residual		6.940	0.069	6.807	7.078		100.0
Total		6.940	0.069	6.807	7.078		100.0

Table 13

Multiple Linear Regression Model – Random Effects ($\hat{y}$ = $CAUTI$ $Scores$)

$$\hat{y} = 3.811 + 2.556b_1 + 0.069b_2 - 0.376b_3 + 0.425b_4 + 0.015b_5 - 0.119b_6 + 0.001b_7 + 0.009b_8 - 0.154b_9 + 0.375b_{10} - 0.012b_{11} - 0.126b_{12} - 0.075b_{13} - 0.002b_{14} - 0.007b_{15} + 0.060b_{16} + 0.055b_{17} + 0.309b_{18} - 0.0149b_{19} - 0.564b_{20} - 0.068b_{21} + 0.833b_{22} - 0.070b_{23} - 0.445b_{24} - 0.158b_{25} - 0.001b_{26} - 0.141b_{27}$$

In continuing to apply the same methodology as the primary multiple linear regression with random effects model, the CDI scores were analyzed next as the outcome variable (see Table 14). Given this, the CDI regression model created an intercept of 3.381 (p = <.001). The estimate value for b_1 (PrePolicy_Pymt_Reduc) notes that by increasing b_1 by one unit, would increase the predicted value of y by 0.196 units (p = <.001). Additionally, increasing b_2 (Year) by one unit would also decrease the predicted value of y by -0.022 units (p = <.001). The negative value of the Year (b_2) predictor may be associated with the fact that the CDI data was only first evaluated in 2015, whereas the previous CAUTI and Composite scores began in 2013 within this data set. However, the interaction term's estimate (b_3) produced an estimate value of -0.061 (p = 0.022), which notes an overall decrease (improvement) in the predictive value by 0.061, by each year of the CDI scoring. Additionally, in reviewing the VIF values, the independent variable, the interaction term, and variables within categorical variables to produced high VIF values noting a high correlation with those predictors (see Table 15). Moreover, no changes were noted within the random effects analysis as the estimate of the variance parameter produced the same value as the Composite analysis (0). See Table 16 for the complete multiple linear regression model with random effects with CDI scores as the outcome variable.

Table 14

Multiple Linear Regression Model (CDI Scores)

Term	*b*	Estimate	Prob>|t|	VIF
Intercept		3.381	<.001	.
PrePolicy_Pymt_Reduc	b_1	0.196	0.205	11.454
Year	b_2	-0.022	0.105	1.341
PrePolicyPymtReduc_Year_INTERACTION	b_3	-0.061	0.022	11.704
CC/MCC Rate	b_4	3.161	<.001	1.361
Bed Utilization Rate	b_5	0.015	<.001	1.783
Hospital Compare Overall Rating	b_6	-0.124	<.001	1.808
# of Licensed Beds	b_7	0.001	0.632	1.898
Average Length of Stay	b_8	0.036	0.113	1.683
Academic Medical Center	b_9	0.348	0.001	1.388
Case Mix Index	b_{10}	0.195	0.005	1.658
Total Performance Score	b_{11}	-0.009	<.001	1.839
Market Concentration Index	b_{12}	0.180	0.013	1.389
Sole Community Hospital	b_{13}	-0.222	0.001	1.384
Payor Mix: Medicaid Days	b_{14}	-0.019	<.001	1.228
Geographic Classification	b_{15}	-0.115	0.131	1.188

Term	b	Estimate	Prob>|t|	VIF
Pt Survey (HCAHPS) Star Rating	b_{16}	0.079	0.001	1.506
Region [Midwest]	b_{17}	0.168	<.001	1.763
Region [Northeast]	b_{18}	0.392	<.001	1.893
Region [Southeast]	b_{19}	-0.545	<.001	1.683
Region [Southwest]	b_{20}	-0.409	<.001	2.010
Ownership [Gov - City/State]	b_{21}	-0.249	0.001	6.170
Ownership [Gov - Federal]	b_{22}	0.906	<.001	31.779
Ownership [Gov - Other]	b_{23}	0.352	0.021	16.151
Ownership [Proprietary]	b_{24}	-0.264	<.001	7.143
Ownership [Voluntary Nonprofit - Church]	b_{25}	-0.521	<.001	6.866
Acred Agency [Joint Commission]	b_{26}	-0.009	0.820	2.122
Acred Agency [HC Facilities Acred Pgm]	b_{27}	-0.112	0.114	2.180

Table 15

Multiple Linear Regression Model – Random Effects (CDI Scores)

Random Effect	Var Ratio	Var Comp	Std Error	95% Lower	95% Upper	Wald p-Value	Pct of Total
Provider ID	0	0	4.749e-15	-9.290e-15	9.288e-15	1.000	0.000
Residual		6.219	0.070	6.084	6.359		100.0
Total		6.219	0.070	6.084	6.359		100.0

Table 16

Multiple Linear Regression Model – Random Effects ($\hat{y} = CDI\ Scores$)

$$\begin{aligned}\hat{y} = 3.3831 &+ 0.37196 - 0.0022b_2 - 0.061b_3 + 3.161b_4 + 0.015b_5 - 0.124b_6 + 0.001b_7 \\ &+ 0.036b_8 + 0.348b_9 + 0.195b_{10} - 0.009_{11} + 0.180b_{12} - 0.222b_{13} \\ &- 0.019b_{14} - 0.115b_{15} + 0.079b_{16} + 0.0168b_{17} + 0.392b_{18} - 0.545b_{19} \\ &- 0.409b_{20} - 0.249b_{21} + 0.906b_{22} + 0.352b_{23} - 0.264b_{24} - 0.521b_{25} \\ &- 0.009b_{26} - 0.112b_{27}\end{aligned}$$

The next outcome variable to be analyzed were the CLABSI scores (see Table 17) and the regression model created an intercept of 4.733 (p = <.001). The estimate value for b_1 (PrePolicy_Pymt_Reduc) notes that by increasing b_1 by one unit, would increase the predicted value of y by 2.2149 units (p = <.001). Additionally, increasing b_2 (Year) by one unit would also increase the predicted value of y by 0.051 units (p = <.001). However, the interaction term's estimate (b_3) produced an estimate value of -0.286 (p = <.001), which notes an overall decrease (improvement) in the predictive value by 0.286, by each year of the CLABSI scoring. Additionally, the independent variable and the interaction term both remained with a moderate correlation of VIF values, and variables within categorical variables remained continued to produce high VIF values noting a high correlation with those predictors (see Table 18). Moreover, no changes were noted within the random effects analysis as the estimate of the variance parameter produced the same value as the Composite analysis (0). See Table 19 for the complete multiple linear regression model with random effects with CLABSI scores as the outcome variable.

Table 17

Multiple Linear Regression Model (CLABSI Scores)

Term	*b*	Estimate	Prob>|t|	VIF
Intercept		4.733	<.001	.
PrePolicy_Pymt_Reduc	b_1	2.149	<.001	4.968
Year	b_2	0.051	<.001	1.349
PrePolicyPymtReduc_Year_INTERACTION	b_3	-0.286	<.001	5.228
CC/MCC Rate	b_4	0.256	0.243	1.345
Bed Utilization Rate	b_5	0.002	0.136	1.710
Hospital Compare Overall Rating	b_6	-0.142	<.001	1.801
# of Licensed Beds	b_7	0.001	0.052	1.894
Average Length of Stay	b_8	0.107	<.001	1.672
Academic Medical Center	b_9	-0.047	0.596	1.410
Case Mix Index	b_{10}	0.045	0.544	1.745
Total Performance Score	b_{11}	-0.009	<.001	1.867
Market Concentration Index	b_{12}	0.005	0.950	1.434
Sole Community Hospital	b_{13}	-0.281	<.001	1.407
Payor Mix: Medicaid Days	b_{14}	0.001	0.868	1.185
Geographic Classification	b_{15}	0.039	0.629	1.126
Pt Survey (HCAHPS) Star Rating	b_{16}	-0.080	0.001	1.602

Term	b	Estimate	Prob>|t|	VIF
Region [Midwest]	b_{17}	-0.125	0.002	1.803
Region [Northeast]	b_{18}	-0.051	0.256	1.945
Region [Southeast]	b_{19}	0.309	<.001	1.709
Region [Southwest]	b_{20}	0.129	0.011	2.065
Ownership [Gov - City/State]	b_{21}	0.260	0.001	7.046
Ownership [Gov - Federal]	b_{22}	-0.676	0.007	43.754
Ownership [Gov - Other]	b_{23}	0.052	0.726	16.355
Ownership [Proprietary]	b_{24}	0.218	0.002	8.267
Ownership [Voluntary Nonprofit - Church]	b_{25}	0.031	0.682	7.959
Acred Agency [Joint Commission]	b_{26}	0.054	0.183	2.138
Acred Agency [HC Facilities Acred Pgm]	b_{27}	0.234	0.001	2.203

Table 18

Multiple Linear Regression Model – Random Effects (CLABSI Scores)

Random Effect	Var Ratio	Var Comp	Std Error	95% Lower	95% Upper	Wald p-Value	Pct of Total
Provider ID	0	0	7.325e-15	-1.1440e-14	1.436e-14	1.000	0.000
Residual		7.167	0.073	7.026	7.313		100.0
Total		7.167	0.073	7.026	7.313		100.0

Table 19

Multiple Linear Regression Model – Random Effects ($\hat{y}$ = CLABSI Scores)

$$\hat{y} = 4.733 + 2.149b_1 + 0.051b_2 - 0.286b_3 + 0.256b_4 + 0.002b_5 - 0.142b_6 + 0.001b_7 + 0.107b_8 - 0.047b_9 + 0.045b_{10} - 0.009b_{11} + 0.005b_{12} - 0.281b_{13} + 0.001b_{14} + 0.039b_{15} - 0.080b_{16} - 0.125b_{17} - 0.051b_{18} + 0.309b_{19} + 0.129b_{20} + 0.260b_{21} - 0.676b_{22} + 0.052b_{23} + 0.218b_{24} + 0.031b_{25} + 0.054b_{26} + 0.234b_{27}$$

In continuing to apply the same methodology the MRSA scores were analyzed next as the outcome variable (see Table 20) and the regression model created an intercept of 4.515 (p = <.001). The estimate value for b_1 (PrePolicy_Pymt_Reduc) notes that by increasing b_1 by one unit, would decrease the predicted value of y by 0.282 units (p = <.001). Additionally, increasing b_2 (Year) by one unit would also decrease the predicted value of *y* by -0.006 units (p = <.001). The negative value of the Year (b_2) predictor may be associated with the fact that the MRSA data, like the CDI data, was only first evaluated in 2015, whereas the previous CAUTI and Composite scores began in 2013 within this data set. However, unlike the previous interaction term estimates, (b_3) produced a non-statistically significant estimate value of -0.035 (p = 0.234), which notes an overall decrease (improvement) in the predictive value by 0.035, by each year of the MRSA scoring. Additionally, in reviewing the VIF values, the independent variable, the interaction term, and variables within categorical variables to produced high VIF values noting a high correlation with those predictors (see Table 21). Moreover, no changes were noted within the random effects analysis as the estimate of the variance parameter produced the same value as the Composite analysis (0). See Table 22 for the complete multiple linear regression model with random effects with MRSA scores as the outcome variable.

Table 20

Multiple Linear Regression Model (MRSA Scores)

Term	*b*	Estimate	Prob>|t|	VIF
Intercept		4.515	<.0001	.
PrePolicy_Pymt_Reduc	b_1	0.282	0.098	11.384
Year	b_2	-0.006	0.711	1.356
PrePolicyPymtReduc_Year_INTERACTION	b_3	-0.035	0.234	11.661
CC/MCC Rate	b_4	1.211	<.001	1.333
Bed Utilization Rate	b_5	0.002	0.149	1.702
Hospital Compare Overall Rating	b_6	-0.181	<.001	1.803
# of Licensed Beds	b_7	0.001	0.035	1.872
Average Length of Stay	b_8	0.096	0.000	1.655
Academic Medical Center	b_9	0.167	0.097	1.411
Case Mix Index	b_{10}	0.214	0.013	1.752
Total Performance Score	b_{11}	-0.011	<.001	1.854
Market Concentration Index	b_{12}	-0.065	0.435	1.429
Sole Community Hospital	b_{13}	0.075	0.335	1.402

Term	b	Estimate	Prob>|t|	VIF
Payor Mix: Medicaid Days	b_{14}	-0.010	0.000	1.177
Geographic Classification	b_{15}	0.132	0.153	1.127
Pt Survey (HCAHPS) Star Rating	b_{16}	-0.082	0.004	1.615
Region [Midwest]	b_{17}	-0.312	<.001	1.809
Region [Northeast]	b_{18}	-0.043	0.405	1.942
Region [Southeast]	b_{19}	0.654	<.001	1.708
Region [Southwest]	b_{20}	0.038	0.523	2.068
Ownership [Gov - City/State]	b_{21}	-0.005	0.953	7.446
Ownership [Gov - Federal]	b_{22}	0.526	0.087	49.708
Ownership [Gov - Other]	b_{23}	-0.263	0.122	16.363
Ownership [Proprietary]	b_{24}	0.098	0.233	8.827
Ownership [Voluntary Nonprofit - Church]	b_{25}	-0.113	0.201	8.477
Acred Agency [Joint Commission]	b_{26}	0.016	0.726	2.129
Acred Agency [HC Facilities Acred Pgm]	b_{27}	0.072	0.372	2.194

Table 21

Multiple Linear Regression Model – Random Effects (MRSA Scores)

Random Effect	Var Ratio	Var Comp	Std Error	95% Lower	95% Upper	Wald p-Value	Pct of Total
Provider ID	0	0	1.126e-14	-2.210e-14	2.206e-14	1.000	0.000
Residual		6.864	0.082	6.706	7.028		100.0
Total		6.864	0.082	6.706	7.028		100.0

Table 22

Multiple Linear Regression Model – Random Effects ($\hat{y}$ = MRSA Scores)

$$\begin{aligned}\hat{y} = 4.515 + 0.282b_1 - 0.006b_2 - 0.035b_3 + 1.211b_4 + 0.002b_5 - 0.181b_6 + 0.001b_7 \\ + 0.096b_8 + 0.167b_9 + 0.214b_{10} - 0.011b_{11} - 0.065b_{12} + 0.075b_{13} \\ - 0.010b_{14} - 0.132b_{15} - 0.082b_{16} - 0.312b_{17} - 0.043b_{18} + 0.654b_{19} \\ + 0.038b_{20} - 0.005b_{21} + 0.526b_{22} - 0.263b_{23} + 0.098b_{24} - 0.113b_{25} \\ + 0.016b_{26} + 0.072b_{27}\end{aligned}$$

The next outcome variable to be analyzed were the SSI scores (see Table 23) and the regression model created an intercept of 5.602 (p = <.001). The estimate value for b_1

(PrePolicy_Pymt_Reduc) notes that by increasing b_1 by one unit, would increase the predicted value of *y* by 0.706 units (p = <.001). Additionally, increasing b_2 (Year) by one unit would also decrease the predicted value of *y* by -0.002 units (p = <.001). The negative value of the Year (b_2) predictor may be associated with the fact that the SSI data was only first evaluated in 2014, whereas the previous CAUTI and Composite scores began in 2013 within this data set. However, the interaction term's estimate (b_3) produced an estimate value of -0.084 (p = <.001), which notes an overall decrease (improvement) in the predictive value by 0.084, by each year of the SSI scoring. Additionally, in reviewing the VIF values, the independent variable and the interaction term both remained with a moderate correlation, and variables within categorical variables remained continued to produce high VIF values noting a high correlation with those predictors (see Table 24). Moreover, no changes were noted within the random effects analysis as the estimate of the variance parameter produced the same value as the Composite analysis (0). See Table 25 for the complete multiple linear regression model with random effects with SSI scores as the outcome variable.

Table 23

Multiple Linear Regression Model (SSI Scores)

Term	*b*	Estimate	Prob>|t|	VIF
Intercept		5.602	<.001	.
PrePolicy_Pymt_Reduc	b_1	0.706	<.001	7.326
Year	b_2	-0.002	0.882	1.350
PrePolicyPymtReduc_Year_INTERACTION	b_3	-0.084	0.001	7.595
CC/MCC Rate	b_4	-0.190	0.400	1.350
Bed Utilization Rate	b_5	0.005	0.001	1.728
Hospital Compare Overall Rating	b_6	-0.058	0.005	1.818
# of Licensed Beds	b_7	0.001	<.001	1.921
Average Length of Stay	b_8	0.035	0.149	1.692
Academic Medical Center	b_9	0.763	<.001	1.414

Term	b	Estimate	Prob>|t|	VIF
Case Mix Index	b_{10}	0.137	0.077	1.718
Total Performance Score	b_{11}	-0.008	0.001	1.877
Market Concentration Index	b_{12}	-0.002	0.974	1.406
Sole Community Hospital	b_{13}	0.214	0.002	1.396
Payor Mix: Medicaid Days	b_{14}	0.007	0.011	1.191
Geographic Classification	b_{15}	-0.335	<.001	1.149
Pt Survey (HCAHPS) Star Rating	b_{16}	0.014	0.562	1.555
Region [Midwest]	b_{17}	0.243	<.0001	1.773
Region [Northeast]	b_{18}	0.184	0.001	1.918
Region [Southeast]	b_{19}	-0.313	<.001	1.682
Region [Southwest]	b_{20}	-0.163	0.002	2.035
Ownership [Gov - City/State]	b_{21}	0.020	0.790	6.525
Ownership [Gov - Federal]	b_{22}	0.476	0.048	36.628
Ownership [Gov - Other]	b_{23}	0.257	0.098	16.258
Ownership [Proprietary]	b_{24}	-0.453	<.001	7.588
Ownership [Voluntary Nonprofit - Church]	b_{25}	-0.384	<.001	7.303
Acred Agency [Joint Commission]	b_{26}	0.100	0.017	2.161
Acred Agency [HC Facilities Acred Pgm]	b_{27}	-0.035	0.628	2.219

Table 24

Multiple Linear Regression Model – Random Effects (SSI Scores)

Random Effect	Var Ratio	Var Comp	Std Error	95% Lower	95% Upper	Wald p-Value	Pct of Total
Provider ID	0	0	1.551e-14	-3.040e-14	3.041e-14	1.000	0.000
Residual		7.123	0.077	6.975	7.275		100.0
Total		7.123	0.077	6.975	7.275		100.0

Table 25

Multiple Linear Regression Model – Random Effects ($\hat{y}$ = SSI Scores)

$$\begin{aligned}\hat{y} = 5.602 + 0.706b_1 + 0.002b_2 - 0.084b_3 - 0.190b_4 + 0.005b_5 - 0.058b_6 + 0.001b_7 \\ + 0.035b_8 + 0.763b_9 + 0.137b_{10} - 0.008b_{11} - 0.002b_{12} + 0.214b_{13} \\ + 0.007b_{14} - 0.335b_{15} + 0.014b_{16} + 0.243b_{17} + 0.184b_{18} - 0.313b_{19} \\ - 0.163b_{20} + 0.020b_{21} + 0.476b_{22} + 0.257b_{23} - 0.453b_{24} - 0.384b_{25} \\ + 0.100b_{26} - 0.035b_{27}\end{aligned}$$

In applying the same methodology as the primary multiple linear regression with random effects model, the PSI 90 scores were analyzed next as the outcome variable (see Table 26). Given this, the PSI 90 regression model created an intercept of 4.121 (p = <.001). The estimate value for b_1 (PrePolicy_Pymt_Reduc) notes that by increasing b_1 by one unit, would increase the predicted value of y by 2.913 units (p = <.001). Additionally, increasing b_2 (Year) by one unit would also increase the predicted value of y by 0.068 units (p = <.001). However, the interaction term's estimate (b_3) produced an estimate value of -0.424 (p = <.001), which notes an overall decrease (improvement) in the predictive value by 0.424, by each year of the PSI 90 scoring. Additionally, in reviewing the VIF values, the independent variable and the interaction term both remained with a moderate correlation, and variables within categorical variables continued to produce high VIF values noting a high correlation with those predictors (see Table 27). Moreover, no changes were noted within the random effects analysis as the estimate of the variance parameter produced the same value as the Composite analysis (0). See Table 28 for the complete multiple linear regression model with random effects with PSI 90 scores as the outcome variable.

Table 26

Multiple Linear Regression Model (PSI 90 Scores)

Term	*b*	Estimate	Prob>|t|	VIF
Intercept		4.121	<.001	.
PrePolicy_Pymt_Reduc	b_1	2.913	<.001	4.949
Year	b_2	0.068	<.001	1.341
PrePolicyPymtReduc_Year_INTERACTION	b_3	-0.424	<.001	5.199
CC/MCC Rate	b_4	1.796	<.001	1.393
Bed Utilization Rate	b_5	0.001	0.610	1.796
Hospital Compare Overall Rating	b_6	-0.300	<.001	1.831
# of Licensed Beds	b_7	0.001	0.001	1.898
Average Length of Stay	b_8	0.142	<.001	1.696

Term	*b*	Estimate	Prob>|t|	VIF
Academic Medical Center	b_9	0.994	<.001	1.387
Case Mix Index	b_{10}	-0.258	<.001	1.664
Total Performance Score	b_{11}	0.002	0.163	1.865
Market Concentration Index	b_{12}	-0.338	<.001	1.390
Sole Community Hospital	b_{13}	0.222	0.001	1.384
Payor Mix: Medicaid Days	b_{14}	0.012	<.001	1.246
Geographic Classification	b_{15}	0.053	0.435	1.192
Pt Survey (HCAHPS) Star Rating	b_{16}	-0.060	0.003	1.506
Region [Midwest]	b_{17}	-0.009	0.797	1.759
Region [Northeast]	b_{18}	0.281	<.001	1.888
Region [Southeast]	b_{19}	-0.070	0.042	1.682
Region [Southwest]	b_{20}	-0.171	0.001	2.006
Ownership [Gov - City/State]	b_{21}	0.230	0.001	5.977
Ownership [Gov - Federal]	b_{22}	-0.344	0.067	29.443
Ownership [Gov - Other]	b_{23}	0.182	0.180	16.040
Ownership [Proprietary]	b_{24}	-0.351	<.001	6.917
Ownership [Voluntary Nonprofit - Church]	b_{25}	0.305	<.001	6.667
Acred Agency [Joint Commission]	b_{26}	0.017	0.639	2.131
Acred Agency [HC Facilities Acred Pgm]	b_{27}	0.018	0.775	2.189

Table 27

Multiple Linear Regression Model – Random Effects (PSI 90 Scores)

Random Effect	Var Ratio	Var Comp	Std Error	95% Lower	95% Upper	Wald p-Value	Pct of Total
Provider ID	0	0	7.299e-15	-1.430e-14	1.431e-14	1.000	0.000
Residual		6.704	0.065	6.578	6.834		100.0
Total		6.704	0.065	6.578	6.834		100.0

Table 28

Multiple Linear Regression Model – Random Effects ($\hat{y}$ = PSI 90 Scores)

$$\hat{y} = 4.241 + 2.913b_1 + 0.068b_2 - 0.424b_3 + 1.796b_4 + 0.001b_5 - 0.3000b_6 + 0.001b_7 + 0.142b_8 + 0.994b_9 - 0.258b_{10} + 0.002b_{11} - 0.338b_{12} + 0.222b_{13} + 0.012b_{14} + 0.053b_{15} - 0.060b_{16} - 0.009b_{17} + 0.281b_{18} - 0.070b_{19} - 0.171b_{20} + 0.230b_{21} - 0.344b_{22} + 0.182b_{23} - 0.351b_{24} + 0.305b_{25} + 0.017b_{26} + 0.018b_{27}$$

Findings

Upon completing both the *t*-tests and the regression models, it is noted that both quantitative methods validated that the null hypothesis should be rejected. The unadjusted analysis of the *t*-tests assessed the mean differences between the pre- and post-policy periods, and found that composite scores overall had improved (decreased) between those time periods and were statistically significant (p = <0.001). However, when the two independent variable groups were assessed through *t*-tests separately, different results were noted. The test results for those hospitals that would have theoretically been penalized in 2013, produced the same findings as the overall *t*-tests results where scores improved for these specific hospitals over the two time periods and were found to be statistically significant (p = <0.001).

However, for the hospitals that would have not been theoretically penalized in the pre-policy, although significance was noted (p = <0.001), the difference in the mean scores from the unadjusted *t*-tests produced a negative result, meaning that scores worsened (increased) within those time periods. Nonetheless, even with these theoretically non-penalized hospitals showing an increase, the overall composite score decreases were heavily associated with those hospitals that would have been penalized. Additionally, by placing the trends of the individual HAI and PSI 90 scores by year in two separate graphs, by those theoretically penalized and those not theoretically penalized (see Figures 1 & 2), although unadjusted, this provided face validity as to why scores increased or decreased over those time periods. This validity is noted through visual depictions of those hospitals theoretically penalized showing sharp decreases in their scores, while those theoretically not penalized, showing increases in their scores between 2013 and 2019.

As the *t*-tests provided significant findings, further analysis of the data was performed through analyzing and computing a multiple linear regression with random effects model. To apply this statistical methodology, the composite scores were first analyzed as they were the primary evaluated data to assess the mean scores in the previous *t*-tests. Further validating the results from the *t*-tests, it was found that between the predictors of hospitals that would have been or not have been in the pre-policy period, and the years associated in the study, hospitals that would have been penalized would have an estimate starting at a composite score 2.570 above those who would not have been penalized which would have started at an estimated intercept of 3.359 ($p = <0.001$). Additionally, in assessing the variable of years, a 0.077 increase of composite scores would occur over each year of the study ($p = <0.001$). However, the key value that provides significance in the regression model is the interaction term between those two predictors, where a negative value of -0.395 was produced, which notes a decrease (improvement) in composite scores by 0.395 across every year in the study ($p = <0.001$). This interaction term’s result further validates the reasoning to reject the null hypothesis.

In further review of the multiple linear regression methodology, significance was noted in each of the predictors and interaction terms (p = <0.001): CAUTI, CLABSI, PSI 90, and composite scores. However, MRSA was found to not be statistically significant (p = 0.234) and its interaction term estimate was not meaningfully significant (b_3 = -0.035). Additionally, although the CDI and SSI scores were found to be statistically significant (p = <0.05), their interaction term estimates (b_3 = -0.061, b_3 = -0.084 respectively) were not meaningfully significant. Other key differences observed in the predictors were noted where several of the estimated values for the year predictor produced negative results. However, these negative results can be tied directly back to HAI variable data (CDI, MRSA, and SSI) that was not included in the study's initial pre-policy data of 2013, which further notes that these variables started at lower scores than the other three variables (CAUTI, CLABSI, and PSI 90).

Additionally, in reviewing this multiple linear regression model, random effects were also assessed through applying the Hospital ID as the random variable. Although expectations were that significant values would be produced in assessing the random effects, applying the Hospital ID variable as a random variable, was found to not be significant as the estimate of variance parameter produced a value of 0.00 within the regression analysis. The same estimate of variance parameter value was produced for the composite, each HAI, and the PSI 90 scores, and the lack of value for random effects may be related to the variability found the fixed portion of the model. Although random effects were not found within this regression analysis, the analysis is effective in validating the rejection of the null hypothesis. Furthermore, from this analysis of the values of the estimates and significance found within the predators and other variables, individual multiple linear regression models were produced for the outcome variables of each HAI, PSI 90, and composite scores.

Discussion

In reviewing these findings, and through the rejection of the null hypothesis, it is noted that an association between the hospital acquired infection scores and the implementation of the HACRP policy. Between both the results of the t-tests and the regression model, the validity of this policy is substantiated. Thus, based on this analysis, negative reinforcement through a financial disincentive was effective in improving (by decreasing) hospital-acquired infections across the hospitals in the most outcomes examined in the study. Although Lee et al. (2012) previously noted that they found no evidence of the effectiveness of financial disincentives from the initial 2008 HAC policy, specifically addressing CLABSI and CAUTI, their analysis was completed prior to the HACRP policy coming into effect in 2014. However, both Waters et al. (2015) and Peasah et al. (2012) noted that they saw improvements in HAIs after the 2008 HAC policy through finding reduction in CLABSI and CAUTI scores in their analyses. In validating the effectiveness of the initial HAC policy in reducing HAIs through literature, the findings from HACRP policy analysis has found that, although causality cannot be proved, HAI scores have improved even more, which substantiates the purpose and intent behind the policy.

As with every study, this study had its own limitations. Initially, availability of the data, and the level of data, may have limited the assessment of the results. As this was a non-experimental study, the researcher had no direct capability of collecting the original data. CMS only provided what HAI, PSI 90, and composite scores they gave the hospitals, reviewing raw data was not possible. Additionally, the 'yearly' data consisted of an average of two years of data, minus the 2019+ year that only had 2019 data, which may have lessened the impact of where much improvement, or lack thereof, may have occurred in specific calendar years. Moreover, another constraint with the data was that, due to the CMS data moving from scored data in 2013 & 2014 to z-scored data in 2015 and beyond, the years from 2015-2019+ had to be converted by the researcher from z-scores to actual scored data. By not knowing the mean or standard deviations of each HACRP variable for those specific years, the researcher had to estimate those values based on the scored data available (2013 & 2014). Thus, based on applying the means and standard deviations from previous years, the data may be skewed more than what the results would have been had CMS produced, and made available, the scored data of each HAI, PSI 90, and composite scores.

Another limiting factor was the population of hospitals analyzed in the study. Out of the total hospitals that could have been analyzed (3,436) within the CMS data set, only 2,896 remained after meeting the requirements within the inclusion criteria. Had those additional 540 hospitals continued in the study, different results and findings may have been produced. Conversely, although 2,896 hospitals remained, the large number of hospitals analyzed in the study may itself have been a constraint because it may have limited the ability to assess outliers and potential confounding variables. Due to this, generalizability of the study's results may be constrained as the study tested for an association between the policy and hospital-acquired infections, but could not test for causality.

On the other hand, several strengths were also noted in this study. The research design itself is a strength for which two statistical methodologies (one unadjusted and one adjusted) were performed in which both found significance (p = <0.001) and validation of the rejection of the null hypothesis. The data analysis built into this research design further allowed to show the different outcomes between the two primary groups evaluated and the implications of implementing a financial disincentive between two groups. Additionally, although the data had its own limitations due to several conversions that had to be made, the data collected, and how it was collected, added strengths to the research design. As this study was non-experimental and used secondary data directly from CMS, the researcher was able to use and apply the same data CMS uses to determine which hospitals are penalized or not. From this structure of data available from CMS, it allowed for consistent and thorough analysis to help legitimize the results of the study. Moreover, the implications discovered within the study to find that financial disincentive was found to be effective mechanism in its association with improving outcomes, in this study's case, decreasing hospital-acquired infections, and has the capability to be applied more into practice within the U.S. healthcare system. Thus, in understanding and applying this financial disincentive across other hospital-acquired conditions has the potential to even further prevent harm from occurring to patients.

Summary

Through the results and findings from this study, associations and significance were found in evaluating the relationship between CMS' reductions in reimbursements from the Hospital-Acquired Conditions Reduction Program (HACRP) policy and hospital-acquired infections across the United States. In initially applying t-tests in the analysis, differences in the mean found showing improvements in HAI composite scores from the pre- to post-policy periods. Secondarily, a multiple linear regression with random effects model was created through applying the HAI composite scores, and its results further substantiated the findings from the t-tests. Based on this, six additional regression models (CAUTI, CDI, CLABSI, MRSA, SSI, & PSI 90 scores) were produced using the same regression methodology for which all found significance and validated the differences between the time periods for each of those variables. Chapter 5 will continue this discussion and will provide a proposed solution and implications for leaders and future research.

CHAPTER FIVE: PROPOSED SOLUTION AND IMPLICATIONS

In efforts to implement this study's findings into application and practice, a solution is proposed to seek further reduction hospital-acquired infections across the United States. Additionally, further examination of procedures for implementation, practical research related implications, and leadership implications will be addressed as well. Overall, this chapter will provide more insight into how maintaining, and improving upon, the current HACRP policy may be effective in the further reduction of hospital-acquired infections in the coming years.

Aim Statement

The aim of this dissertation in practice is to better understand how negative reinforcement of reduced reimbursements to hospitals from CMS has impacted hospital-acquired infections.

Proposed Solution

Based on the findings of the study, the proposed solution would be to maintain the HACRP policy and further expand upon it. Overall, improvements were found in the reduction of HAIs from the pre-policy to the post-policy periods. However, when analyzed separately, the two groups (those hospitals that would have been penalized in the pre-policy period and those who would not have been) that make up the entire population of the study shaped the overall study results in different ways. Due to this, the proposed solution would add to the current HACRP policy to penalize or reward each hospital for their efforts in reducing HAI's by evaluating each hospital's composite score against itself, year to year. As the HACRP policy stands, hospitals that fall in the worst-performing quartile receive a 1% reduction in the CMS reimbursement, this proposal would add the value of .25% for penalty or reward for every hospital. For penalty, hospitals that see an increase (worsening) in their composite scores, will receive a .25% reduction in their CMS reimbursement. For reward, hospitals that show improvement (through a decrease in composite scores), will be rewarded and additional .25% in their CMS reimbursements. Therefore, the CMS reimbursement reduction/ reward would range overall from -1.25% to +.25%.

Accomplishing and implementing this solution will help to spread the purpose and impact of the HACRP policy across every hospital, not just those that fall in the fourth quartile. Additionally, the greatest impacts of the solution would be that those worst-performing hospitals that show improvements year to year, will not be decremented as much on their reimbursement as they would have been with maintaining or worsening their scores (reducing the reduction from 1% to .75%). Likewise, hospitals that have not previously seen reductions (due to falling in the first three quartiles), will then be assessed on how well they decrease their HAI's year to year. Essentially, a larger proportion of hospitals made improvements in preventing infections because they were being directly, negatively reinforced; should all hospitals be evaluated year to year on their improvements, there is likely a chance that HAIs can further be decreased across the entire U.S. healthcare system. The discussion of this proposed solution will offer further opportunities to improve and expand upon the current HACRP policy through efforts more focused at the hospital level.

Evidence that Supports the Solution

In reviewing the results from Table 29, it is noted that of those hospitals that would have been penalized in 2013 for falling within the worst-performing group, 98% showed improvement in their 2019 composite scores compared to their 2013 scores. However, even though most of those worst-performing hospitals had shown improvement in their composite scores, roughly 29% of those hospitals were still found to be in the worst-performing hospital group in 2019. Essentially, although these hospitals showed improvement in their composite scores, they still were receiving reductions in their reimbursements from CMS. Conversely, the group of hospitals that would not have been penalized pre-policy only improved their composite scores in 38.8% of the hospitals, leading to approximately 61.2% (1,328/2,171) hospitals having worse composite scores in 2019 than in 2013.

However, although worsening scores indicated that higher occurrences of HAI, only about one-third (462/2,171) of those hospitals were penalized due to their worsening scores which moved them into the worst-performing hospital, 4th quartile. The remaining two-thirds (866/2,171) of the hospitals that had worse scores in 2019 were not substandard enough to be downgraded from their placement in the first, three quartiles. Therefore, they received no punishment in their CMS reimbursements. Unfortunately, under the current premise of the policy, only 25% of the hospitals are penalized for falling into the worst-performing quartile, but there are no penalties or rewards to denote changes and efforts made year to year at the composite level for each and every hospital.

Table 29

*Pre-Post Payment Reductions * Composite Improvement Pre-Post Crosstabulation (count)*

		Composite Improvement Pre-Post		
		Yes	No	Total
Pre-Post Payment Reductions	2013 (No) - 2019 (Yes)	47	462	509
	2013 (No) - 2019 (No)	796	866	1662
	2013 (Yes) - 2019 (No)	506	0	506
	2013 (Yes) - 2019 (Yes)	205	14	219
Total		1554	1342	2896

Note: Out of the 725 hospitals that would have been penalized in the pre-policy period, 711 (98.1%) improved their composite scores. Whereas, of the 2,171 hospitals not penalized in the pre-policy period, only 843 (38.8%) improved their composite scores.

Evidence that Challenges the Solution

Changing a policy at the Federal level is no easy task. Although value-based purchasing has been around the healthcare system for years, creating further change at the hospital level, across the nation, will take time and potentially receive a lot of pushback. Between seeking agreements with lawmakers, additional parties of lobbyists (hospital, healthcare, insurance, etc.) could potentially add to the difficulty in seeking change through this solution. Many different entities could feel that those they represent may have excessive financial impacts or be overwhelmed due to reacting on every incremental change that potentially occurs year to year.

Additionally, one potential secondary issue that could arise due to this proposal would be, what if every hospital (or even just most hospitals) saw an improvement from one year to another; would CMS be able to reward that many hospitals if they did not have enough hospital reimbursement reductions to balance the costs? Being as though CMS is funded through taxpayer money and budgeted through appropriations in Congress, the ability, or need, to spend more on positively enforcing hospitals to continue to decrease their hospital-acquired infections, could potentially lead to an imbalance in funding, leading to decrements from other programs or policies within CMS. Although efforts as such may drive the improvements in HAI reductions across the United States, therefore keeping patients safe and free from preventable infections, the ability to financially reward (positive reinforcement) or penalize (negative reinforcement), will likely be the primary driving force in whether this solution would be added to the current policy.

Implementation of the Proposed Solution

Given the difficulties with creating change at a policy level, implementing such change at the hospital level could also have its own complications. With the overall purpose of the proposed policy solution to seek the reduction in hospital acquired infections, the efforts to hold each hospital accountable for their actions or inactions to reduce such infections, is where the change needs to be made. These efforts will come down to the leaders of those hospitals and hospital systems to help transform and give a purpose driven approach at the organization level to reduce preventable HAIs within their own scope in influence across their organization.

Factors and Stakeholders Related to the Implementation of the Solution

Leaders of healthcare institutions are ultimately responsible for managing budgets and enabling actions to seek positive outcomes with the care they provide to their patients. These leaders make the decisions for whether change should be made and how the changes should occur. How a hospital organization chooses to change its posture within its own policies and its investments into initiatives to decrease hospital-acquired infections, will ultimately lead to how this updated policy will affect these organizations financially, and their patients, personally. To reduce any ambiguity within the purpose of the change solution, leaders within these healthcare organizations will need to be on the forefront of these changes to help direct and discuss the nature of the change and why it is needed to occur (Battilana et al., 2010). To accomplish this, transformational leaders are needed within every healthcare organization as employees want to identify with these leaders, which ultimately leads to increased trust and confidence in the organization (Bass, 1990).

Of note, it is not that hospitals are not already trying to prevent infections, the outcomes seen from their current prevention efforts may just not be totally meeting the needs of the patient stakeholders. Additionally, the clinical staff working in these healthcare establishments are not working there because they want to harm patients, but there may be local policies and procedures in place that may limit a clinician's, as well as the hospital's, ability to totally prevent infections from occurring. Ultimately, clinicians want to heal their patients; providing clinicians the tools and resources to enable the healing process and decrease infections will likely prove beneficial to the hospital and the patients they care for.

At the organization level, these transformational leaders are going to help demonstrate to the decision makers in the institution, the impact of maintaining business as usual versus investing in HAI prevention initiatives. In financial terms, this would be seen as the return on investment. With many HAI prevention training programs, consultation firms, and even the healthcare supply industry's changes in creating products to prevent infections, the lack of options or resources is not the issue; the issue often comes down to how much an organization is willing to invest to decrease their HAI's.

Without investing in any of these options, there is potential that an organization may not be able to meet the expected outcomes to reduce HAI's. Leaders create change and purpose; without either, patients in healthcare institutions are likely to continue to be at risk for acquiring a preventable hospital infection.

Upon a successful agreement by the leaders of a healthcare organization to decide how best to invest in HAI prevention efforts, seeking change at the employee level will be the next step in meeting these outcomes. Mobilizing and empowering organizational personnel to improve buy-in with the proposed changes in prevention practices, will be an important feat to accomplish as individuals have different personal and professional viewpoints for how the changes will affect them (Battilana et al., 2010). This mobilization across the organization is likely to develop the capacity of employees to commit to, and be a part of, the planned change in prevention efforts (Battilana et al., 2010; Huy, 1999). Thus, the efforts at change will need to be directed towards achieving outcomes across numerous levels and individuals within the organization to succeed with the desired change (Swanson & Holton, 2009). Once employees understand how they themselves fit in the bigger picture of preventing hospital acquired infections, and how they can help affect change through the organization's HAI prevention investment solution, it is likely that the organization may discover improvement within their HAI outcomes. Sequentially, implementing a change at the federal level to hold every hospital more directly accountable for their own levels of infections, may in turn, empower these hospitals to help their clinicians truly do no harm to their patients they are caring for.

Timeline for Implementation of the Solution

As COVID-19 has prevented further evaluation of the HACRP since the beginning of the pandemic, the time to start this proposed solution is now so that it is set in place for when HACRP composite scores are evaluated once again by CMS. Still currently, under the COVID-19 public health emergency, no hospital is receiving a payment reduction for the HAC Reduction Program for FY 2023 (Quality Net, n.d.). However, as the U.S. healthcare systems continues to advance in post-pandemic world, it is likely that evaluations of the HACRP metrics will begin in 2024. Due to this, with the primary HACRP policy already in place, working on adding in these definitive details on further rewards and penalties now will likely enable these positive and negative reinforcements to be in place upon CMS starting back up the HACRP evaluation process. Additionally, adding these reward and penalties into the current HACRP now may lead hospitals to start reviewing and improving their infection prevention efforts, which will further benefit their patients, as well as potentially their financial well-being upon evaluation of their HACRP composite scores when evaluated once again.

Evaluating the Outcome of Implementing the Solution

To appropriately evaluate this solution at a hospital level, healthcare leaders need to first understand what prevention efforts are currently being performed in their organization before implementing these changes. Then upon implementation of the chosen changes to be made to prevent these infections, hospital leaders should monitor the process and outcomes of these changes through a continuous quality improvement (CQI) methodology. One of these methodologies is the plan-do-study-act (PDSA) cycle. This cycle enables the evaluation of processes, safety, and patient care improvements, and may lead to enhancement of operations, outcomes, systems processes, improved work environment, and even regulatory compliance (O'Donnell & Gupta, 2022). As with many changes that occur in an organization over time, procedures and policies need to be adapted and updated often while implementing change, which is sometimes due to unforeseen events, issues, or unplanned outcomes. The PDSA cycle will help healthcare organization become aware of these issues and allow the organization the ability to react and make further changes to procedures and policies in order to continue to decrease, and potentially end, hospital-acquired infections from occurring.

To evaluate this solution at the national level, the analysis would come through assessing trends of the individual HAI's and PSI 90 scores, in addition to the composite scores, over the years post implementation. By establishing this analysis, evaluation of effectiveness and appropriateness of the solution can be analyzed. Although some changes may be noted within the first-year, post implementation, the true 'value' of this solution will come through several of years' worth of data to see if hospitals are truly invested in reducing their HAI's. Although there will be no direct capacity to understand how much a healthcare organization invested in their prevention efforts, one can posit that should notable improvements be found at the hospital level over time, prevention efforts were likely implemented or enhanced to accomplish such improvements.

Implications

Practical Implications

Based on this study's findings, it was found that financial negative reinforcement, through a reduction in CMS reimbursements, was associated with a reduction in hospital acquired infections. Patients across the entire United States have already benefited from the original policy being implemented, thus maintaining the policy at its current capacity, has the potential to continue to see further decreases in hospital-acquired infections. Different stakeholders within healthcare systems can continue to benefit with maintaining, and even improving upon, such a policy because patients do not want to be harmed, clinicians do not want to harm, and CMS (i.e., taxpayer money) does not want to pay for when harm occurs. Additionally, other payers/insurers, and patients that are covered under those care plans, could also further benefit from value-based purchasing policies such as the HACRP to find further reductions in hospital-acquired infections, costs, and ultimately put the onus on the hospitals to keep their patients safe and free, from healthcare harm.

Implications for Future Research

As the HACRP policy was not in effect during the current COVID-19 public health emergency, upon the reimplementation of the policy in 2024 (or later based on CMS), further studies can be performed to assess changes in hospital-acquired infections in the pre-pandemic and post-pandemic time periods. Although not much data was available to assess HAI's during the pandemic, this research could provide insight into changes implemented at the hospital level over that time period, which in turn may still be in effect during the post-pandemic time period. It is likely that the benefits of implementing stronger infection control mechanisms during the pandemic have continued in the post-pandemic period, which may lead to overall decreases in HACRP composite scores in the coming years. Additionally, given the current HACRP policy in place, continuing to analyze HAI, PSI 90, and composite scores in the post-pandemic period will be of great value in the ongoing assessment of the effectiveness of the policy, and may help foster potential change needed to further decrease hospital-acquired infections over the next several years.

Furthermore, should the aforementioned proposal be implemented, future research could also assess the effectiveness of those positive and negative reinforcements on the hospital-acquired infection scores year to year at every hospital included in the analysis across the entire United States. Research such as this, will allow the assessment of whether equitable punishment/rewards across every hospital evaluated truly had an impact on the reduction of HAIs. Whether the policy continues upon its original reduction methodology, or the proposed solution is added, CMS has other value-based purchasing programs for which the same methodology of analysis as this study, could be applied to those programs in order to assess their effectiveness of negative reinforcement in those programs as well. Additionally, for any future research, due to the pandemic and the timeframe between the most recent data, it is possible that some of the population of hospitals previously reviewed may not be operational anymore, so the numbers and types of hospitals evaluated, may likely be different in future studies.

Implications for Leadership Theory and Practice

Healthcare harm occurs at the local, hospital level. Although some health policies are created at the state and federal levels, how a hospital chooses to respond to, adapt to, and change from those policies to further prevent harm, are all contingent upon the leadership of the healthcare organization. These healthcare leaders are the ones who inherently decide that change needs to be made and how those changes are to occur. As with any business, earning more money (revenue) than the costs of goods and services, is essential for viability; healthcare organizations are no different. Deciding where and how the healthcare organization uses its revenue, takes knowledgeable and competent leaders focused on taking care of their stakeholders; their patients, their staff, and their community or shareholders (depending on for-profit or not for profit status). Based on the span of effect from decisions made by healthcare leaders, the ethical prowess of these leaders is crucial to meeting the needs of these stakeholders. Does one stakeholder's priority outweigh the other? Is the only purpose of the healthcare organization to make revenue to pay out dividends to its shareholders? If so, then that truly takes away from taking care of the employees who work in the organization and their ability to care for their patients. Additionally, due to a healthcare organization's ability to change its payer mix, decisions can be made to shift to payers/insurers who will pay full price for care, no matter if harm was done. Truly, how important is nonmaleficence to the bottom line? This is where healthcare leaders need to stand the line to do what is right for how they care for their patients by investing in infection prevention opportunities.

These investments can be large or small, the key is for organizational leaders to 'invest' in their resources for infection prevention. On the monetary side, budgeting for these initiatives is crucial. Although potentially the return on investment may not always show direct returns, through indirect means of patient satisfaction, staff satisfaction, and decreasing of overall rate of infections can prove validity behind the money invested. Additionally, on the human-capital side, as healthcare leaders hire, grow, and remove employees in the organization, they need to be able to apply the many leadership theories to help move the employees through any organizational change. Adopting organizational behavior skills to motivate, work in teams/groups, and pursuing buy-in for change initiatives, is foundational for any leader in a healthcare organization. A healthcare leader able to transform their sphere of influence, will likely find employees who want to help be a part of the change, want to make a difference in the organization, and essentially, want to improve the care provided to their patients by preventing harm and the spread of hospital-acquired infections. Investing in resources and human capital to prevent these infections is vital to meeting the mission of 'to do no harm'. The question of how much to invest and when to proceed, truly falls on the leaders of the healthcare organization. Leadership drives change; without effective leadership, change for the betterment of all stakeholders will be unlikely.

Summary of the Dissertation in Practice

Through evaluation and analyzation of the data in this study, associations were found that financial disincentives, through the reduction of CMS reimbursements for hospitals under the HARCP policy, has in turn, reduced HAIs as intended. Through the usage and application of *t*-tests and multiple linear regression with random effects models, significant differences were found in the pre-to post policy periods. Due to this, as the HACRP has been found to be an effective policy and maintenance of the policy the least that should be done. Additionally, due to the effectiveness of financial disincentives, HAIs have the potential to be further reduced by evaluating hospitals at the individual level, and penalizing or rewarding those hospitals for their improvements, or lack thereof, in the reduction of HAIs. As these efforts will take time and resources, leadership of these hospital organizations will need to continue, or start, to invest in HAI prevention efforts to reduce the burden from decreased reimbursements, and ultimately provide better, safer, quality care their patients deserve.

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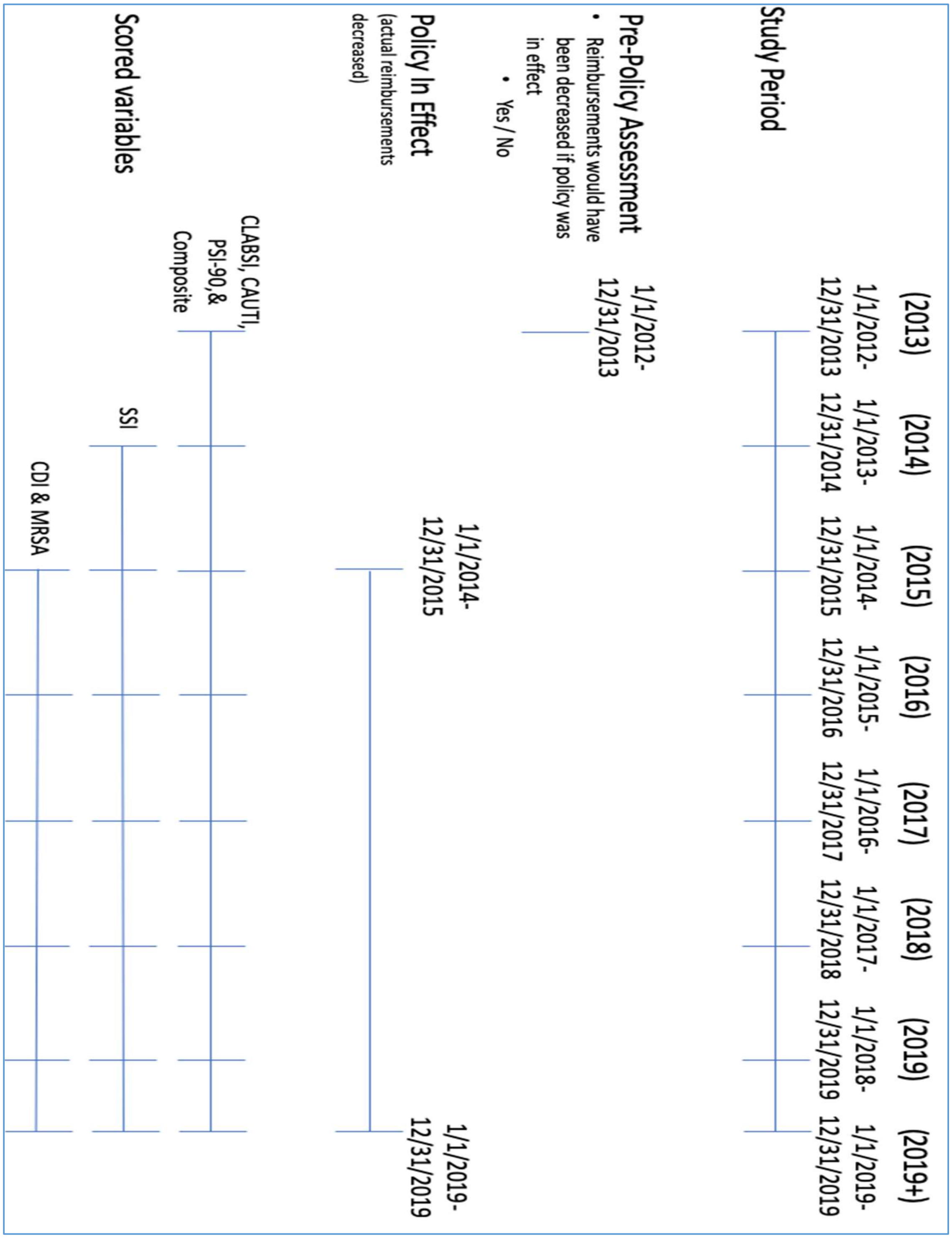
Appendix A

HACRP Study Data Timeline



Appendix B

Variable Table List

Concept	Source	Measure/ Variable	Variable Name	Values	Type	Measurement Level
Demographic	CMS / Definitive Healthcare	CMS Provider - Hospital ID Number	Provider Number	-	Numeric	Scale
Independent	CMS	Pre-Policy Payment Reduction	Pre-Policy Payment Reduction	0 = No Penalty, 1 = Penalty	Numeric	Nominal
Dependent	CMS	Year	Year	1 = 2013, 2 = 2014, 3 = 2015, 4 = 2016, 5 = 2017, 6 = 2018, 7 = 2019, 8 = 2019+	Numeric	Nominal
Interaction	CMS	Interaction Term: Pre-Policy Payment Reduction & Year	Pre-Policy Payment Reduction_Year_INTERACTION	-	Numeric	Scale
Dependent	CMS	HACRP Composite Score	HACRP Composite	-	Percent	Scale
Dependent	CMS	Central line-associated bloodstream infection	CLABSI	-	Percent	Scale
Dependent	CMS	Catheter-associated urinary tract infection	CAUTI	-	Percent	Scale
Dependent	CMS	Surgical site infection	SSI	-	Percent	Scale
Dependent	CMS	Methicillin-resistant Staphylococcus aureus	MRSA	-	Percent	Scale

Dependent	CMS	Clostridium difficile infection	CDI	-	Percent	Scale
Control	Definitive Healthcare	CC/MCC Rate	CC/MCC Rate	-	Percent	Scale
Control	Definitive Healthcare	Bed Utilization Rate	Bed Utilization Rate	-	Percent	Scale
Control	Definitive Healthcare	Hospital Compare Overall Rating	Hospital Compare Overall Rating	-	Numeric	Scale
Control	Definitive Healthcare	# of Licensed Beds	# of Licensed Beds	-	Numeric	Scale
Control	Definitive Healthcare	Average Length of Stay	Average Length of Stay	-	Numeric	Scale
Control	Definitive Healthcare	Academic Medical Center	Academic Medical Center	0 = No Teaching, 1 = Teaching	Numeric	Nominal
Control	Definitive Healthcare	Case Mix Index	Case Mix Index	-	Numeric	Scale
Control	Definitive Healthcare	Total Performance Score	Total Performance Score	-	Numeric	Scale
Control	Definitive Healthcare	Market Concentration Index	Market Concentration Index	-	Numeric	Scale
Control	Definitive Healthcare	Sole Community Hospital	Sole Community Hospital	1 = Yes, 2 = No	Numeric	Nominal

Control	Definitive Healthcare	Payor Mix: Medicaid Days	Payor Mix: Medicaid Days	-	Numeric	Scale
Control	Definitive Healthcare	Geographic Classification	Geographic Classification	1 = Rural, 2 = Urban	Numeric	Nominal
Control	Definitive Healthcare	CMS Region	Region	1 = Midwest, 2 = Northeast, 3 = Southeast, 4 = Southwest, 5 = West	Numeric	Nominal
Control	Definitive Healthcare	Ownership	Ownership	1 = Gov - City/State, 2 = Gov - Federal, 3 = Gov - Other, 4 = Proprietary, 5 = Voluntary Nonprofit - Church, 6 = Voluntary Nonprofit - Other	Numeric	Nominal
Control	Definitive Healthcare	Patient Survey HCAHPS Summary Star Rating	Pt Survey (HCAHPS) Star Rating	-	Numeric	Scale
Control	Definitive Healthcare	Accreditation Agency	Accreditation Agency	1 = The Joint Commission, 2 = Healthcare Facilities Acred Program, 3 = Det Norske Veritas Healthcare	Numeric	Nominal

Appendix C

IRB Approval

Creighton
UNIVERSITY

Office of the Provost
Research Compliance

DETERMINATION DATE:	11-Nov-2022
TO:	Dan Wood
FROM:	Social / Behavioral IRB
PROJECT TITLE:	The Impact of the Hospital-Acquired Conditions Program on Hospital-Acquired Infection Rates
REVIEW CATEGORY	Not Human Subjects Research
SUBMISSION #:	2003434-01
SUBMISSION TYPE:	Initial Application
REVIEW METHOD	Exempt Review
DETERMINATION:	**Acknowledged**

Thank you for your submission of Initial Application materials for this project. The following documents were reviewed:

- Creighton University HS eForm

It has been determined that this project does not meet the definition of human subjects research per 45CFR46.102(e)(1). No further action is required.

If you have any questions, please contact the IRB Office at 402-280-2126 or irb@creighton.edu. Please include your project title and number in all correspondence with this Board.

This letter has been electronically signed in accordance with all applicable regulations, and a copy is retained in Creighton University's IRB records.

Institutional Review Board
T 402.280.2126 | T 402.280.3200
Dr. C.C. and Mabel L. Criss Health Sciences Complex I
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