**THE ROLE OF BUILT ENVIRONMENT AND PRIVATE ROOMS**

**FOR REDUCING HOSPITAL ACQUIRED INFECTIONS**

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**ABSTRACT**

Increased use of private patient rooms may be an important adjunct to traditional process-based interventions to prevent hospital-acquired infections (HAIs) in inpatient settings. We examined whether private room assignment lowers the risk of developing hospital-acquired methicillin-resistant staphylococcus aureus (HA-MRSA) infection and whether percent private rooms at the hospital level explain hospital-to-hospital variation in HA-MRSA incidence.

We used 2016 Texas Department of State Health Services inpatient data from 340 acute care hospitals to evaluate HA-MRSA incidence. We used matched cohorts generated from 2.7 million Texas inpatients to estimate attributable incidence and outcomes of HA-MRSA or other (methicillin-sensitive) staphylococcus infection. We also simulated potential financial impacts of an all-private room design for two dissimilar hospitals using the Monte Carlo method. MRSA and relevant conditions were assessed via ICD-10-CM diagnosis codes.

We found a significant negative relationship between increased private room presence and use and HA-MRSA risk. The value of these protections can be quantified—we estimated each HA-MRSA infection prevented could have saved $12,100 in cost and reduced mortality risk by 4%. Additional simulation estimated substantial cost-savings, up to about $3 million, for a large public safety-net hospital if it were renovated to an all-private room design, with an 11% return on investment on average.

Overall, our findings support renovation of existing bay-room oriented facilities to an all-private room design as an effective and potentially efficient means to increase inpatient safety. Our methods provide a useful means for policy makers, hospital boards, and others to evaluate

the costs and benefits of such changes. Finally, we conclude that private room related metrics could provide an important quality indicator if included in public reporting.

# CHAPTER I

# STATEMENT OF THE PROBLEM

## Overview

The purpose of this chapter is to introduce the general topics of this thesis, related findings, and some unanswered questions in literature. While in-depth discussion regarding study-specific topics will follow in subsequent chapters, various foundational concepts of methicillin-resistant Staphylococcus aureus (MRSA) and related topics must be explained first. Therefore, this chapter presents a broad overview of MRSA and hospital-acquired infections (HAIs), including two different scopes of HAI, medical background of MRSA, known treatments and their cost nature, organizational risk factors of hospital-acquired MRSA (HA-MRSA), prevention and reduction programs, and existing study results and applicational challenges. Then, one recent work published in 2018, focusing on hospital-acquired central line-associated bloodstream infection (HA-CLABSI), is discussed regarding how this thesis details and enhances the prior work of HA-CLABSI. Finally, the specific aims of this thesis will be presented at the end of this chapter.

## Hospital-acquired vs. Healthcare-associated Infections

When it comes to patient safety in hospitals, both “hospital-acquired infections” and “healthcare-associated infections” have often been interchangeably used despite their slight difference. To avoid any potential confusion regarding the terminology, we begin by defining the two terms and clarifying that we focus on the former throughout this thesis.

The term “hospital-acquired infection” (also known as “nosocomial infection”) was initially defined as an acute infection acquired by a patient during the hospital stay (Mayhall, 2012). However, the definition and scope of “hospital-acquired infection” has since been expanded to include “healthcare-associated infection,” as these infections can also occur in non-hospital facilities, such as long-term care facilities, outpatient clinics, and home care services (Archibald & Gaynes, 1997; Mayhall, 2012).

Compared to hospital-acquired infections, non-hospital infections of the same virus/bacteria are difficult to assess, and risk factors for these non-hospital infections are relatively unknown (Mayhall, 2012; Ostrowsky, 2013). While both routes of transmission (i.e., hospitals and non-hospital healthcare facilities) are equally important, this thesis focuses on applications from a hospital management perspective. Thus, the studies reviewed in this thesis are concerned with infections acquired in acute care hospital settings (henceforth abbreviated as “HAI”), excluding non-hospital routes of transmission.

**MRSA Infections as a Major Source of HAI**

One out of every 25 hospitalized patients are affected by at least one HAI in the United States every year (Magill et al., 2014). HAI causes complications, morbidity, and mortality, resulting in a substantial increase in healthcare costs (P. Pronovost et al., 2006; Slayton et al., 2015). Staphylococcus aureus is one of the costliest and most dangerous human pathogens in the context of HAI. Staphylococcus aureus infections (also called “staph infections”) – including both methicillin-sensitive Staphylococcus aureus (MSSA) and methicillin-resistant S. aureus (MRSA) – can commonly lead to fatal complications such as pneumonia and sepsis, which

spread locally and globally, colonize in numerous human body parts, and persist in various environments outside of hosts (Safdar & Abad, 2008). MRSA differs from MSSA in that MRSA bacteria is resistant to many cost-friendly antibiotics as the name (i.e., "methicillin-resistant") suggests. Due to limited and costly treatments, MRSA has been one of the most feared strains of S. aureus. Hospitalized patients have an increased risk of developing MRSA infections because this population is more likely to have undergone surgeries and have reduced immunity, open wounds, and other post-surgical complications (Graffunder & Venezia, 2002).

While MRSA infections have been declining in recent years (Office of Disease Prevention and Health Promotion, n.d.), statistics confirm that MRSA remains a major health threat (CDC, 2016). More than 80,000 new hospital-acquired MRSA (HA-MRSA) cases are reported annually, resulting in more than 11,000 deaths of patients in healthcare facilities (CDC, 2016, 2018b). The Centers for Medicare and Medicaid Services (CMS) have monitored HA-MRSA and have adjusted reimbursement to penalize hospitals with high rates of various HAIs since 2015. Starting in 2017, HA-MRSA was added to this "penalizing" group of HAIs along with four other infections (CLABSI, surgical site infections, catheter-associated urinary tract infections, and clostridium difficile colitis) (CMS, 2017b).

In practice, it is expense to implement most of the HA-MRSA prevention and reduction programs. Hence, these programs need to demonstrate significant cost savings to justify the expense to control HR-MRSA. However, the relationship among core constructs of HA-MRSA (i.e., predictors, infection risks, and healthcare outcomes) has not yet been clarified, so it is not obvious how much end-benefit (e.g., cost-saving) is expected from MRSA interventions (e.g.,

compliance to hand hygiene). Moreover, the validity of assessing cost-savings derived from economic analyses requires an elimination (or at least adjustment) of over- and under-prediction risk in developing models, which introduce many theoretical and practical challenges. For those reasons, evidence found in the literature is mixed or inconsistent at best.

**Costly Nature of MRSA Treatments due to Resistance to Antibiotic Treatment**

The importance of MRSA studies should not be overlooked regardless of seemingly "green" signals – for example, public reports present already low incidence of a certain type of MRSA infections (e.g., 18 MRSA bloodstream infections per 100,000 patients in 2013) (Office of Disease Prevention and Health Promotion, n.d.) Apart from the appropriateness of current MRSA reporting measure (i.e., as of the time of this thesis), we believe that studying HA-MRSA is still of importance at least from two perspectives: 1) it may be a leading indicator of general antibiotic resistance; and 2) it serves as a driving factor of huge treatment costs (Grundmann, Aires-de-Sousa, Boyce, & Tiemersma, 2006).

Speaking of the former, HA-MRSA rates may be particularly high in hospitals with both a high prevalence of staph infections (i.e., infections due to staph bacteria) combined with antibiotic resistance. Therefore, high incidence rates of HA-MRSA may be a "bellwether" signaling overuse of antibiotics and indicating a dangerous level of antibiotic resistance, which effectively limit the treatment options available to physicians. Our recent data shows MRSA and related conditions take a major percentage of drug-resistant (DR) conditions: 1) MRSA accounting for 49% of DR; 2) resistance to other beta-lactam antibiotics accounting for 7% (i.e., MRSA is a dominant beta-lactam resistant condition); and 3) vancomycin-resistant conditions

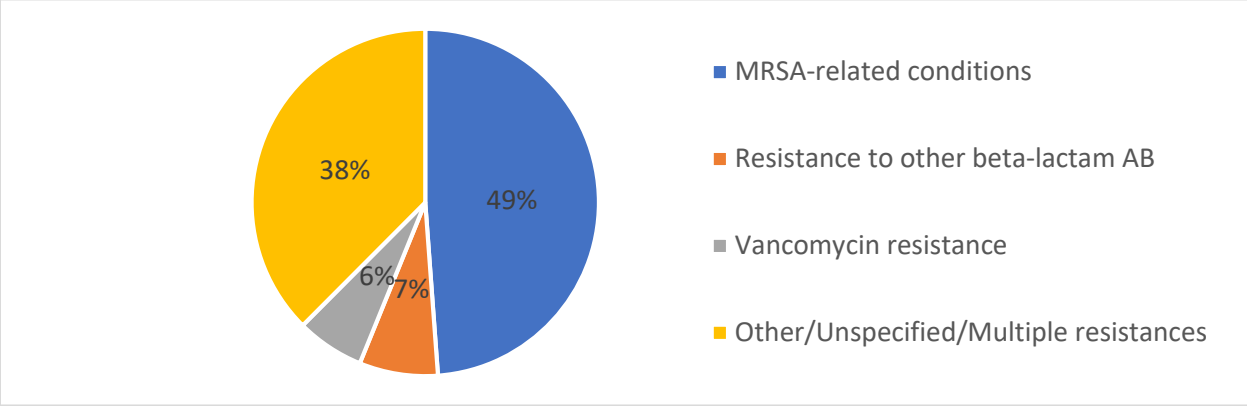
(i.e., vancomycin is mostly used in MRSA treatments – explained later in this section) contributing 6% (Figure 1). This, combined with the alerts in literature (Ventola, 2015), suggests that understanding MRSA is connected to the general problem of antibiotic resistance, a significant threat to public health.

Antibiotic resistance developed by staph bacteria causes problems, particularly in hospital settings (Ducel, Fabry, Nicolle, Organization, & others, 2002). In general, the mechanisms through which pathogens become antibiotic-resistant are largely categorized as either intrinsic or acquired. On one hand, intrinsic resistance may be caused by impermeability of the membrane to the agent or by the lack of the molecular target for an antibiotic. Acquired resistance, on the other hand, is caused by one or more of the followings: drug inactivation, reduced permeability, drug-efflux, and/or target modification (Lin et al., 2015). The bacteria that cause disease in hospitals typically achieve a significant level of resistance to antimicrobial therapies because many patients with such diseases receive antibiotics as preventative treatment during hospitalization. For example, in intensive care units (ICUs), more than 60% of patients receive antibiotics including penicillin and methicillin, potentially making the ICU a hazardous environment in which resistant pathogenic strains are developed (Lin et al., 2015).

The antibiotic resistance of MRSA contributes to a significant rise in treatment costs, not to mention often fatal outcomes when delayed or not treated urgently (Ficalora & Mueller, 2013; Mangiadi, Facs, & Morcovici, 2010). MRSA has multiple drug resistance (MDR) to beta-lactam antibiotics, which are a broad-spectrum group including penicillin derivatives (e.g., methicillin and oxacillin) and cephalosporins (Gurusamy, Koti, Toon, Wilson, & Davidson, 2013).

Such MDR limits the effectiveness of these antibiotics. Vancomycin is a standard antibiotic used to treat MRSA patients (Schentag et al., 1998). However, using vancomycin also introduces newer practical problems: (1) vancomycin treatments can be complicated by the inconvenient route of intravenous administrations (Janknegt, 1997); (2) the treatment costs of vancomycin against MRSA is severely higher than that of cheaper penicillin beta-lactam antibiotics against MSSA (Chang et al., 2003; Siegman-Igra, Reich, Orni-Wasserlauf, Schwartz, & Giladi, 2005); and (3) several newly discovered MRSA strains develop antibiotic resistance even to vancomycin, named as vancomycin intermediate-resistant S. aureus (VISA) (Schito, 2006). Daptomycin, a costlier antibiotic than already expensive vancomycin, is required for VISA infections (Catherine Liu et al., 2011). According to a UK simulation study (Browne et al., 2016), daptomycin and vancomycin treatments cost $24,195 and $23,179, with an average lengths-of-stay (LOS) of 28 and 42 days, respectively, to treat MRSA infections.

Figure 1: Drug-resistant conditions for Texas inpatients (FY 2016)



**Control and Prevention of HA-MRSA**

To encourage effective controls of HA-MRSA and multidrug-resistant pathogens, CDC released multiple guidelines for health care providers (Siegel, Rhinehart, Jackson, & Chiarello, 2007; Siegel, Rhinehart, Jackson, Chiarello, et al., 2007). These guidelines emphasize hand hygiene, disinfection, and environmental cleaning and recommend implementing contact precautions and to place MRSA-colonized patients under contact precautions (Salgado & Farr, 2006). Contact precautions require medical staff to wear gowns and gloves before entering the isolation rooms of infected or colonized patients. Antimicrobial stewardship, reducing hospital stays, ensuring a good staff-to-patient ratio, staff cohorting between cares for infected/colonized patients, and those for uninfected/uncolonized patients are also often suggested as effective control strategies (Henderson, 2006). The CDC guideline also recommends using multiple interventions together (e.g., contact precautions and environmental cleaning) to control transmissions of MDR pathogens – including MRSA (Siegel, Rhinehart, Jackson, Chiarello, et al., 2007).

In the context of this thesis, it is worth noting that the CDC explicitly describes patient isolation in patient private rooms (PPRs) in their guidelines (Siegel, Rhinehart, Jackson, Chiarello, et al., 2007). A recent study examining the effectiveness of PPRs in controlling cross-transmission of MDR bacteria confirmed the importance of PPR-ICU designs (Halaby et al., 2017).

**Inconsistent and Insufficient Empirical Evidence**

Ten benchmark studies from the literature on MRSA-attributable outcomes are presented in Table 1. As shown in Tables 1 and 2, a huge disparity is noticeable across the studies – mean attributable LOS ranges from 0.3 days (Adrian G. Barnett et al., 2009) to 15 days (Engemann et al., 2003a), and mean attributable costs range from $8,817 (Cosgrove et al., 2005) to $33,077 (S. P. Kim et al., 2012) after adjusting to 2018 US dollars. These heterogeneous results, combined with the major issues discussed below, make it challenging for US hospitals to translate the existing findings into decision making process regarding MRSA.

First, a half of the benchmark studies were conducted in European hospitals, which may differ from US hospitals in healthcare access and biological demographics (Adrian G. Barnett et al., 2009; Browne et al., 2016; De Angelis et al., 2011a; De Kraker et al., 2011; Macedo-Vinas et al., 2013).

Second, seven studies were conducted with limited sample sizes (<10,000) and in one or (at most) two medical facilities. Only three studies used samples larger than 10,000 (S. P. Kim et al., 2012; Nelson, Samore, et al., 2015b; R. J. Rubin et al., 1999).

Third, six studies did not identify the source of MRSA infection (i.e., hospital-acquired versus community-acquired) (Adrian G. Barnett et al., 2009; Cosgrove et al., 2005; De Angelis et al., 2011a; De Kraker et al., 2011; Engemann et al., 2003a; Macedo-Vinas et al., 2013). Community-acquired MRSA (CA-MRSA) and HA-MRSA are known to have discernable levels of impact on hospital costs (Beigi, Bunge, Song, & Lee, 2009; J. E. Brown, Dengler, & Lodise Jr,

2016; Hogea, Van Effelterre, & Cassidy, 2014; B. Y. Lee et al., 2013). Moreover, the impacts of HA-MRSA are of more concern from a patient-safety perspective for hospitals.

Fourth, only three studies utilized matched controls. (De Kraker et al., 2011; Engemann et al., 2003a; Nelson, Samore, et al., 2015b). Methodological effort to minimize selection bias and endogeneity is essential due to an inherent nature of HA-MRSA infections (e.g., prolonged hospitalization due to HA-MRSA).

Lastly, some studies investigated only the incremental effect due to antibiotic resistance (i.e., MRSA vs MSSA), rather than the total effect of MRSA (i.e., MRSA vs No MRSA) (Cosgrove et al., 2005; De Angelis et al., 2011a; R. J. Rubin et al., 1999). While antibiotic effects are still meaningful, management applications for hospitals require complete understanding about MRSA effects (i.e., both total and marginal effects), rather than only either piece.

Table 1: Previous studies of attributable outcomes of MRSA infections

| Study | HAI | MRSA compared to | Country | Number of hospitals studied | Sample size | LOS results* (Mean, 95%CI) | Cost results* |
|---|---|---|---|---|---|---|---|
| Barnett et al. (2009) | No | No MRSA | UK | 2 | 4,569 | APACHE2=10: +0.3 days (0.1, 0.5) APACHE2=30: +1.2 days (0.5, 2.0) | |
| Browne et al. (2016) | No | No MRSA | UK | Not applicable | N/A | Daptomycin used: 28 days Vancomycin used: 42days | Daptomycin used: GBP 17,917 Vancomycin used: GBP 17,165 |
| Cosgrove et al. (2005) | No | MSSA | US | 1 | 348 | +2.2 days (1.8, 2.7) | USD +6,916 (5,390, 8,899) |
| De Angelis et al. (2011) | No | No MRSA, MRSA colonization | Swiss | 1 | 1,041 | Vs No-MRSA: +14.5 days (7.8, 21.3) Vs MRSA col: +5.9 days (0.1, 11.7) | |
| De Kraker et al. (2011) | No | MSSA, No MRSA | 13 European countries | Not reported | 2482 | Vs No-MRSA: +9,2 days (5.2, 13.5) Vs MSSA: +0.6 days (-3.7, 5.3) | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Engemann et al. (2003) | No | MSSA, No MRSA | US | 2 | 479 | Vs No-MRSA: +15 days (7, 30) Vs MSSA: +5 days (3, 13) | Vs No MRSA: USD +23,336 (13,437, 50,041) |
| Kim et al. (2012) | Yes | No MRSA | US | 1,175 | 10,856 | +30.73% of prolonged hospitalization (>90$^{th}$-pct LOS) | USD +30,500 (19,059, 41,943) |
| Macedo-Viñas et al. (2013) | No | No MRSA | Swiss | 1 | 26,350 | +11.5 days (7.9, 15) | CHF +10,166 (6,984, 13,260) |
| Nelson et al. (2015) | Yes | No MRSA | US | 114 | 386,794 | Primary method: +11.43 days (10.44, 12.43) Alt. method: +13.97 days (10.49, 17.44) | Primary method: USD +24,015 (10,882, 37,149) Alt. method: USD +26,855 (22,583, 31,126) |
| Rubin et al. (1999) | Yes | MSSA | US | Not reported | 1,351,362 | | Total cost: USD 31,400 Vs MSSA: USD +3,700 |

* Values are presented with plus and minus signs if a study reported excess outcomes (compared to the baseline). Otherwise, results were presented without signs.

Table 2: Previous studies of the effects of private rooms on MRSA infections

| Study | Country | Number of hospitals studied | Sample size | Number of beds studied | Level of care | MRSA reduction significance |
|---|---|---|---|---|---|---|
| Bracco et al. (2007) | Canada | 1 | 2,522 | 14 | ICU | Significant |
| Cepeda et al. (2005) | England | 2 | 866 | 28 | ICU | Not significant |
| Ellison et al. (2014) | Canada | 1 | 1,687 | 35 | Acute | Not significant |
| Julian et al. (2015) | USA | 1 | 1,823 | 73 | ICU | Not significant |
| Levin et al. (2011) | Israel | 1 | 210 | 12 | ICU | Significant |
| Teltch et al. (2011) | Canada | 2 | 19,343 | 49 | ICU | Significant |

| | | | | | | |
|---|---|---|---|---|---|---|
| Vietri et al. (2004) | USA | 1 | 249 | 32 | Acute/ICU | Not significant |

**Private-room Effects on MRSA**

In microeconomics, externality is defined as the external cost or benefit which affects society or larger economic groups but is not included in the individual-level (e.g., customer, producer) decision making process (Jaeger, 2012). External cost is called “negative” externality and external benefit is called “positive” externality.

Pollution is a typical example of negative externality. When a factory generates water pollution, it may result in social costs such as cleaning cost or health problems in neighboring communities. But this social cost is not internalized in manufacturers’ decisions. Without regulations or legal punishment, they are not incentivized to reduce pollution.

National safety is an opposite example (generally regarded as “positive externality”), resulting in social benefits (e.g., less mental stress) but not entering the individual decision-making process as a benefit factor.

Using this analogy, we believe PPRs may lead to both direct and indirect benefits, which we hereafter refer to as "positive externalities". For example, multiple studies have argued that PPRs were associated with both higher patient satisfaction and improved patient safety (Devers, Brewster, & Casalino, 2003; Hall & Kamerow, 2013; Lenfestey, Denham, Hall, & Kamerow, 2013; Stiller, Salm, Bischoff, & Gastmeier, 2016). Some studies also concluded that PPRs were associated with a lower risk of HA-MRSA (Bracco, Dubois, Bouali, & Eggimann, 2007;

Levin, Golovanevski, Moses, Sprung, & Benenson, 2011; Teltsch et al., 2011). Contrary to such "direct" benefits (difference in benefits between "good" and "bad" rooms with a hospital being equal), however, little is known about "indirect" benefits (difference in benefits between "good" and "bad" hospitals with room types fixed) from the organizational effects of PPRs in preventing HA-MRSA.

Our conventional wisdom also favors systematic benefit of hospitals with more private rooms in terms of HAI-safety. As exemplified in the white paper of JPS Health Network (JPS Health Network, 2016), a hospital with more private rooms may position itself as a 'safer' hospital in the market, luring more consumers (patients) and generating greater revenue. This can stimulate the need of hiring more nurses and prioritizing safety-related issues. As a result of repetitions of such an iterative process, the hospital becomes actually safer. Note that this virtuous cycle affects hospitals on the organizational level, meaning that even patients in bad (non-private) rooms can enjoy benefit from increased safeties.

This idea is in line with the analogy of "herd-immunity", as an extension of positive externalities discussed above. HA-MRSA infections are infectious diseases that can be transmitted through doctors and nurses. PPRs are linked to many good traits of preventing HA-MRSA through reductions of cross-transmissions of bacteria. More PPRs in a hospital mean larger personal space and less crowding which are associated with higher compliance with hand hygiene of staffs (Borg, Suda, & Scicluna, 2008; Salge, Vera, Antons, & Cimiotti, 2017). Better control of the aerial dispersion of pathogen and hand contamination are predicted in PPRs, compared with multi-bed rooms (King, Noakes, & Sleigh, 2015). Communication and

coordination among staffs are strongly encouraged in PPRs (Bartley & Streifel, 2010). Hospitals with fewer PPRs typically hire fewer nurses per bed, which may result in understaffing or excessive workload levels that can worsen the risk of HA-MRSA (Borg, 2003; Dancer et al., 2006). One recent study examining UK hospitals argued the importance of stable and well-isolated hospitalization to reduce MRSA transmissions (Tosas Auguet et al., 2018). All the above scenarios imply that HA-MRSA in a hospital with mostly PPRs may act as an infectious disease in a highly vaccinated society (i.e., analogy-wise, protective effects of PPR may play a similar role with those of vaccine.)

Unfortunately, evidence from previous studies is both limited and mixed. We carefully reviewed seven benchmark PPR studies (Table 2) cited most frequently. These studies leave major potential problems unresolved.

First, conclusions are mixed. Three studies found that PPRs significantly reduced HA-MRSA (Bracco et al., 2007; Levin et al., 2011; Teltsch et al., 2011) while the other four studies found no significant effects (Cepeda et al., 2005; Ellison et al., 2014; Julian et al., 2015; Vietri et al., 2004).

Second, most studies were conducted outside the US. Only two out of seven studied US hospitals (Julian et al., 2015; Vietri et al., 2004). This will be discussed with more details in the next section.

Third, all the benchmarks examined relatively small samples and two facilities at most. Smaller samples and too few facilities prevent researchers from controlling organizational or environmental factors (e.g., staffing, physical spaces). Lacking adjustments to organizational

factors give rise to potential bias due to confounding or moderating effects of environments and may also be a serious drawback in generalizations.

Last, only two studies studied non-ICU patients (Ellison et al., 2014; Vietri et al., 2004). However, the entire inpatient population is likely to better support hospitals' management decisions of building new towers and expanding old rooms.

Indeed, these four problems are largely related among one another. Mutually contradicting conclusions may be attributed to the discrepancy of varying and small experiments. Such challenges introduce the lack of validity and reliability required in practical applications.

**Needs of Representative Results**

As commonly shown in Tables 1 and 2, most literature comes from studies conducted outside of the US. We are concerned that this can give rise to serious lack of external validity (Marsh & Hau, 2004; Rothwell, 2005). In the context of this thesis, "external validity" is defined as the extent to which the study results and findings regarding HA-MRSA can be reproduced under situations in US hospitals, while "internal validity" is the extent to which the results avoid confounding and represent the causal relationship between HA-MRSA and the variables of interest in the study (i.e., either determinants or outcomes) (Black, 1996; Victora, Habicht, & Bryce, 2004).

Compared to US studies, non-US study results may require tremendous cautions and strong assumptions in supporting US hospital management decisions regarding facility designs and organizational changes. Alongside the fundamental difference in healthcare delivery

structure, which is well discussed elsewhere (Van Doorslaer et al., 2000), US and European hospitals face very different environments and regulations regarding MRSA and HAI-safety (Aiken et al., 2012). The leading European countries[1] have more aggressive and successful controls/policies for HA-MRSA (Kavanagh, Saman, & Yu, 2013; Klevens et al., 2006). The US and European countries also use different surveillance measures for HA-MRSA (Hansen et al., 2012). According to recent OECD statistics, organizational characteristics of US hospitals may also differ from leading European countries (OECD, 2017). For these reasons, we strongly believe that the results of HA-MRSA and PPR from European hospitals may introduce intensive challenges to transform into practical uses for US healthcare settings.

One may make a similar criticism of lacking external validity (i.e., generalizability) toward this study, because we used Texas data. Hence, the result of this thesis may not be expanded to other US states. While we acknowledge such limitation, we would like to emphasize that it is much easier to disarm threats to external validity in this thesis. Analysis and modeling framework can be re-applied to newer data sets of other states (once such database becomes available to us) with zero or minimal changes (i.e., nearly the same set of variables and their definitions). On the contrary, this may not be the case for European findings (i.e., predictive models must change massively to apply such models to US hospitals) due to some inherent differences For example, the percentage of Medicaid-insured patients (highly associated with safety-net hospitals) in a hospital is neither controlled in European studies

[1] Note that European countries themselves have a large within-Europe variation.

among our benchmark studies, nor discussed in the same analysis frameworks. Similar problems can be posed for many demographic (e.g., the percentage of Hispanic patients) and hospital variables (e.g., ownership type).

**Fallacy of "One size fit all"**

This thesis study intends to develop an expandable cost-benefit analysis (CBA) model (primarily expandable to US hospitals) to estimate the level of cost-saving benefits due to HAI reductions as justifying costly investments. We hypothesize that these benefits of PPRs are disproportionate to hospital characteristics and environmental factors (as opposed to invariant benefits across hospitals). Accordingly, CBA simulations which do not take these organizational and structural factors into consideration are likely to suffer limitations in applying to various hospitals. Such results are only held if we assume that interactions regarding PPR will not vary as a function of organizational or environmental elements, and that the benefits of PPR will be similar enough, no matter how hospital types and characteristics differ. Unfortunately, the current state of organizational science regarding PPR is more like a "collection of anecdotes." Many studies including our benchmarks demonstrated whether or not a PPR is effective in a specific hospital (usually a large teaching hospital located outside of the US). We are concerned with that these one-size-fits-all approaches may lead to lack of comprehensive understanding and impose limitations on policy and management. For example, a base health policy in the US cannot be evidenced by studies performed at single or a small number of teaching Canadian hospitals.

One recent study simulating the economic benefit of PPRs conducted by one research team is worth discussing in this respect (Sadatsafavi, Niknejad, Zadeh, & Sadatsafavi, 2016). While this study made interesting points in modeling PPR effects on the financial outcome, there still leaves unfilled gap in translating the study result into real-life management decision making process in US hospitals. The authors of the mentioned study used only one infection study to estimate the probability distributions of MRSA infection risk, one of the critical information of the analysis. Moreover, the underlying infection model was derived from one Canadian hospital (Hôtel-Dieu de Montreal Hospital) with fewer than 3,000 patients (Bracco et al., 2007), which did not integrate any environmental, organizational, or structural factors into the model. Hence, other type of hospitals (e.g., safety net hospitals in Fort Worth, Texas, or small for-profit hospitals located in a rural area) may face immediate difficulties in extrapolating this simulation. As discussed earlier, different research design and setting cause varying conclusions in MRSA infection risk and costs. The simulation conclusion can flip easily with the choice of differently derived models. Taken together, even if the discussed simulation has a good internal validity, lacking external validity may be problematic – the results may not effectively facilitate practical uses in managements and policies.

It is important to understand that what we argue in this section is indeed a practical problem which all the potential real-life applications immediately face, as opposed to trivial or minor limitations. If any policy makers or hospital managers use the simulation results discussed above, they might also have to accept an implicit assumption that the simulated reduction of MRSA can be obtained proportionately across different hospitals within the

estimated range. However, there found obvious evidence to counter the assumption, at least for Texas hospitals. For example, our data shows that nurse staffing (measured by nurse-to-patient ratio) is correlated with MRSA incidence (Correlation coefficient=-0.19; $p$=0.0045; among 229 valid hospitals). What is worse, this measure varies intensively across hospitals, ranging from 0.12 to 7.44. It is highly likely that the simulation results may not fit applications for Texas. The issue of non-linear improvements potentially due to externality would aggravate the fit even further. The expected improvement (i.e., reduced MRSA infections) depends on how many PPRs currently exist in the hospital, as we found. In other words, MRSA reduction effects present non-linear and marginally decreasing response as more PPRs exist in the hospital.

We seek to fill this gap in the literature. The results of this thesis might arguably achieve a stronger generalizability (i.e., external validity to Texas hospitals) by utilizing more than 300 hospitals and by addressing the effect of environmental factors. Generalizability to all US hospitals will be obtained by reprocessing and recalibrating with nationally representative data (not available at the time of this study due to resource and time constraints). To increase internal and face validity, we also verified the results by closely working with JPS Hospital.

**Public Reporting and Induced Antibiotic Overuse**

Benchmarking of surveillance data for HAIs has been used for more than 30 years to inform prevention strategies and improve patient safety. In recent years, public reporting of HAI indicators such as incidence rates has been mandated in several states in the US (Talbot, 2013). Other high-income countries with an emerging awareness of patient safety also force

public reporting of HAI indicators, but some countries report differently than the US. For example, the US and England have predominantly focused on reporting of infection rates, while France emphasizes process and structure indicators. For example, the incidence of bloodstream infections due to MRSA is publicly reported in the US, but not in France. Instead, the rate of isolation of MRSA from diagnosis specimens is publicly reported in France, not in the US (Haustein et al., 2011). A comparative study based on four countries – including the US – argues that mandatory public reporting has a strong benefit in an increasing commitment of hospital leadership to combat HAIs and providing external reinforcement for organizational changes (Haustein et al., 2011).

Many researchers agree that public reporting of HAI would effectively lead to reductions of the infections as long as the reporting process is transparent and efficient (Allen, 2006; Daneman, Stukel, Ma, Vermeulen, & Guttmann, 2012; Haustein et al., 2011; Martin et al., 2013; Passaretti, Barclay, Pronovost, Perl, & Committee, 2011). However, studies have also warned of unintended consequences (Edmond & Bearman, 2007; Muller, 2010; Talbot, 2013). One of the risks commonly indicated is incentivized and induced under-reporting from hospitals (Haustein et al., 2011; Talbot, 2013). Also, public disclosure might impose the risk of skewing of priorities or misinterpretation by the public and the media (Haustein et al., 2011). Some researchers argued that the current reimbursement policies of HAI might not be as effective as intended mainly because the policy generally used individual case-based measures rather than structure-based or process-based ones (J. Brown, Doloresco, & Mylotte, 2009).

The issue of antibiotic resistance becomes more complicated when combined with the negative side of public reporting and related regulations (i.e., when there are some players gaming "the regulation"). (See the section of "Costly nature of MRSA treatment…" in this chapter for general explanations.) MRSA was defined as one of "never events" by CMS and used for a quality payment adjustment, including Medicare nonpayment for HAI and Hospital-acquired condition reduction program. While this policy achieved a success of HA-MRSA reduction (Waters, Daniels, & Bazzoli, 2015), the true story was confounded with the fact of increasing antibiotic overuse in recent years (Fleming-Dutra et al., 2016; Llor & Bjerrum, 2014; Ventola, 2015). Some researchers have suspected that the public reporting and regulation regarding never-events might "encourage" inappropriate use or overuse of antibiotics (Collins, 2008; Chenxi Liu et al., 2016; Ventola, 2015). This indicates at least two important challenges: concept and methodology. Conceptually, hospitals and policy makers need stronger evidence regarding public reporting of HAIs in terms of effectiveness of reporting (i.e., "Does the reporting effectively incentivize hospitals to reduce HA-MRSA infections in right ways?") as well as accuracy of reporting measure (i.e., "Do hospitals or governments measure and report the right thing linked to patient safety? Does such measure not induce serious side effects?"). Methodologically, the likelihood of receiving antibiotics must be controlled in research designs for any MRSA studies to minimize positive confounding (i.e., the observed association is biased away from the null).

We strongly believe that which indicators to measure, how to define a composite measure, and whether or not to disclose them publicly are all difficult problems. They must be verified with science evidence, not motivated by political arguments.

In this regard, our studies aimed for better public reporting of MRSA in at least two aspects. First, impacts due to MRSA infections would be more accurately examined. As discussed in the previous sections, most of MRSA effects are evidenced by the studies lacking internal (i.e., not controlling organizational confounders) and external validity (not applicable for general US populations). In addition, only MRSA bloodstream infections are mandated to report. Our goal is to challenge the unanswered questions and to develop a more robust predictive model regarding health outcomes (will be discussed with more details in the following chapters). Second, our result regarding PPR-MRSA relationships may hint the need of mandatory and public reporting of hospitals' patient room information. This thesis shows that PPR serves as a good healthcare-safety indicator. Note that the unintended consequences of PPR public reporting would be presumably less problematic, due to the nature of structural measure (i.e., unlikely endogeneity/reverse causality), than the outcome reporting measures such as MRSA bloodstream incidence. Patients are likely to benefit from this information in that they can choose a safer place to get care. Hospitals are also incentivized to invest in improving the quality of patient rooms and facility safety to obtain competitive advantages on the market.

**Our Previous Work on CLABSI**

In recent years, Dr. Liam O'Neill and I have been examining on Texas inpatient discharge data to better understand private-room effects on HAI, focusing on CLABSI. In 2018, we

published our results confirming that there were non-linear but monotonically decreasing relationship between the risk of HAI and the percentage of PPRs in a hospital, regardless of which room an individual patient actually stayed (O'Neill, Park, & Rosinia, 2018). This suggests a new perspective of the built environments as a determining organizational factor associated with between-hospital difference in HAI risk, rather than a traditional view of within-hospital difference (i.e., a patient assigned to a private room vs a bay room).

While this CLABSI work revealed many important relationships among HAIs, physical environment and organizational characteristics, we were also motivated to extend the lessons learned to the next stage, including the following points. First, there was a clear need to include other HAIs other than CLABSI in the analysis to get a more comprehensive picture of HAI-associated patient safety. MSRA must be considered along with CLABSI due to the well-established risk of mortality and/or its high cost of treatment (CDC, 2016; Salge et al., 2017). Second, analyzing aggregated data (i.e., by facility) can improve our understanding of both determinants and outcomes of HAIs at the hospital level, reducing potential bias due to inherent collinear interactions between internal and external effects: For example, a patient is affected not only by the patient's own disease, but also hospital-wide disease level (i.e., the aggregation of individual disease status). Finally, cost-benefit analysis results presented as monetary term help potential stakeholders have a better sense in practical applications, compared to (academically oriented) statistical inferences. For example, there is a high demand to transform statistical point and interval estimates (e.g., conditional mean and 95% confidence interval of the adjusted incidence rate of HA-MRSA) to end-result predictions such as how many

dollars can be saved by converting a bay room to a private room. Note that point-value results are imperfect for comprehensive understanding, as many underlying factors are estimated within a certain uncertainty. Distributional presentations such as multi-variate confidence intervals and empirical distribution plots may help in this regard.

All things considered, this thesis intends to extend our previous work in this area, address all the needs discussed above, and ultimately add to the emerging body of research by providing higher dimensional evidence.

**Specific Aims of This Thesis**

The aims of this thesis are three-fold:

Aim 1. Develop hospital-level predictive models that link the effect of facility design to HA-MRSA reductions and hospital cost. Based on representative large data, this thesis will examine the association between facility design, primarily focusing on patient rooms, and HA-MRSA infections. This thesis will also examine the attributable impact of the change of HA-MRSA infections at the hospital level to hospital cost (measured by Medicare reimbursement). While it is known that HA-MRSA is associated with worse health outcomes, the evidence to date is insufficient to get practical and robust predictions for actual hospitals regarding facility constructions or renovations. Our thesis intends to reduce this gap in the literature by estimating how many infections can be prevented due to facility design factor, as well as the potential cost savings.

Aim 2. Examine the effects of "positive externalities" of private patient rooms (PPRs) with regard to the risk of HA-MRSA at the patient level. Positive externality in this context is

defined as indirect hospital-wide effects on patients regardless of assigned room types. The hypothesis for this aim is that, the patients' benefits due to PPR are decomposed into individual (direct) and hospital (indirect) effects. This implies that, even if a patient is assigned to a bay room, this patient would be safer against HA-MRSA compared to the equivalent patient assigned to non-PPR at a "worse" hospital (i.e., lower percentage of private rooms), other factors being equal.

Aim 3. Develop a probabilistic cost-benefit analysis (CBA) simulation model and apply the simulation model for actual hospitals as a practical application of this thesis. This CBA intends to inform hospitals how much financial investments can be justified by cost-saving benefits from reduced HAIs by converting existing facilities to an all-private room design. While the main HAI scope of this thesis is HA-MRSA, we also included hospital-acquired MSSA and CLABSI[2] to predict benefits to suggest more comprehensive and useful results for the stakeholders. Among the five specific HAIs monitored by the CMS (HA-CLABSI, HA-MRSA, HA-C.Diff[3], HA-CAUTI[4], and SSI[5]) (CMS, n.d.), these two HAIs (HA-MRSA and HA-CLABSIs) were chosen based on the data availability. Our CBA simulation model was supported by the patient-level predictive models for cost-saving from HA-MRSA reductions and the previous work of HA-CLABSI. Note that we expect this simulation model to have a strong external validity due to 1) a

[2] Central Line-Associated Blood Stream Infections
[3] Hospital-acquired clostridium difficile colitis
[4] Hospital-acquired catheter-associated urinary tract infection
[5] Surgical site infection

large representative sample and 2) possibly a better model-specification that includes structural and organizational factors. While two hospitals of different facility types are examined as examples, the simulation framework is flexible enough that it can be applied to any type of US hospitals.

**Next Chapters**

Chapters II through V include introductions to common methodologies, the study of the relationship between private rooms and MRSA, the analysis of the economic impact of MRSA on hospital cost, the study of the decomposed private-room effects at the patient level, and the cost-benefit simulation of private-room facility designs via HAI reductions. Chapter VI summarizes the common themes and implications of this thesis.

# CHAPTER II

# RESEARCH METHODS AND DATA SOURCES

## Overview

The purpose of this chapter is to give readers a brief overview of the research methods for the studies of this thesis. Specifically, this chapter explains data sources, operational definitions, comorbidity measures, conceptual models, risk-adjustment models, and statistical models.

## Data Sources

### Texas inpatient discharges.

The Texas Inpatient Public Use Data File (IP PUDF) (Texas Department of State Health Services, 2017) is the primary data source for this thesis. These data are collected by the Texas Department of State Health Services on a quarterly basis. The dataset includes all discharge records for more than 600 participating hospitals in Texas. It contains 266 data fields in a base data file, 13 data fields in a detailed charge file, and 12 data fields in a facility data file. The data include information of patient demographics, lengths of stay, discharge status, 26 diagnosis codes (i.e., containing 1 primary diagnosis, 1 admitting diagnosis, and 24 secondary diagnoses), 25 surgery procedure codes, total patient charges, and separate charges for various utilizations (e.g., charges for patient rooms and charges for ICU). Each year of data includes about 2.5 - 3 million patient records.

The current thesis focuses on the data obtained in the fiscal year 2016. This specific time point of data collection (i.e., the fourth quarter of calendar year 2015) was chosen because ICD-

10-CM diagnosis code reporting was not available until October 2015. The data include 98.6% of all hospital discharges in the state excluding small hospitals (i.e., containing less than 25 licensed beds). Specific inclusion and exclusion criteria will follow in subsequent chapters.

**Medicare payment data.**

Medicare Provider Utilization and Payment Data (CMS, 2017b) was used to assess hospital costs. This database includes hospital-specific charges for the more than 3,000 US hospitals that receive Medicare Inpatient Prospective Payment System payments for discharges paid under Medicare based on a rate per discharge using the Medicare Severity Diagnosis Related Group (MS-DRG). For each MS-DRG, an average charge, an average total payment, and an average Medicare payment are calculated at the individual hospital level as well as at the state level. We merged this Medicare payment data with our IP PUDF to define and calculate hospital costs.

**Hospital annual survey.**

The American Hospital Association (AHA) annual survey is a database for in-depth analysis on hospitals and healthcare industry (AHA, n.d.). AHA annually conducts a survey of hospitals to compile a comprehensive database on hospitals. This database contains various hospital-specific organizational and structural data from more than 6,000 hospitals and more than 450 healthcare systems. The number of data fields included in this database exceeds 700. One practical problem in using this database for this thesis was that the hospital identifiers of AHA were not compatible with IP PUDF. To address this problem, two databases (i.e., DB1 and DB3) were matched by the similarity of hospital names. The distance between a geographical

location of a hospital (i.e., drawn from DB3) and two dominant patient counties (i.e., drawn from IP PUDF) was calculated to increase matching accuracy for otherwise ambiguously matched hospitals. Manual Internet inspections were conducted to check whether a hospital experienced serious business or operational changes (e.g., bankruptcy, M&A, and organizational integrations) during the data collection period (i.e., fiscal year of 2016).

**Income tax statistics.**

This thesis used the Individual Income Tax Return Statistics for 2016 (IRS, 2017), collected and archived by the Internal Revenue Service (IRS). The database contains income and tax items classified by state, zip code, and intervals of adjusted gross income. For each zip code, we defined a mean household income by using the sum of adjusted gross incomes and dividing the sum by the numbers of returns for each zip code. Although median incomes are known to be more robust against outliers, available data sources for median incomes (i.e., the United States Census Bureau data or community survey) have their own limitation – they are sampled investigations and present error margins of 10-15% (i.e., of estimated medians). In contrast, mean incomes are calculated by the United States tax return statistics and free from sampling errors by nature. In this thesis, we tried both income data (i.e., mean and median household incomes) and found only a small difference between the two income approaches. Therefore, we decided to use mean incomes because of its comparative completeness (i.e., population-based statistics).

**Consumer assessment of hospitals survey.**

The Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey is a national survey of patients' perspectives of hospital care (CMS, 2017d). Participants (i.e., discharged patients) are surveyed about their perceptions of hospital experience and satisfaction using 27 questions. For this thesis, we focus on perceived qualities (i.e., cleanness/quietness and whether the nurses communicated well) and patient satisfaction (i.e., overall satisfaction rating of hospital stay). Because publicly released HCAHPS data set does not contain the exact distribution of 0-10 (i.e., 0 as the lowest satisfaction and 10 as the highest satisfaction) ratings[6], we used percentages of respondents who rated highly (9 or 10 out of 10). This method also reduces ceiling and floor effects due to censoring that typically appeared in hospital quality surveys (Dell-Kuster et al., 2014). The same matching strategy used to match DB3 with DB1 (i.e., matching by hospital names and distances, with additional internet inspections) was used to match DB5 with the rest of the databases.

**Introduction to ICD-10-CM**

ICD-10 stands for the tenth revision of the International Statistical Classification of Diseases and Related Health Problems, a medical classification list established by the World Health Organization (WHO) (WHO, n.d.). It contains codes for diseases, signs and symptoms, abnormal findings, complaints, social circumstances, and external causes of injury or diseases.

[6] Alternatively, HCAHPS provides percentages of survey participants: patients who gave their hospital a rating of 6 or lower, 7 or 8, and 9 or 10 (highest).

The code set in the base classification allows for more than 14,400 different codes and permits the tracking of many new diagnoses compared to the legacy ICD-9 (WHO, n.d.). The number of codes can be expanded to over 16,000, with the use of optional sub-classifications. The International Classification of Diseases, tenth Revision, Clinical Modification (ICD-10-CM) was developed by the National Center for Health Statistics (NCHS), for medical coding and reporting, serving as a morbidity classification for classifying diagnoses and reason for visits in all healthcare settings (CMS, 2017c; NCHS, 2016).

**Administrative Data and ICD-10-CM**

Since HA-MRSA pathogen involves unmeasurable or unknown factors in infection and transmission processes, the ideal study design would be a randomized controlled trial (RCT) with sufficient sample size. However, conducting an RCT is not feasible to study HA-MRSA for many reasons that are well documented elsewhere (Benson & Hartz, 2000). Primary reasons are that covariates of MRSA are impossible to control and random allocation of participants to treatment groups are likely unethical. Thus, most research on MRSA has been observational studies based on primary data (i.e., data observed or collected directly from investigators). Despite known limitations of publicly available data, many researchers have suggested that a study of large-scale administrative data can serve as a viable alternative to an RCT and outperform smaller primary data-driven observational studies (Jhung & Banerjee, 2009; Schweizer et al., 2011). Note that large and representative samples of administrative data meet the criteria of this thesis (i.e., focusing on management and policy use). Nevertheless, administrative data still face practical challenges in identifying MRSA infections (Goto, Ohl,

Schweizer, & Perencevich, 2013; Schweizer & Rubin, 2012). (See the "Identifying MRSA infections" section.) A set of suggestions has been proposed to improve the quality of detecting HAI for studies using administrative data (Jhung & Banerjee, 2009). We followed these recommendations: 1) use of as many (up to 26) diagnosis fields; and 2) validation against other estimates (i.e., the number of HA-MRSA infections reported by the CMS). We also address endogeneity and distinguish direct effects from indirect effects in our analyses.

In addition to well-established general benefits of using ICD-10-CM, such as higher sensitivity (sick people correctly identified as having the condition) and specificity (healthy people identified as not having the condition) due to increased details (Brooks, 2016), ICD-10-CM improves the quality of MRSA research over ICD-9-CM for at least two reasons.

First, the legacy ICD-9-CM contains multiple confusing MRSA definitions. Before 2008, there was a single ICD-9-CM code (V09.0 – "infection with microorganisms resistant to penicillin") for generic MRSA infections. MRSA infections were assessed through combinations of this code with complicated infections (Tehrani, Cao, Kwark, & Huang, 2013). For example, pneumonia with MRSA was coded as 482.4 (Staphylococcus aureus pneumonia) plus V09.0. Newer recommendations – that replace V09.0 with a single combination code for MRSA and complications – were released in 2008 (CDC, 2011). For example, pneumonia due to MRSA is coded as 482.42. The biggest problem of such an approach (i.e., the combination of general MRSA code and separate diagnosis code) is that one patient may have multiple conditions. Thus, it is likely unclear whether or not a certain infection is induced by MRSA in practice. For this reason, the later guideline prohibited the outdated V09 MRSA code (CDC, 2011) and

instead required to code MRSA with newer set of codes (038.12, 482.42, 041.12, and V02.54) (See Table 3 for more). Nevertheless, our observation on IP PUDF revealed that hospitals used newer and older codes interchangeably and inconsistently as recently as in 2014, possibly due to the legacy billing software. This may introduce serious inaccuracies and biases that could undermine the validity of data. ICD-10-CM eliminates the coding ambiguity of "generic MRSA," and also integrates various MRSA infections into its structure in a more consistent way. However, to the best of our knowledge, few studies have used ICD-10-CM because this revised rubric has become available very recently. In Texas, for example, the first quarter of data that included ICD-10-CM (i.e., the fourth quarter of 2015) was not released until late 2016.

Second, the validity of ICD-9-CM coded MRSA in research may be problematic. One study examined the accuracy and validity of the ICD-9-CM V09.0 code and concluded its low sensitivity (mean: 24%) and low positive predictive value (mean: 31%) (Schweizer et al., 2011). Another study reported low sensitivity (mean: 58%) but high positive predictive value (mean: 93%) (Schaefer et al., 2010). These results suggest that MRSA might have been under-coded with the legacy coding system. While no studies have validated newer ICD-10-CM codes yet (Goto et al., 2013), a recent systematic review suggested that ICD-10-CM would better record some HAIs such as nosocomial pneumonia, and noted that the validity of ICD-10-CM coded data would increase as coders gain more experience with ICD-10-CM (Redondo-González, Tenías, Arias, & Lucendo, 2017). Another recent study performed at Canadian hospitals found a strong association (i.e., mean Pearson's correlation coefficients ranging from 0.79 to 0.92) between

administrative data (coded with ICD-10[7]) and surveillance result (Ramirez Mendoza et al., 2017) regarding MRSA infections.

In other words, the legacy coding system (i.e., ICD-9-CM) has a potential risk of underreporting of MRSA and coding inaccuracy. By contrast, ICD-10-CM has clearer and more consistent definitions of MRSA with five separate codes, containing A41.02 (sepsis due to MRSA), J15.212 (pneumonia due to MRSA), B95.62 (MRSA infection as the cause of diseases classified elsewhere), A49.02 (MRSA infection, unspecified site) and Z22.322 (carrier or suspected carrier of MRSA). Thus, a higher level of coding sensitivity is expected, because there will be fewer false negatives with ICD-10-CM than ICD-9-CM (e.g., MRSA pneumonia falsely coded with V09 versus correctly identified with J15.212). Moreover, the use of ICD-10-C<M in the present thesis allows for the comparison of our results with the MRSA rates that are reported by the CMS. Note that the current MRSA surveillance measure used by the CMS is based on a specific category of MRSA (i.e., lab-identified MRSA bacteremia), as opposed to entire MRSA conditions.

HA-MRSA infections at both patient and hospital levels are included in our models of this thesis as key variables. We identified HA-MRSA at the patient level by using 26 diagnosis codes and 26 present-on-admission (POA) indicators corresponding to diagnoses. Table 3 presents five MRSA conditions and corresponding ICD-10-CM codes – consistent with the CMS ICD-10-CM guidelines (NCHS, 2016). Note that this thesis does not consider "MRSA

[7] ICD-10-CA (study conducted in Canada)

colonization," because our purpose is to investigate cases when MRSA is acquired during hospitalization. Colonization of MRSA is typically determined by MRSA screening test, documentation of previous MRSA/MSSA colonization , and documentation of a disease process due to MRSA (Boyce, 2001; NCHS, 2016). However, multiple studies commonly indicated difficulty and inaccuracy in identifying the place at which MRSA is colonized, due to the non-active nature of colonization (Boyce, 2001; Callejo-Torre et al., 2016; K. A. Davis, Stewart, Crouch, Florez, & Hospenthal, 2004). Furthermore, we are more interested with conditions that can significantly change end outcomes such as cost or mortality – colonization may be related only weakly at best. Note that HA-MRSA is defined with the combination of Present-On-Admission (POA) indicators provided by IP PUDF (i.e., POA not contained in ICD-10-CM). For example, a septicemia due to HA-MRSA is defined if ICD-10-CM diagnosis code is A41.02 that is not present on admission (i.e., POA=0). For hospital-level analyses, all three types of patient-level HA-MRSA infections (i.e., septicemia, pneumonia, and other infections) were aggregated to generate hospital-level HA-MRSA counts.

Table 3: Various MRSA infections and ICD-CM codes

| Description | | ICD-9-CM (prior to 2008) | ICD-9-CM (after 2008) | ICD-10-CM | Active infection | Examined |
|---|---|---|---|---|---|---|
| MRSA Septicemia | | - | 038.12 | A41.02 | Yes | Yes |
| MRSA Pneumonia | | - | 482.42 | J15.212 | Yes | Yes |
| Other MRSA infections | Unspecified MRSA infections | - | - | A49.09 | Yes | Yes |
| | MRSA as the cause of other disease | - | 041.12 | B95.62 | Yes | Yes |
| Generic MRSA | | V09.0 | - | - | Yes | No |

| | | | | | |
|---|---|---|---|---|---|
| MRSA colonization | - | V02.54 | Z22.322 | No | No |

**Costing Measure and Controversies**

Accurately assessing costs is desirable in order to estimate the economic impact of HA-MRSA. Scott et al. (2009) deconstructed the structure of HAI costs into three categories: 1) direct hospital costs of fixed (e.g., building, equipment) and variable (e.g., medications, treatments) parts; 2) indirect costs (e.g., lost wages); and 3) intangible costs (e.g., psychological effects, pain). There are also long-term effects of MRSA infections, such as diminished worker productivity and the loss of life. The report also found that most previous studies only considered direct hospital costs.

Cost estimates can also vary depending on how they are measured. For example, recent systematic reviews indicate that cost estimation from a top-down approach (e.g., direct charge multiplied by cost-to-charge ratio) can differ from a bottom-up approach, also known as micro-costing (Hussey, Wertheimer, & Mehrotra, 2013; Macario, 2010).

Consistent with cost benchmark studies in this area (Cosgrove et al., 2005; Engemann et al., 2003b; S. P. Kim et al., 2012; Macedo-Viñas et al., 2013; Nelson, Samore, et al., 2015a), presented in Table 4, the present thesis focused on the direct cost of hospital inpatient treatment primarily due to data limitations. Indirect costs also lack empirical evidence (Scott, 2009). Furthermore, hospitals can directly appreciate benefits from investing in infection controls in that empirical evidence of direct costs of inpatient treatment for MRSA infections can support managerial decisions (e.g., building or expanding patient towers).

Cost benchmark studies mostly measured hospital charges to patients (Cosgrove et al., 2005; Engemann et al., 2003b; S. P. Kim et al., 2012; Nelson, Samore, et al., 2015a; Robert J. Rubin et al., 1999) with a few exceptions (Browne et al., 2016; Macedo-Viñas et al., 2013). While there are some benefits of using hospital charges such as less ambiguity or easier data collection (Kaplan & Porter, 2011; Painter & Chernew, 2012), the charge measure is subject to critical biases in generalizability due to large between-hospital and between-department variabilities criticized by many researchers (Daffner, Beimesch, & Wang, 2010; Dormont & Milcent, 2004; Kaplan & Porter, 2011; Lave & Leinhardt, 1976; Painter & Chernew, 2012; Rapoport, Teres, Lemeshow, Avrunin, & Haber, 1990; Stover et al., 1998). One of the common criticisms of charge-based approaches is, as discussed by Painter and Chernew (2012), that charges are unrelated to actual costs. Kaplan and Porter's analysis (2011) indicated that the charges were very likely inappropriate and misleading as a cost proxy, because the charges were often irrelevant to an actual allocation of resource (e.g., physicians, spaces). The patient charges are also very sensitive to billing and charging systems of hospitals (Dormont & Milcent, 2004) as well as their cost reduction policy (Kaplan & Porter, 2011). A recent empirical study has verified extreme variations of hospital-charges across hospitals (Bai & Anderson, 2015), showing that the charges of the top 50 hospitals are about 10 times higher than their Medicare-allowable costs (c.f. a national mode of 2.4 times). All the above evidence implies that hospital charges are inappropriate in assessing hospital cost for the purpose of this thesis due to low validity.

To address the limitation of charge-based cost assessments, alternative costing methods have been suggested in the literature: using relative resource allocation, like measuring reflected payments for healthcare services by health plans, beneficiary, or other payers (Hussey et al., 2013). This thesis used average Medicare payments by diagnosis-related groups (DRGs) as a proxy variable for hospital costs. We believe that this measure reflects resource allocation more consistently than hospital charges. Better performance as a cost measure is expected because Medicare payment weights by DRGs (DRG weights) are based on relative resource amounts used to treat patients in each DRG (CMS, 2017a) and because our simple analysis revealed that 98% of the average Medicare payments by DRGs are explained by those DRG weights (CMS, 2017a, 2017b). This method has also earned awareness of concerned researchers (Baicker & Chandra, 2004; Birkmeyer, Gust, Dimick, Birkmeyer, & Skinner, 2012; Englesbe, Dimick, Fan, Baser, & Birkmeyer, 2009). While such studies mostly targeted the relationship between hospital cost and quality rather than an association between MRSA and cost, there are at least four major advantages of using Medicare payments as a hospital costs approximation, regardless of some shared limitations with charge-based methods (e.g., true costs are independent from reimbursements).

First, MRSA patients in Texas are dominantly (53%) eligible and insured by Medicare, followed by the uninsured (11%), those covered by Medicaid (10%), and those covered by commercial insurances (8%). (See Figure 2 for details.) In this respect, Medicare prices are representative of those which hospitals pay for MRSA treatments.

Second, Medicare price is a more consistent cost measure because it is derived from large data collections with standardized protocols and forms. Moreover, this information is transparent, in that the CMS publicly release average payments (i.e., prices) by providers along with summary statistics on a regular basis (CMS, n.d.-a).

Third, the between-hospital consistency of Medicare payments (c.f., hospital charges vary massively across hospitals with different billing system and software) fits to analysis containing multiple hospitals and mixed payers. Note that Medicare prices also serve as a good reference. Non-Medicare patients can be adjusted by applying a payment ratio between Medicare and other payers, which enables consistent analyses of mixed patient pool no matter how each patient is insured. According to a recent survey (American Hospital Association, n.d.-b), the Medicare payment rate represents approximately 89% of a hospital's actual costs in 2014. Using appropriate multipliers, we can estimate the actual payment to the hospital from Medicaid and commercial payers. For example, commercial payers are likely to use the amount paid by Medicare as a benchmark rate of payment so that they may negotiate to pay 162% (calculated from data points in 2014) of Medicare price for a given DRG (American Hospital Association, n.d.-a). Detailed ratios are presented in Table 5. Finally, even though Medicare payments are only approximations of the true costs of hospitals, they account for how much the entire society in the economy pays for HA-MRSA - Medicare payments are Medicare's cost, mostly funded by taxpayers' money, by definition (CMS, n.d.-c; Moeller, 2016).

Some may pose concerns regarding Medicare non-payment policy. This policy of Medicare denies incremental payment for eight "never events" (i.e., serious but preventable

complications of hospital care), implemented in 2008 (NCSL, 2008). If HA-MRSA is not paid by Medicare, it may contradict our underlying assumption when using Medicare payments as cost proxy. However, many experts countered that this nonpayment policy might affect only a small portion of hospital reimbursement at best, because Medicare incremental payments to hospitals would only be rejected when HAI is the only factor causing a case to be reclassified into a more expensive payment (Stone et al., 2010). Moreover, Texas data for the fiscal year 2016 failed to support that HA-MRSA nonpayment worked. The data indicated that HA-MRSA increased both LOS and covered charges (i.e., defined by the subtraction of non-covered charge from total charge) among Medicare patients even after adjusting demographics and medical confounders.

Admittedly, there is no consensus of "the right way" to assess hospital costs for HAI with administrative data to date (Painter & Chernew, 2012; Scott, 2009). Future studies may test and verify robustness and validity of various costing methods. However, it is beyond the scope of this thesis.

Table 4: Cost literature

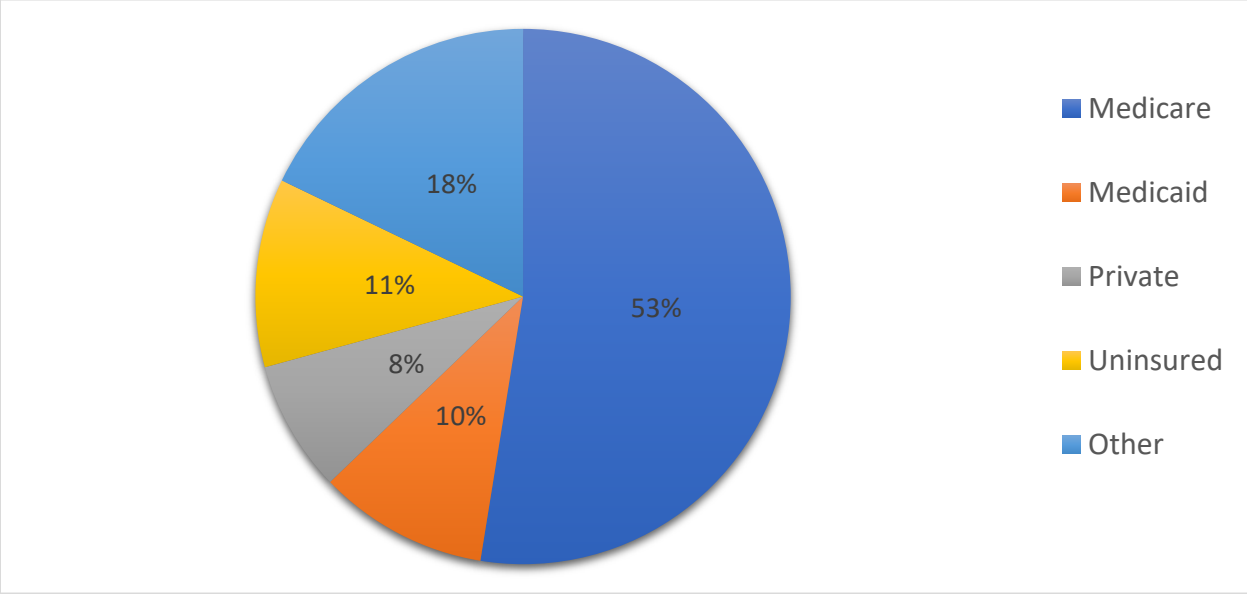
| Study | Costing method | Country | Number of hospitals studied | Sample size |
|---|---|---|---|---|
| Cosgrove et al. (2005) | Hospital charge – Patient charge adjusted by cost-charge ratio | US | 1 | 348 |
| Browne et al. (2016) | Accounting information | UK | N/A (decision-tree simulation) | N/A |
| Engemann et al. (2003) | Hospital charge – Direct patient charge | US | 2 | 479 |

| | | | | |
|---|---|---|---|---|
| Kim et al. (2012) | Hospital charge – Patient charge adjusted by cost-charge ratio | US | 1,175 | 10,856 |
| Macedo-Viñas et al.(2013) | Nationally collected cost-per-case database | Swiss | 1 | 26,350 |
| Nelson et al. (2015) | Hospital charge – Direct patient charge | US | 114 | 386,794 |
| Rubin et al. (1999) | Hospital charge – Direct patient charge | US | Not reported ("I analyzed data for hospitals in the following New York City metropolitan area counties: Bronx, Dutchess, Kings, Manhattan, Nassau, Orange, Putnam, Queens, Richmond, Rockland, Suffolk, Ulster, and Westchester") | 1,351,362 |

Table 5: Percentages of reimbursements from various payers relative to costs

| Payer | Payment-to-cost Ratio (%) |
|---|---|
| Medicare | 88.5 |
| Medicaid | 90.0 |
| Private payers | 143.7 |

Figure 2: Texas MRSA patients by insurance (*n*=25,484)



**Donabedian's Structure-Process-Outcome Framework**

The conceptual model for this thesis comes from Donabedian's classic framework of healthcare quality. Donabedian's Structure-Process-Outcome (SPO) model defines three domains regarding health care quality (Donabedian, 1980, 1988). "Structure" is stable and fixed context in which healthcare services are delivered, including physical facility and information system. The structure is often easy to observe and may be an upstream cause of later problems identified in "process" or "outcome" (Donabedian, 2005). "Process" denotes transactions and interactions between patients, healthcare providers, and hospital staff throughout the service delivery system, activities, and technical and interpersonal aspects of performance (Hearld, Alexander, Fraser, & Jiang, 2008). Process is more variable and controllable in the short term than structure. "Outcome" refers to all the effects of healthcare on patients, including changes to health status, behavior, or knowledge, as well as patient satisfaction and health-related quality of life (Donabedian, 1988). Note that these three categories are not attributes of quality; they are rather classifications for the types of information that can be obtained in order to infer whether the quality of healthcare is good, fair, or poor.

While many researchers in this study area agree with conceptualization of the SPO model, the importance of structural measures has been overlooked and ignored: documentations regarding structure-outcome relationships being rare (Gray, 1986; Hammermeister, Shroyer, Sethi, & Grover, 1995; L. Moore, Lavoie, Bourgeois, & Lapointe, 2015), and quality recommendations ignoring structural measures (Akachi & Kruk, 2017; Corrigan, Swift, & Hurtado, 2001; Harvey et al., 2016; Lohr, 1997). Meyer and Massagli (2001)

suggest that the continuing development of structural measures would be helpful because generalization of studies of process and outcome requires equalizing heterogeneous environments under which relationships are tested and found. These authors also emphasize the need of measuring aspects of physical environment, working conditions, organizational culture, and provider satisfactions. We try to address this gap in the following ways.

Using the SPO framework as a hypothetical way of modeling private room effects, we conceptualize private patient rooms (PPRs) in two domains: structure and process. On the one hand, a patient in a PPR has a lower risk of developing HA-MRSA than in a bay room. Many favorable traits of PPR (i.e., direct benefits) regarding MRSA safety are verified by multiple studies, including better hand hygiene compliance (Borg et al., 2008; Salge et al., 2017) and more effective communications among staff (Bartley & Streifel, 2010). Note that these interactions are categorized as process measure in the SPO model. On the other hand, the proportion of private rooms in a hospital is a structural consideration that may affect all the patients systematically (i.e., effects not restricted within patients assigned to PPRs). This structural characteristic may reduce HA-MRSA risk by affecting multiple processes – including (1) a room assignment process (i.e., the more PPRs in a hospital, the higher chance of being assigned to a PPR) and (2) other processes potentially related to HA-MRSA (e.g., decreased nurse work load). With this decomposition of structure-process domains regarding private rooms, it is interesting to see a clear distinction of related decisions. Structural decisions include a new hospital design and an existing facility renovation. These decisions are made for a relative long-term period (5 to 10 years) by hospital management board and/or architects. By

comparison, process-related decisions are made on a shorter-term basis (e.g., daily operations, monthly or quarterly reflections) by physicians and nurses and include developing priority rules for bed assignments and applying such rules to patients. See Table 6 for details.

Unlike many other previous studies in this study area, which did not consider patient rooms as a modelling factor, this thesis explicitly includes private rooms in the model of patient safety (i.e., MRSA-safety) and outcomes as a major structural variable from a "fixed-effect"[8] perspective, implying a certain part of private-room effects is constant over patients in the same hospital. There are several studies that examine the difference between patients in bay rooms and those in private ones, like Bracco et al. (2007). Such analyses can shed a light on the effect of private rooms as a "process". However, we hypothesize a patient's MRSA-safety (or hospital-wide MRSA-safety as an extension) is affected not only by a room assignment process, but by external effects of patient rooms. The latter is unable to test or investigate without the aid of large-scale data collected from multiple facilities. Hence, we regard the percentage[9] of private rooms in a hospital as an important variable. Furthermore, employing this structural variable may also benefit practical applications, because structural consideration usually needs more careful justification than process-related issues in the context of patient rooms. For

[8] Note that there are various (at least five) and mutually-different definitions about fixed-effects and random-effects (Gelman, 2005). We follow more intuitive interpretations in the literature (Kreft & De Leeuw, 1998; Searle, Casella, & McCulloch, 2009) – summarized as "Fixed effects are constant across individuals, and random effects vary."

[9] We use "percentage" rather than "count" of private rooms, because an absolute count of rooms may introduce collinearity issues (i.e., all our models contain licensed beds) while relative quantity like percentages is independent from a hospital volume/size. (i.e., also included in the model.)

example, assigning a patient to a private room is much less controversial (i.e., mostly prioritized based on clinical criteria and resource availability at the decision moment) than renovating an existing facility and legacy rooms. It is also worth noting that our studies try to incorporate other various organizational variables – including but not limited to medical staffing, patient satisfactions, physical space for patients, and ownership styles. This is in line with recommendations in the literature, discussed earlier in this section.

In this thesis, we intend to deliver a comprehensive understanding of private rooms regarding MRSA-safety. To meet this need, studies detailed in Chapters 3 and 4 (i.e., hospital-level analyses) examine the effect of private rooms on MRSA-risk and MRSA-induced costs, considering the structural effect of private rooms as granted. Patient-level analysis detailed in a subsequent chapter tests the presence of structural (external) effect of private rooms and illustrates how two different aspects (process and structure) of private room effects differ and interact.

Table 6: Structure and process aspects of private patient rooms

| Criterion | Structure | Process |
|---|---|---|
| Decision maker | Hospital management board, CEO, architects/designers | Physicians, nurses |
| Decision frequency | Low<br>(Once every five or ten years) | High<br>(relatively shorter-term: daily, weekly, monthly, or quarterly) |
| Decision type | Designing a new hospital<br>Renovating an existing facility | Developing priority rules for bed assignments<br>Assigning patients to beds |
| Sustainability of effects | Long (almost permanently) lasting | Subject to fail to continue in the long run (e.g. management/policy changes) |
| Assessment of effects | between-hospital difference<br>(i.e., hospitals with different private room percentages) | within-hospital difference<br>(i.e., patients with different room assignments) |

| # of Hospitals to verify | Multiple (at least more than 50) hospitals needed | One (or a few) may be enough |
|---|---|---|
| Measurability of effects | Very difficult | Relatively easy |
| Repeatability of effects | Impossible | Possible |
| Previous literature | Very rare | Many |

**Estimating the Percentage of PPR**

Regarding the use of private rooms as a structural measure, studies using large-scale data have suffered from the lack of available data in secondary datasets – even the potential value of such data has been overlooked. In order to address this major obstacle, the present thesis use "hospital charges" at the patient level, which is drawn from IP PUDF. This approach is suggested and introduced by our previous work (O'Neill et al., 2018). While the referred study focuses on HA-CLABSI[10], we assume that the underlying logic of assessing the built-in environment remain unchanged across different HAIs.

IP PUDF contains hospital room charges. The database includes several pre-defined[11] variables regarding patient rooms: private room charges, semi-private room (i.e., often called "bay room") charges, ward charges, and intensive care unit (ICU) charges. We are able to infer the hospital's physical layout by examining the percentage of patients who were assigned to private rooms among all hospitalized patients. Suppose that 90% of a hospital's acute-care beds are in private rooms. The probability to assign a patient to a private room would be

[10] Hospital-acquired Central-Line Associated Bloodstream Infection
[11] Calculated using Medicare Provider Analysis and Review (MEDPAR) algorithm

asymptotically 90% -- implying that we can expect 90% of patients to be assigned to PPR if a sufficient sample is given. Note that actual PPR assignment rate may be affected by numerous factors: bed assignment rules, occupation rates, and intra-hospital transfers (O'Neill et al., 2018). Nonetheless, this thesis regards the percentages of PPR as a robust approximation of hospitals' physical layout for currently available databases.

Operationally, the percentage of PPR is defined as the percentage of patients who are assigned to a PPR and remain in the same room throughout their hospital stay. Thus, the numerator for each hospital consists of the number of patients assigned to a PPR (i.e. positive private room charges and zero charge for other room types) while the denominator consists of the number of patients assigned to either a PPR or a non-PPR (i.e. bay room or ward room). Note that we exclude intra-hospital transfers (i.e., defined as positive charges on multiple room types) from the denominator. Also, ICU is excluded from both the numerator and the denominator because IP PUDF did not have the information on whether ICU beds were located in private rooms.

**Controlling Comorbidity**

In developing predictive models regarding MRSA, patients with different medical conditions must be adjusted against comorbidity before being compared (i.e., ideally only similar conditions should be compared.) This is also important for hospital-level analyses, because the distribution of clinical burdens for a hospital may significantly differ across hospitals (e.g., rural clinics vs. specialized cardiac hospitals). In addition to controlling facility types and medical burdens, we controlled comorbidity in the following approach.

First, among various ways to define comorbidity, we follow the Elixhauser comorbidity definitions according to the "Elixhauser Comorbidity Software for ICD-10-CM" (AHRQ, 2018). The Elixhauser comorbidity measure, proposed in 1998, was initially developed with California inpatient data containing more than one million patients to predict hospital resource use and in-hospital mortality (Elixhauser, Steiner, Harris, & Coffey, 1998). This comorbidity measure contains 29-31[12] comorbidity conditions relying on ICD-9-CM and ICD-10-CM coding systems. Recent studies further developed and validated weighted indices (i.e., presented as a score) (B. J. Moore, White, Washington, Coenen, & Elixhauser, 2017; Sharabiani, Aylin, & Bottle, 2012).

There are alternative definitions of comorbidities – including Charlson comorbidity index (Manitoba Centre for Health Policy, n.d.), Johns–Hopkins Adjusted Clinical Group Indices ("Concept: Adjusted Clinical Groups® (ACG®) - Overview," n.d.), Chronic Disease score, and the crude number of diagnoses. All the referred approaches along with Elixhauser were carefully tested and reviewed with literature as well as actual data. Finally, we decided to follow Elixhauser's definition regardless of wide acceptance and handy implementations of Charlson index[13] (Quach et al., 2009; Southern, Quan, & Ghali, 2004). Our decision was made based on a number of recent comparative studies and systematic reviews (Menendez, Neuhaus, van Dijk, & Ring, 2014; B. J. Moore et al., 2017; Sharabiani et al., 2012; van Walraven, Austin, Jennings, Quan, & Forster, 2009; Velu et al., 2018). One common conclusion of such studies was that the

[12] The number of conditions differ slightly across comorbidity software versions.
[13] When this thesis was first proposed, we planned to use Charlson index to assess comorbidity.

Elixhauser comorbidity index outperformed other alternatives in terms of true positive rates (i.e., statistical power) at the same cost of false positive rates (i.e., type-1 error). We also tested both comorbidity measures with Texas inpatient data and found that Elixhauser comorbidity yielded a better suitability (i.e., greater explanatory power for both HA-MRSA risk and healthcare outcomes.

In this thesis, the 29 separate conditions (defined by the most recent software of AHRQ) were controlled in our patient models, while the weighted index was used in generating matched groups for patient-level analysis and between-hospital comparison (as well as hospital models).

**Risk-Adjustment Model**

The purpose of a risk adjustment process is to account for disproportionate conditions across patients in terms of medical (e.g., chronic conditions) and healthcare-access (e.g., how a patient is insured) aspects, and to ensure a certain level of unbiasedness throughout statistical inferences. Risk-adjustments also address several shortcomings of administrative data and quasi-experimental designs – including contamination by confounding variables and lacking control over extraneous variables (DiNardo, 2010; Harmon, Morgan, Gliner, & Harmon, 2000). Note that risk adjustment is particularly of importance for the research design of the present thesis – relying on large data collected from many facilities with different characteristics. For example, safety-net hospitals contain numerous patients with severer medical conditions. By contrast, other types of hospitals (e.g., rural for-profit hospital) have relatively healthier patients. If medical severity is not properly controlled in analyses, the prediction such as

private-room effect on MRSA would be biased and overestimated. Hence, we need as a good risk-adjustment model as possible.

In this thesis, covariates are grouped into several categories: demographic, socio-economic, medical (burden/status), organizational, and structural factors. Please note that "organization" and "structure" are often interchangeably used in this study area. For convenience, the studies of this thesis distinguished these two in that structural variables are more directly involved in design and construction of new hospitals (e.g., the percentage of PPR among patient rooms) while organizational variables are other variables related to hospitals' nature and characteristic (e.g., ownership style). This is largely to focus on the main purpose of this thesis – to predict the effect of facility designs.

Demographic (patient age and gender) and socio-economic (health insurance and ZIP income) factors were controlled in this thesis. Elixhauser comorbidity indicators were used to control individual patients' medical burden. (See Table 7 for details.) A composite index of the weighted sum was used to control the average clinical burden of hospitals (in hospital analyses) and generate matched groups (in patient analyses). For definitions of each comorbidity condition and weights of a composite index, we follow the Elixhauser Comorbidity Software for ICD-10-CM (AHRQ, 2018) and the Elixhauser Comorbidity Index Program developed by the AHRQ (AHRQ, 2017). Procedure classes (i.e., containing major diagnostic procedure, minor diagnostic procedure, major therapeutic procedure, and minor therapeutic procedure), as defined by the Healthcare Cost and Utilization Project (HCUP) (AHRQ, n.d.-a, n.d.-b), were

adjusted in the models. Urgent/emergency admissions, transferred patients, and the presence of local skin infections were also controlled.

A recent study validated risk adjustment factors in modeling HA-MRSA and tested reliability of the model (Callejo-Torre et al., 2016). This study confirmed independent risk factors of HA-MRSA, including patient age, patient gender, severity of medical burden, previous antibiotic treatments, transferred patients, local skin infections. Most of these risk factors are included in our risk models, except previous antibiotic treatments. While it is possible to infer a patient's antibiotic resistance (i.e., as a proxy of antibiotic treatments) by assessing drug resistance-related diagnosis codes, the cross-sectional nature of our studies could not ensure that such resistance precedes the onset of MRSA infections. Also, the preliminary analysis result indicated that HA-MRSA incidences might have an endogenous relationship with general drug-resistance. Hence, we decided not to include previous antibiotic treatments due to the inability to establish a causal linkage. That is, the antibiotic resistance may only be evident in hindsight, after MRSA has been diagnosed.

Table 7: List of Elixhauser comorbidity conditions

| | | |
|---|---|---|
| Acquired immune deficiency syndrome | Drug abuse | Peptic ulcer disease |
| Alcohol abuse | Fluid and electrolyte disorders | Peripheral vascular disease |
| Chronic blood loss anemia | Hypertension | Psychoses |
| Chronic pulmonary disease | Hypothyroidism | Pulmonary circulation disease |
| Coagulopathy | Liver disease | Renal failure |
| Congestive heart failure | Lymphoma | Rheumatoid arthritis |
| Deficiency Anemias | Metastatic cancer | Solid tumor w/out metastasis |

| | | |
|---|---|---|
| Depression | Obesity | Valvular disease |
| Diabetes w/ chronic complications | Other neurological disorders | Weight loss |
| Diabetes w/o chronic complications | Paralysis | |

**Negative-Binomial Regression Model**

The negative binomial model (NBM) has been widely adopted for analyzing count outcomes when a dependent variable shows an over-dispersed distribution (i.e., the sample variance is much greater than the mean) (Cameron & Trivedi, 2013). In healthcare and medical context, previous studies from various research areas used NBM, ranging from epidemiology of infectious diseases (An, Wu, Fan, Pan, & Sun, 2016) to hospital adverse events (Kovner, Jones, Zhan, Gergen, & Basu, 2002, 2008) and HAI (Morton et al., 2001; Waters et al., 2015; Yin, Schweizer, Herwaldt, Pottinger, & Perencevich, 2013). The popularity of NBM is largely due to its ability to model varying degrees of overdispersion. The distribution is expressed in terms of the mean *m* and dispersion parameter *k* such that the probability of observing a non-negative integer x (e.g., the specific count of "bad but rare" hospital event X) is expressed as follows:

$$\Pr(\mathrm{X}=\mathrm{x}) = \frac{\Gamma(\mathrm{k}+\mathrm{x})}{\mathrm{x}!\,\Gamma(k)}\left(\frac{m}{m+k}\right)^{\mathrm{x}}\left(1+\frac{m}{k}\right)^{-k}, \mathrm{m}>0 \text{ and } \mathrm{k}>0 \quad [14] \qquad \text{(Eq 1)}$$

The variance of negative binomial distribution is $\mathrm{m}\left(1+\frac{m}{k}\right)$, and hence decreasing about k, the dispersion parameter. Because of this characteristic, NBM can also be viewed as a

[14] In this section, the gamma function (represented by *Γ*,the capital Greek alphabet letter gamma) is defined as an extension of the factorial function. See Davis (1959) for more details.

generalized version of major discrete probability distributions. Note that the probability mass function of the Poisson distribution can be obtained as the dispersion parameter approaches infinity. Similarly, the logarithmic distribution is obtained when the dispersion parameter approaches zero. Geometric distribution is derived from the unit dispersion parameter (i.e., k=1). Therefore, the dispersion parameter k is also known as the "shape" parameter, as it determines the shape of the distribution.

Assuming the dependent variable Y follows the negative binomial distribution, NBM is expressed:

$$\ln Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p \,, \qquad \text{(Eq 2)}$$

where the predictor variables $x_1, x_2, \ldots, x_p$ are given, and the regression coefficients $\beta_0, \beta_1, \ldots, \beta_p$ are to be estimated. Given a random sample of size n (i.e., n observations), we observe for subject *i* the dependent variable $\mathrm{y_i}$and the predictor variables $x_{1i}, x_{2i}, \ldots, x_{pi}$. Utilizing a matrix notation, we let $\beta = \left(\beta_0\ \beta_1 \ldots \beta_p\right)^T$, and the design matrix X, the collection of predictors, as follows:

$$\mathrm{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1p} \\ 1 & x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix}$$

Designating the i-th row of X to be $\mathrm{x_I}$, we can get the probability distribution of Y by combining (Eq 1) and (Eq 2):

$$\Pr(\mathrm{Y} = \mathrm{y_i}) = \frac{\Gamma(1/\alpha + \mathrm{y_i})}{\Gamma(\mathrm{y_i} + 1)\Gamma(1/\alpha)} \left(\frac{1}{1 + \alpha e^{x_i \cdot \beta}}\right)^{1/\alpha} \left(\frac{\alpha e^{x_i \cdot \beta}}{1 + \alpha e^{x_i \cdot \beta}}\right)^{\mathrm{y_i}} , \mathrm{i} = 1,2, \ldots, \mathrm{n}. \text{ where } \alpha = 1/\mathrm{k}$$

The regression coefficients $\beta$ and the inversed dispersion parameter $\alpha$ are estimated using the maximum likelihood estimation, which seeks the values of $\alpha$ and $\beta$ that maximize the log-likelihood function. The likelihood and log-likelihood functions are expressed as (Eq 3) and (Eq 4) respectively:

$$L(\alpha,\beta) = \prod_{i=1}^{n} \Pr(\mathrm{Y} = \mathrm{y_i}) = \prod_{i=1}^{n} \frac{\Gamma(1/\alpha+\mathrm{y_i})}{\Gamma(\mathrm{y_i}+1)\Gamma(1/\alpha)} \left(\frac{1}{1+\alpha e^{x_i\cdot\beta}}\right)^{1/\alpha} \left(\frac{\alpha e^{x_i\cdot\beta}}{1+\alpha e^{x_i\cdot\beta}}\right)^{\mathrm{y_i}} \text{(Eq 3)}$$

$$\ln L(\alpha,\beta) = \sum_{i=1}^{n} \left(y_i \ln\alpha + y_i(x_i\cdot\beta) - \left(y_i+\frac{1}{\alpha}\right)\ln\left(1+\alpha e^{x_i\cdot\beta}\right) + \ln\Gamma\left(y_i+\frac{1}{\alpha}\right) - \ln\Gamma(y_i+1) - \ln\Gamma\left(\frac{1}{\alpha}\right)\right) \qquad \text{(Eq 4)}$$

In this thesis, we used the negative binomial regression model to compare the difference in infection rates across hospitals. (See Chapters 3 and 4 for more details). This regression model was chosen over the Poisson regression model because the count dependent variable (i.e., the count of HA-MRSA infections) was overly dispersed (i.e., the variance was 13.6 times larger than the mean). When such overdispersion exists, many hospital-level HAI studies including the standardized infection ratio (SIR) model, also employ NBM. Various statistical tests, such as the likelihood ratio test, confirmed the choice of NBM, as compared to similar models, such as Poisson regression.

# CHAPTER III

# HOW THE BUILT ENVIRONMENT AFFECTS MRSA AT THE HOSPITAL LEVEL

## Background

With emerging awareness about patient safety and hospital-acquired infections (HAIs), an increasing number of consumers (patients) and suppliers (hospitals) may want to know how to identify a "safe" hospital. Public reporting can be one useful tool to fulfill such need – it provides patients with an actual incidence of HAIs for individual hospitals and incentivize hospitals to reduce HAIs. For example, the Hospital Compare website (CMS, n.d.-b), created and operated by the Centers for Medicaid and Medicare Services (CMS), is a large public-reporting program that measures and reports hospital outcomes such as heart failures and acute myocardial infarctions.

However, the current "case-oriented" public reporting approaches in the United States (i.e., mainly focusing on incident infections or adverse events) have been criticized for unintended consequences: hospitals may skew priorities or game reporting to avoid negative financial or other consequences. Reported examples include inappropriate under-reporting (Haustein et al., 2011; Talbot, 2013) and antibiotic overuse (Collins, 2008; Chenxi Liu et al., 2016; Ventola, 2015). At the same time, research suggests that structure-based reporting and reimbursement may result in stronger and more robust results (e.g., long lasting improvements) (J. Brown et al., 2009).

Unfortunately, evidence from literature establishing the relationship between structural factors (also called "built-in environment" or "design factors") and HAI[15]/HA-MRSA[16] (needed for proposing a better way of structure-based public reporting) remains weak.[17] Previous results have insufficient external validity due to their small sample sizes and potential confounding bias. The lack of multisite studies potentially weakens the transition from knowledge to practice (e.g., applications in managerial decision-making or to support health systems policy).

The goal of this chapter is to suggest a feasible public reporting measure based on structural components. This is partially driven by a frequently-asked question during practical construction projects – "for our hospital, how many MRSA infections can be prevented if we go for an all-private room design?" We examined how design factors affect HA-MRSA, developed a statistical model to predict HA-MRSA incidence at a hospital level, and paid particular interest to the effect of private patient rooms (PPRs) on HA-MRSA incidence.

## Method

### Unit of analysis.

This analysis differs from previous studies of the PPR-MRSA relationship in that the unit of analysis is the hospital. We hypothesized that the relationship between PPR and HA-MRSA has at least two distinct dimensions: (1) decreased MRSA risk by being assigned to a PPR (i.e.,

[15] Hospital-acquired Infection
[16] Hospital-acquired methicillin resistant staphylococcus aureus
[17] See the "Private-room Effects on MRSA" section in Chapter I for more details.

internal effect) and (2) hospital-wide reduced cross-transmissions (i.e., external effect). These two dimensions introduce methodological challenges at the patient-level analysis, including measuring difficulty and collinearity (i.e., interaction between external and internal effects), which may cause inaccuracy in estimating PPR effects. By contrast, hospital-level analyses with total[18] PPR effects can prevent potential challenges, though at a cost of inability to distinguish internal and external effects of PPR. Therefore, we believe that both hospital-level and patient-level analyses are complimentary, and that together may allow comprehensive understanding of the topic. The analysis in this chapter focuses on the hospital level[19].

**Data.**

The Texas Inpatient Public Use Data File (IP PUDF) for the 2016 fiscal year (Texas Department of State Health Services, 2017) was used to obtain patient demographics and diagnoses while hospital information (e.g., ownership) was accessed via the American Hospital Association (AHA) annual survey (AHA, n.d.).[20] To validate our data and model, the observed and expected HA-MRSA bacteremia events during the 2016 fiscal year were also accessed from the Hospital Compare Data Archive (CMS, n.d.-b)

[18] combining both direct and indirect benefits
[19] This does not imply that we overlook the importance of patient-level modeling. A patient-level model is developed and estimated in the study detailed in Chapter V to compare internal and external effects of PPRs.
[20] See the "Data Sources" section in Chapter II for detailed explanations of each database.

**Variables.**

We used the count of HA-MRSA infections as a key dependent variable and the percentage of PPR in a hospital as a key independent variable. Our operational definitions of HA-MRSA included MRSA septicemia, MRSA pneumonia, and other types of MRSA infections, as presented in Table 3.

PPRs are defined as single-bed (private) patient rooms, and "bay rooms" (non-PPRs, operationally defined as the union of semi-private rooms and ward rooms) as patient rooms with equal to or more than two beds. Consistent with our prior work (O'Neill et al., 2018), the percentage of PPRs in a hospital was calculated by dividing the count of regular private room discharges by the count of regular room (i.e., non-ICU) discharges. Each patient room assignment was identified from hospital room charges.

We adjusted numerous confounding factors of HA-MRSA in our multivariate model, based on established associations in the literature. Comorbidities, as defined using the Elixhauser comorbidity score definition (B. J. Moore et al., 2017), were controlled in the model because of known association with high risk of HA-MRSA (Callejo-Torre et al., 2016; Goto et al., 2017; Nelson, Stevens, Jones, Samore, & Rubin, 2015). Percentages of black and Hispanic race/ethnicity were also controlled because these populations had higher MRSA incidences in multiple studies and surveys (Bakullari et al., 2014; Bratu et al., 2006; Graham, Lin, & Larson, 2006). We controlled some hospital characteristics that were known to be associated with MRSA (Edelsberg et al., 2009; Panlilio et al., 1992; Wakefield, Pfaller, Massanari, & Hammons, 1987), such as teaching facility, ownership, hospital location (rural or metropolitan), and

licensed beds. The percentage of uninsured or Medicaid-insured patients were controlled as a proxy indicator of safety net hospitals (Kovner & Gergen, 1998; G. M. Lee et al., 2012). Nurse staffing levels, as defined by patient-to-nurse ratio[21], were adjusted based on previously revealed associations with MRSA (Afif, Huor, Brassard, & Loo, 2002; Hugonnet, Harbarth, Sax, Duncan, & Pittet, 2006; Penoyer, 2010). We also included occupancy rates and physical area per bed based on our previous work (O'Neill et al., 2018).

Note that all the unbounded continuous variables (e.g., licensed beds) were log-transformed before putting into regression analyses. Percentage variables (i.e. ranged from zero [0] to 1) were multiplied by 100 to make a unit marginal change being 1 (i.e., a range from zero [0] to 100).

**Statistical analysis.**

In our descriptive analysis, we compared various characteristics across 3 different groups[22] of hospitals: (1) Group 1 hospitals (*n*=113) contain fewer than 62% PPRs among all patient rooms; (2) Group 2 hospitals (*n*=114) contain 62%-82% PPRs; and (3) Group 3 hospitals (*n*=114) are those where more than 82% of patient rooms are PPRs.

Our multivariate regression used the negative binomial model (NBM) to compare the difference in infection rates across hospitals with various PPR rates. NBM was chosen over the

[21] Productive nursing hours (including both registered nurses and licensed practical nurses) – nurse full-time equivalents times 1,788 – divided by patient days times 24; definition comes from literature (Spetz, Donaldson, Aydin, & Brown, 2008)

[22] Hospitals were grouped into three categories of the same size, based on the percentage of PPR, so that each group has nearly the same number of hospitals.

Poisson model because the dependent variable (HA-MRSA count) was overly dispersed, as the variance was 13.6 times larger than the mean, potentially due to the nature of HAI in terms of unobserved heterogeneity and clustering (Kelly, Bull, Russo, & McBryde, 2008; Morton et al., 2001). We also performed likelihood-ratio test of the inversed overdispersion parameter and confirmed that NBM was more suitable for our regression ($p$<0.001).

## Results

### Descriptive results.

Table 8 presents the full descriptive and unadjusted results. One-way analysis of variance (ANOVA) tests show that hospital Groups 1-3 significantly differ in the following ways (all $p$<0.001): (1) ownership types, (2) percentages of publicly insured or uninsured patients, (3) racial patient-mix, (4) average medical burden, (5) nurse staffing, (6) dominant procedure class, and (7) physical occupancy. Group 1 hospitals – relatively low PPR facilities – were predominantly located in rural areas (31.6%) and contained more public hospitals (Group 1=26.3% versus Group 2=2.9% and Group 3=11.5%). Group 1 also showed the largest portion of Hispanic patients (Group 1 = 34.1% versus Group 2=15.6% and Group 3=27.4%) but the smallest portion of African American patients (Group1=9.2% versus Group2=10.6 and Group3=11.4%). Group 1 hospitals were characterized by lower comorbidity and lower occupancy rate than Groups 2 and 3. Group 3 hospitals – relatively high PPR facilities – were located largely in urban areas (87.1%) and contained many for-profit hospitals (61.4%). Distinct characteristics of Group

3 include the least percentage of publicly insured or uninsured patients (55.3%)[23], the fewest patients, the most nurses (1.6 nursing hours per patient-hour), and the largest percentage of major therapeutic procedures (46.2%).

We also found that the incidence of HA-MRSA was associated with PPR per our grouping categories. Group 1 presented the highest incidence rate of HA-MRSA with mean incidence of 536 per 100,000 cases (95% CI=346-726 per 100,000 cases). Group 3 showed the opposite: the lowest mean incidence rate of 251 per 100,000 cases (95% CI=146-355 per 100,000 cases). A one-way ANOVA test also verified that the three groups differed in HA-MRSA incidence ($p$<0.001). Additionally, pairwise t-tests confirmed that Group 1 is risker than Groups 2 and 3 in terms of HA-MRSA (Group 1 versus Group 2: $p$=0.008; Group 1 versus Group 3: $p$<0.0001).

Table 8: Descriptive results

| Variable | Group 1 (PPR<62%) | Group 2 (PPR=62-82%) | Group 3 (PPR>82%) | P-value | | | |
|---|---|---|---|---|---|---|---|
| | Mean and 95%CI | Mean and 95%CI | Mean and 95%CI | All | G1 vs G2 | G2 vs G3 | G1 vs G3 |
| # Hospitals | 113 | 114 | 114 | | | | |
| # Discharges | 900,340 | 1,154,687 | 615,828 | | | | |
| Teaching facilities (%) | 5.5 | 7.0 | 5.7 | | | | |
| Rural location (%) | 31.6 | 17.2 | 12.9 | | | | |
| Ownership type (%)<br>- Public<br>- Non-profit<br>- For-profit | <br>26.3<br>27.6<br>46.1 | <br>11.5<br>50.6<br>37.9 | <br>2.9<br>35.7<br>61.4 | 0.000 | | | |
| HA-MRSA incidence (per 100,000 cases) | 536 (346, 726) | 341 (236, 447) | 251 (146, 355) | 0.000 | 0.008 | 0.116 | 0.000 |
| # Licensed beds | 262 (181, 343) | 259 (213, 306) | 185 (124, 247) | 0.175 | 0.479 | 0.027 | 0.071 |
| Publicly insured or uninsured (%) | 63.9 (60.1, 67.6) | 63.1 (60.3, 65.8) | 55.3 (61.2, 59.3) | 0.001 | 0.366 | 0.001 | 0.001 |

[23] possibly associated with safety-net hospitals

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Race and ethnicity (%)<br>- Hispanic<br>- Black<br>- Asian | <br>34.1 (28.2, 40.1)<br>9.2 (7.3, 11.1)<br>1.8 (0.3, 3.3) | <br>27.4 (22.1, 32.6)<br>11.4 (9.5, 13.3)<br>2.1 (1.5, 2.6) | <br>15.6 (12.1, 19.1)<br>10.6 (8.5, 12.7)<br>1.8 (0.3, 3.3) | <br>0.000<br>0.298<br>0.052 | <br>0.046<br>0.055<br>0.363 | <br>0.000<br>0.281<br>0.000 | <br>0.000<br>0.175<br>0.052 |
| Physical space per bed (sqft) | 2,045 (1,549, 2,541) | 2,147 (1,970, 2,325) | 3,663 (1,606, 5,720) | 0.084 | 0.343 | 0.052 | 0.057 |
| Mean Elixhauser score | 2.6 (2.2, 3.0) | 3.4 (3.1, 3.6) | 2.7 (2.2, 3.2) | 0.018 | 0.001 | 0.002 | 0.355 |
| Nurse-to-patient ratio | 0.9 (0.8, 1.1) | 0.7 (0.6, 0.8) | 1.6 (1.2, 2.0) | 0.000 | 0.000 | 0.000 | 0.001 |
| Major therapeutic procedures (%) | 33.2 (29.5, 36.8) | 28.8 (27.5, 30.1) | 46.2 (41.7, 50.8) | 0.000 | 0.013 | 0.000 | 0.000 |
| Occupancy rate (%) | 34.1 (30.3, 37.9) | 45.4 (41.9, 48.9) | 37.6 (32.9, 42.4) | 0.000 | 0.000 | 0.004 | 0.122 |

**Multivariate results.**

As shown in Table 9, the protective effect of PPR on the risk of HA-MRSA was confirmed again in our multivariate analysis. After adjusting potential confounders, each 1% increase of PPR as a proportion of all rooms was associated with 0.8% decrease of log count of HA-MRSA infections ($p$<0.001).

Other factors associated with the count of HA-MRSA include licensed beds (IRR=1.616; $p$<0.001), African American patients (IRR=1.006; $p$<0.001), major therapeutic procedures (IRR=1.007; $p$<0.001), nurse-to-patient ratio (IRR=0.536; $p$<0.001), average medical burden (IRR=1.034; $p$=0.038), occupancy rates (IRR=1.012; $p$<0.001), and teaching facility (IRR=1.257; $p$=0.001). Additionally, compared to for-profit hospitals (as reference), public and not-for-profit ownership styles were also associated with more HA-MRSA infections (IRR=1.235 and 1.129 respectively; $p$=0.004 and 0.019 respectively). Physical space per bed in square feet is also negatively associated with HA-MRSA incidence, but with slight variability across hospitals (IRR=0.941; $p$=0.056).

We also examined predictive margins to estimate marginal effects of PPR on HA-MRSA incidences. As presented in Figure 3, a non-linear relationship between the percentages of PPR and the counts of HA-MRSA is observed. There is a marginal "improvement" in relation to a unit increase (i.e., 1%) of PPR percentage became smaller as a hospital already contained more PPRs. If an "average"[24] hospital with zero PPR renovates all its legacy rooms to private ones, the expected annual count of HA-MRSA would be reduced from 19.7 to 9.17.

Finally, we examined variance-inflation factors (VIFs) to test collinearity among our model variables. All our variables had VIFs well below 5, implying that there is no critical collinearity in our model.

Table 9: Negative binomial regression results for predicting HA-MRSA infections (*n*=340)

| Variable | β | IRR (Exp β) | P-value | Lower | Upper |
|---|---|---|---|---|---|
| Percentage of PPR | 0.008 | 0.992 | 0.000 | 0.991 | 0.994 |
| Licensed beds (log-transformed) | 0.480 | 1.616 | 0.000 | 1.524 | 1.713 |
| Publicly insured or uninsured patients (%) | 0.003 | 1.003 | 0.049 | 1.000 | 1.006 |
| African American patients (%) | 0.006 | 1.006 | 0.009 | 1.001 | 1.010 |
| Hispanic patients (%) | 0.000 | 1.000 | 0.949 | 0.998 | 1.002 |
| Major therapeutic procedures (%) | 0.007 | 1.007 | 0.000 | 1.004 | 1.011 |
| Nurse-to-patient ratio (log-transformed) | 0.624 | 0.536 | 0.000 | 0.892 | 0.356 |
| Physical space per bed (sqft; log-transformed) | 0.061 | 0.941 | 0.056 | 0.885 | 1.002 |
| Mean Elixhauser score | 0.034 | 1.034 | 0.038 | 1.002 | 1.068 |
| Occupancy rate (%) | 0.012 | 1.012 | 0.000 | 1.009 | 1.016 |
| Teaching facility | 0.229 | 1.257 | 0.001 | 1.102 | 1.434 |
| Rural location | 0.070 | 1.072 | 0.380 | 0.918 | 1.252 |
| Public ownership (ref: for-profit) | 0.211 | 1.235 | 0.004 | 1.070 | 1.425 |
| Not-for-profit ownership (ref: for-profit) | 0.122 | 1.129 | 0.019 | 1.021 | 1.250 |

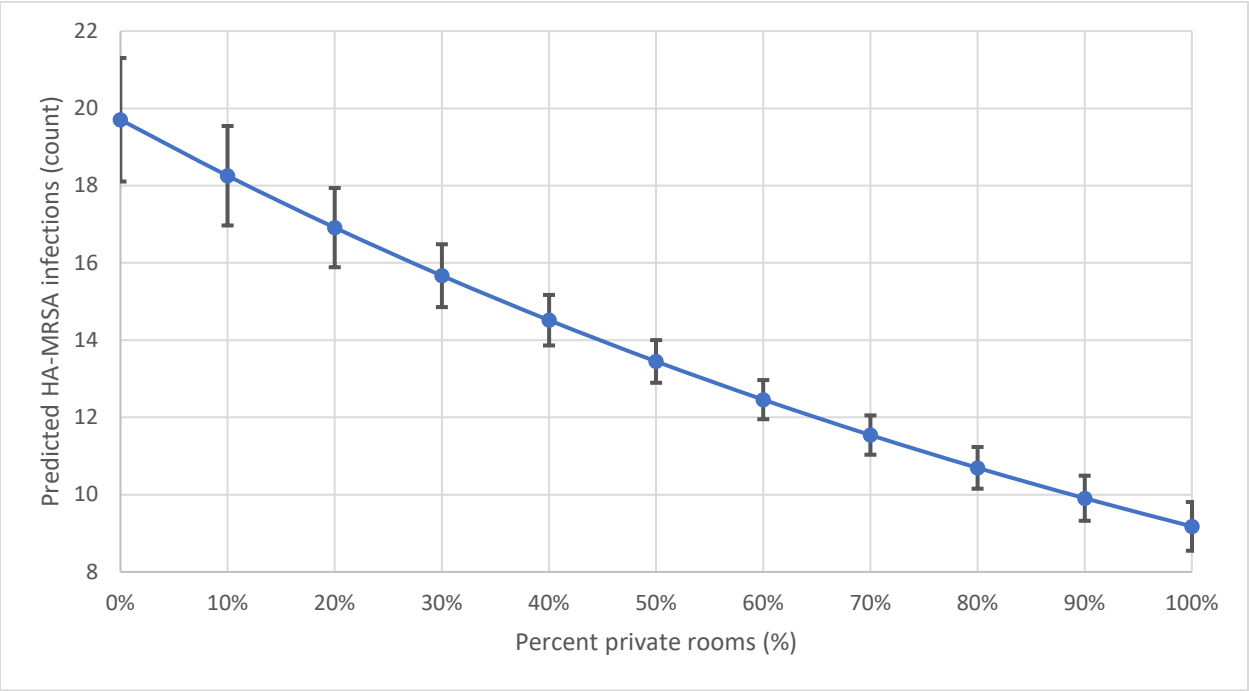
[24] other parameters except PPR, such as beds, being mean

* Goodness-of-fit was tested in two ways: (1) likelihood test passed with *p*=0.001 (i.e., negative binomial model is more suitable than Poisson model); and (2) McFadden's adjusted pseudo R2 was 0.284

Table 10: Negative binomial regression results for predicting HA-MRSA infections, by hospital group

| Variable | Group 1, *n*=113 (Fewer PPRs than 62%) | | | | Group 2, *n*=114 (PPR between 62%-82%) | | | | Group 3, *n*=114 (More PPRs than 82%) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IRR (Exp β) | P-value | Lower | Upper | IRR (Exp β) | P-value | Lower | Upper | IRR (Exp β) | P-value | Lower | Upper |
| Percentage of PPR | 0.993 | 0.001 | 0.989 | 0.997 | 0.986 | 0.051 | 0.972 | 1.000 | 1.007 | 0.485 | 0.988 | 1.027 |
| Licensed beds (log-transformed) | 1.715 | 0.000 | 1.560 | 1.885 | 1.558 | 0.000 | 1.393 | 1.744 | 1.743 | 0.000 | 1.514 | 2.007 |
| Publicly insured or uninsured patients (%) | 1.002 | 0.338 | 0.998 | 1.007 | 1.005 | 0.052 | 1.000 | 1.011 | 1.004 | 0.251 | 0.997 | 1.010 |
| African American patients (%) | 1.006 | 0.112 | 0.999 | 1.013 | 1.005 | 0.246 | 0.997 | 1.013 | 1.010 | 0.070 | 0.999 | 1.021 |
| Hispanic patients (%) | 1.001 | 0.599 | 0.998 | 1.003 | 1.000 | 0.908 | 0.997 | 1.003 | 0.998 | 0.537 | 0.993 | 1.004 |
| Major therapeutic procedures (%) | 1.007 | 0.003 | 1.002 | 1.012 | 1.009 | 0.118 | 0.998 | 1.021 | 1.002 | 0.676 | 0.994 | 1.010 |
| Nurse-to-patient ratio (log-transformed) | 0.406 | 0.001 | 0.239 | 0.691 | 0.692 | 0.221 | 0.383 | 1.249 | 0.628 | 0.045 | 0.399 | 0.990 |
| Physical space per bed (sqft; log-transformed) | 0.984 | 0.766 | 0.888 | 1.091 | 0.950 | 0.627 | 0.773 | 1.168 | 0.867 | 0.012 | 0.775 | 0.969 |
| Mean Elixhauser score | 1.076 | 0.003 | 1.024 | 1.129 | 1.053 | 0.091 | 0.992 | 1.117 | 0.867 | 0.001 | 0.799 | 0.941 |
| Occupancy rate (%) | 1.007 | 0.041 | 1.000 | 1.014 | 1.013 | 0.000 | 1.008 | 1.018 | 1.016 | 0.000 | 1.008 | 1.024 |
| Teaching facility | 1.001 | 0.993 | 0.794 | 1.262 | 1.541 | 0.001 | 1.203 | 1.974 | 0.862 | 0.365 | 0.626 | 1.188 |
| Rural location | 1.021 | 0.871 | 0.796 | 1.309 | 1.085 | 0.555 | 0.827 | 1.424 | 1.140 | 0.514 | 0.769 | 1.690 |
| Public ownership (ref: for-profit) | 1.117 | 0.333 | 0.893 | 1.397 | 1.302 | 0.082 | 0.967 | 1.751 | 2.707 | 0.000 | 1.764 | 4.155 |
| Not-for-profit ownership (ref: for-profit) | 1.113 | 0.213 | 0.940 | 1.317 | 1.220 | 0.024 | 1.027 | 1.449 | 1.291 | 0.054 | 0.996 | 1.674 |

Figure 3: Predictive margin of HA-MRSA infections regarding percent private rooms with 95% confidence intervals




**Discussions**

**Validation of HA-MRSA measure and model.**

It is important to verify that our measures are consistent with the current MRSA surveillance measure in the US, because a huge result discrepancy among MRSA studies is often caused by measure difference (CDC, 2014; Kavanagh, Abusalem, & Calderon, 2017; Klein, Sun, Smith, & Laxminarayan, 2013).

While various infections due to MRSA exist, the MRSA tracking system in the US adopts only bloodstream or invasive infection metrics detected by laboratory-based case finding (CDC, 2018b). Severe infections might be mostly captured by this definition. However, there are still significant number of MRSA-induced/associated infections which would not necessarily be reportable under the current tracking metrics (e.g., skin infections, pneumonia) (Kavanagh et

al., 2017). Recent studies report that such a narrow definition may cause potential and unintended bias. One interesting example is a contradiction between a Veterans Administration study reporting an 80% reduction in non-ICU MRSA infections during 2007-2015(Evans, Kralovic, Simbartl, Jain, & Roselle, 2017) and a Hospital Compare-based study that identified little change in the rate of MRSA bloodstream infections during 2010-2015(Kavanagh et al., 2017).

In addition to MRSA-event measure discrepancy, risk-adjusted MRSA measure is also different between the US surveillance relative to our methods. The Centers for Disease Control and Prevention (CDC) and the national Healthcare Safety Network (NHSN) use the standardized infection ratio (SIR) to compare HA-MRSA across hospitals (CDC, 2018b). They argue:

> "The SIR adjusts for various facility and/or patient-level factors that contribute to HAI risk within each facility."

How an SIR is generated is very similar with the calculation of an SMR[25]. HA-MRSA SIR is derived by dividing the count of observed HA-MRSA bloodstream events by the predicted count. In predicting HA-MRSA bloodstream infections, NBM is used with the following risk-adjustment factors: (1) inpatient community-onset prevalence rate, (2) outpatient community-onset prevalence rate, (3) average length of stay, (4) medical school affiliation, (5) facility type, and (6) number of ICU beds. Many of those variables are not available in our data (IP PUDF), which may cause a departure from the SIR predictions. We tested estimation consistency

[25] The standardized mortality ratio

between our model and the SIR, because the target audience of this thesis would be sensitive to the SIR predictions (i.e., Medicare/Medicaid reimbursement is adjusted by the SIR results).

We found that our HA-MRSA definition was correlated with the reported MRSA bacteremia events (i.e., Pearson correlation coefficient=0.78; $p<0.001$). Considering that our definition covers more HA-MRSA conditions (i.e., not restricted within bloodstream infections), this result seems to suggest a good level of consistency[26].

To test predictions between the two models, we developed a proxy measure of CMS MRSA measure.[27] After trying all the possible combinations among MRSA-related ICD-10-CM codes, we determined the weighted sums of A41.01 (MRSA septicemia) and A49.09 (MRSA bacterial infections) counts as the proxy of the reported MRSA bacteremia (i.e., Pearson correlation coefficient>0.9; $p<0.001$). Figure 4 indicates that this proxy measure tends to underestimate MRSA incidence. This may be explained in one or more of the following ways: (1) inherent difference in data collection process, (2) possible difference in coding for some bacteremia events (e.g., coded as "MRSA other"), and (3) inaccuracy of present-on-admission (POA) indicators. Admittedly, there is also a chance that hospitals may under-code or under-report HA-MRSA to avoid financial disadvantages.

[26] Note that this statement is rather a conjecture or speculation, because consistency between MRSA measures have never been defined and verified operationally. Interpretations of correlations largely differ relying on context.
[27] As discussed, there were no exactly matched single ICD-10-CM code to MRSA bloodstream bacteremia lab-identified event (i.e., MRSA measure used by the SIR).

By incorporating this proxy measure into our model, we obtained a strong correlation between the two models (Pearson correlation coefficient=0.79, $p<0.001$), as presented in Figure 5.

Figure 4: Observed HA-MRSA bacteremia from CMS and this thesis; Pearson correlation coefficient=0.919; p<0.001

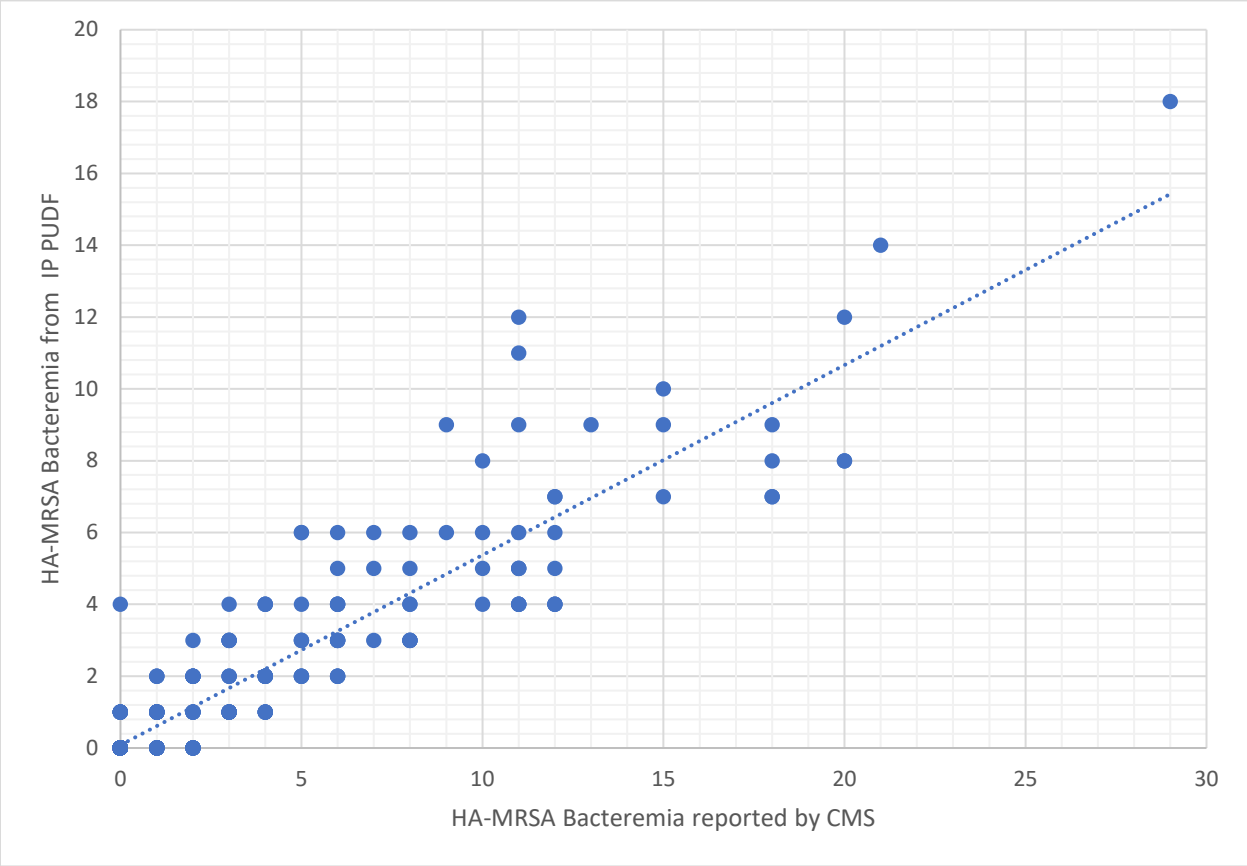
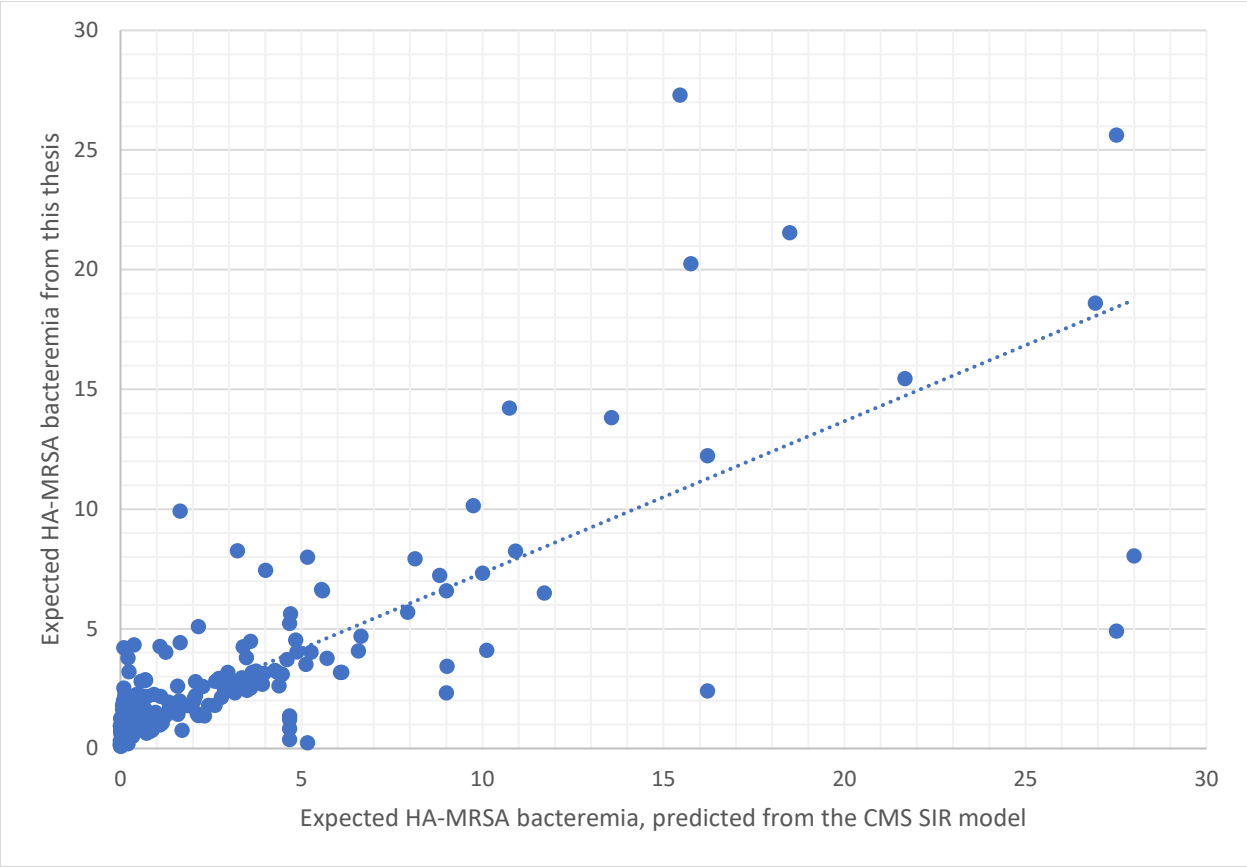


Figure 5: Expected HA-MRSA bacteremia from CMS and this thesis; Pearson correlation coefficient=0.791; p<0.001




**Interpretation of the findings.**

Our results are strong evidence that private rooms provide substantial protection from MRSA, and predict an 0.8% decrease of expected incidence for each 1% increase in PPR as a proportion of all rooms, with the average facility expected to enjoy an over 50% reduction in incidence should it transition from wholly non-PPR to fully PPR. It is worth noting that these effects are not linear. For instance, a 10% increase of private rooms (i.e., 10 times 1%) may not result in 8% of MRSA reductions (i.e., 10 times 0.8%).

Our findings are consistent with previous studies (Bracco et al., 2007; Levin et al., 2011; Teltsch et al., 2011), while our much more broad data sample counters the limited generalizability, constrained settings, and non-representative samples of these.

As shown in Table 8, the protective effect of private rooms is disproportionate across hospital groups. When a hospital reaches to a certain PPR percentage, the private-room effect is no longer significant. This discrepancy is better displayed in our plot of predictive margins[28], presented in Figure 5. The marginal change in HA-MRSA depends on how many private rooms currently exist in a hospital – the diminishing marginal rate of improvement.

Importantly, small changes of PPR may not suffice to induce significant improvements. All the adjacent confidence intervals largely overlap with each other (e.g., PPR=10% versus PPR=20%). However, larger changes in PPR percentages are significantly associated with HA-MRSA reductions (e.g., PPR=30% versus PPR=50%), which may hint at the need for large-scale construction or renovation projects to obtain a tangible benefit.

Overall, for an average hospital (i.e., all model parameters except PPR are at the mean of the study hospitals), HA-MRSA infections will be prevented by 54% if it goes for an all-PPR facility design, compared to zero-PPR design. This non-linear and diminishing marginal effect of private rooms can be explained by positive externality that we discussed in Chapter I. All the patients in a hospital with the higher percentage of private rooms may benefit from a safer environment, both directly and indirectly (Borg et al., 2008; Salge et al., 2017).

[28] Predictive margins track the effect of one parameter with fixed setting for the other regressors.

We also found that physical space in a hospital plays an important role in preventing MRSA infections. Interestingly, physical space was less distinct among hospital groups in our descriptive result: one-way ANOVA was insignificant potentially due to huge variance, although Group 3 (having the most private rooms) differed from Groups 1 and 2 ($p$=0.052 and 0.059 respectively). The effect became more evident after risk-adjustments. Our result indicates that unit marginal increase in log count[29] of a patient room space may result in approximately 6% reduction of HA-MRSA.

Space is indeed another core design parameter in healthcare facility design. Our finding is consistent with literature in justifying spacious private rooms for patients – particularly previous studies and reviews arguing that both workspace and patient space can contribute to reducing errors, falls, and infections (Huisman, Morales, van Hoof, & Kort, 2012; Lateef, 2009; Reiling, Hughes, & Murphy, 2008). The effect of space, as argued by literature, may be highly correlated with human error and cognitive functioning by design. Space-related issues were frequently reported by nurses as performance obstacles, including insufficient workspace for completing paperwork (Gurses & Carayon, 2007), the available space for medical equipment, and the available space for charting (Varni et al., 2004). It is also worth noting that nurse managers and unit directors have reported the benefit of private rooms as enhanced patient safety and reduced unnecessary transfers (Rashid, 2007).

[29] Due to the characteristic of log function, this means "2.7 times" (multiplicative increase).

Nevertheless, our result of physical space must be interpreted with caution as we found that the "space" factor affects MRSA-safety differently across hospital groups. As presented in Table 10, the effect of physical space is robust only for Group 3. This implies that return on better and larger patient space would be more meaningful only when germ transmissions from "roommates" barely occur (i.e., average patient in Group 3 hospitals). Another implication is that hospitals would better prioritize to secure enough number of private rooms before caring room space, to maximize facility efficiency.

**Management and policy implications.**

Evidence-based design for constructing new facilities or renovating existing ones is growing (Dettenkofer et al., 2004; Lenfestey et al., 2013). While private rooms are now considered as the minimum standard for newer hospitals, some legacy hospitals (e.g., rural hospitals, public hospitals, or safety-net hospitals) still contain many bay rooms. And patients who are forced to choose such hospitals for geographical or financial reasons must face a greater risk of HA-MRSA. Our results encourage such hospitals to proactively renovate their facilities and build safer environments, and suggest that the cost for such renovation may be offset by safety benefits and reimbursement gains obtained from HA-MRSA reductions.

From a policy perspective, this study may shed light on some neglected aspects in public reporting and surveillance. To be specific, the current thesis emphasizes the following two issues.

First, a MRSA surveillance measure should be expanded to cover a more comprehensive set of whole infections, as opposed to a narrowed definition of bloodstream infections. This is

consistent with unintended consequences alerted by recent studies (Kavanagh et al., 2017; Schuts et al., 2016; Winters et al., 2016). Our results support that expanding the MRSA definition does not necessarily lose surveillance consistency.[30]

Second, hospitals should publicly disclose how many private rooms they contain. We found that the number and percentage of private rooms were significantly associated with the risk of HA-MRSA. However, as of the time of this manuscript, it is impossible to easily access patient room information without complicated analyses as outlined in this thesis[31]. From a public health perspective, this might be a meaningful "opportunity cost" because a tangible improvement on patient decisions and informational transparency could have been achieved if a publicly available measure for patient rooms of each hospital existed.

**Limitations.**

This study has methodological and other limitations that may influence the practical applications of findings.

First, due to data limitations, we had to assess private room percentages of each hospital based on charge data. This is likely affected by room utilizations and/or occupancy. While this approach has its own validity (i.e., only count actually assigned rooms), future

[30] For example, the distinction between better performing hospitals and worse performing hospitals does not dramatically change as MRSA definitions expand.

[31] We could define a proxy measure for a patient room based on hospital charges. However, doing so required a significant amount of data processing, certain assumptions, and variable modeling – not suitable for general population.

research should verify the robustness of our conclusion if “real” figures of private room data are used.

Second, the cross-sectional nature of this study has inherent limits and our predicted improvement is better understood as a comparative result (i.e., hospital A versus hospital B), rather than an actual improvement within the same hospital (i.e., time-series study design may be needed for this verification).

Third, both private room effects and hospital-acquired infections involve complicated interactions among staffs, patients, and facilities and it is likely that the effect of hidden predictors and confounders is not fully controlled for in our analyses.

Finally, the majority of our focus is only one aspect of private rooms – the protective effect for preventing HA-MRSA. Yet there are many other potential benefits of private rooms, including patient privacy, reduced errors, increased nurse and patient satisfaction, etc. (Habib Chaudhury, Mahmood, & Valente, 2005, 2006; Huisman et al., 2012; Reiling et al., 2008) Future research should extend our analysis to include a broader and comprehensive scope of patient safety and satisfaction.

# CHAPTER IV

# EFFECT OF PRIVATE ROOMS ON HOSPITAL COSTS

## Background

## Overview

The goal of Chapter IV is to explore nosocomial staphylococcus aureus infections (Staph infections) and related conditions at the patient level, particularly focusing on the patient's perspective of a full pathway from private rooms to end healthcare outcomes. Specifically, this chapter aims to assess the following two domains: private room effects on the incidence and rate of hospital acquired staph infections and attributable healthcare outcomes.

### Private rooms to staph infections.

One of our core hypotheses is that private rooms may benefit patients directly and indirectly, where direct benefits are defined as the difference of benefit (e.g., better patient safety) between private (marked as "good" in this thesis) and bay (marked as "bad") rooms; indirect benefits are defined as the difference of benefit between "good" and "bad" hospitals[32], no matter where patients stay. We already recognized these two distinct benefits in our previous study regarding CLABSIs[33] (O'Neill et al., 2018) although these effects were assessed in separate models, leaving single-model integration as a further recommendation. Unfortunately,

[32] In this context, good hospitals are conceptualized as hospitals with a high percentage of private rooms while bad hospitals are those with high percentage of bay rooms. Operationally this concept is deeply linked to hospital Groups 1-3 defined in Chapter III.

[33] Central-Line Associated Blood Stream Infections

as of the date of this thesis, no study has specifically focused on the 'external[34]' effect of private rooms. We extended our previous CLABSI work, to develop an integrated statistical model to simultaneously evaluate internal and external effects and predict the risk of hospital acquired staph infections, including MRSA[35] and MSSA[36].

**Staph infections to healthcare outcomes.**

It is of interest to obtain representative and accurate assessments of the attributable impact of hospital acquired (HA) staph infections on healthcare outcomes. In the context of this thesis, such an assessment is required to examine cost as an end outcome attributable to predicted infections. As discussed earlier, previous findings regarding HA staph infection outcomes in the literature have been mixed, inconsistent, and non-generalizable (mostly conducted at 1 or 2 sites) (Chacko et al., 2017; Stone, Braccia, & Larson, 2005; Zimlichman et al., 2013). We believe many such limitations faced by extant outcome studies are effectively addressed or at least remedied with large and representative data and a bias-resistant statistical method such as an optimal matching algorithm. Thus, the second purpose of Chapter IV is to estimate and examine the attributable impacts of staph infections on three major healthcare outcomes – in-hospital death risk, inpatient length of stay, and hospital costs, enabling subsequent cost-benefit analysis without the need for patching incompatible results.

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[34] Throughout this thesis, we call systematic differences between private and bay rooms as "internal" effects and hospital-wide protective benefits as "external" effects.
[35] Methicillin-Resistant Staphylococcus Aureus
[36] Methicillin-Sensitive Staphylococcus Aureus

## Method

### Two-fold analyses.

The analyses detailed in Chapter IV are two-fold to obtain a comprehensive causal pathway from private rooms to patients' end outcomes – patient rooms to infections and infections to outcomes. We developed two separate models for each part of the process: (1) the first statistical model (Model 1) predicts the likelihoods of HA-MRSA and HA-MSSA for a given patient and room assignment; and (2) the second model (Model 2) estimates excess costs based on different staph infection states.

### Unit of analysis and model logic.

The unit of analysis in either model is the patient, largely due to the nature of our Models 1 and 2.

The analysis compares infection conditions across different patient levels and hospital levels to evaluate our hypothesis that private rooms may affect patient outcomes for those assigned to private rooms vs those not (internal effect) and/or outcomes for patients admitted to hospitals with many private rooms vs those not (external effect). Furthermore, our main outcome variables for Model 2 are defined and measured more clearly at the patient level. For example, in defining excess costs, at the patient level, the presence of staph infections and related conditions can be modeled as two-level discrete status (Staph present or not). Thus, an excess cost is estimated as the cost difference between case and compatible control (a similarly conditioned patient only differing in undiagnosed staph infections). This definition can be flexibly extended to multiple states (e.g., MSSA and MRSA) because the baseline (control) is

already defined as the absence of MSSA and MRSA infection (i.e., no staph infection). By contrast, infections at the hospital level are technically a continuous count variable as modeled in Chapter III. Defining excess costs in such context may introduce new ambiguities or arbitraries at least, leaving the individual patient as a more suitable unit of analysis for this study.

**Data.**

The Texas Inpatient Public Use Data File (IP PUDF) for the 2016 fiscal year (Texas Department of State Health Services, 2017) continued to serve as our primary data to obtain patient demographics and diagnoses. Hospital parameters like ownership or nurses were accessed via the American Hospital Association (AHA) annual survey (AHA, n.d.). See Chapter III for the validation of these data.

We used Medicare provider utilization and payment data to assess hospital costs. These include hospital-specific charges for the more than 3,000 US hospitals that receive Medicare Inpatient Prospective Payment System payments for discharges (CMS, 2017b). Such payments based on a rate per discharge adjusted for the Medicare Severity Diagnosis Related Group (MS-DRG) (CMS, n.d.-a; Hartmann et al., 2012). For these MS-DRGs, average charges, average total payments, and average Medicare payments are reported at the individual hospital level. We merged this data set with IP PUDF to define a proxy of hospital costs, as discussed in Chapter II.

**Variables.**

***Staph infection category (STAPH CAT).*** Extending our HA-MRSA definitions in the previous chapter, we define a new variable, staph infection category (STAPH CAT), to add

"finer" steps between No MRSA and HA-MRSA to achieve more meaningful details. STAPH CAT is defined as a 5-level cardinal categorical variable including the following states: (1) neither MSSA nor MRSA diagnosed (as the baseline; STAPH CAT=0), (2) MSSA present on admission (STAPH CAT=1), (3) MSSA acquired in the hospital (STAPH CAT=2), (4) MRSA present on admission (STAPH CAT=3), and (5) MRSA acquired in the hospital (STAPH CAT=4). This variable is operationally defined as the combination of ICD-10-CM MRSA/MSSA diagnosis codes, as presented in Table 3, and present-on-admission (POA) indicators. For example, if MRSA was diagnosed but not present on admission, we assigned "4" to STAPH CAT variable, meaning "MRSA acquired in the hospital".

It is worth mentioning that we used POA indicators to define whether a staph infection is not a nosocomial onset (i.e., an infection developed before being hospitalized). Reversely, if POA indicator is off (meaning not present on admission or NPOA), the diagnosed staph infections is developed after admission – this state is defined as "Hospital-acquired", which will further be split into either HA-MSSA or HA-MRSA. This POA variable is reported in IP PUDF data, and has gained acceptance from a wide variety of recent studies of HAIs and hospital adverse events in the literature to ensure that events of interest is occurred in hospitals (Coomer & Kandilov, 2016; Kawai et al., 2015; Miller, Polgreen, Cavanaugh, & Polgreen, 2015; Smith, Snyder, McMahon Jr, Petersen, & Meddings, 2018; Van Mourik, van Duijn, Moons, Bonten, & Lee, 2015).

Including this new STAPH CAT variable allows evaluation of useful but potentially easy to overlook conditions such as antibiotic resistance. For example, if confounding conditions are

carefully adjusted, MRSA-MSSA difference is associated with antibiotic resistance impact, as frequently argued by literature (Cosgrove et al., 2005; De Angelis et al., 2011b; R. J. Rubin et al., 1999). In addition, the place of infection acquisition may have important implications (e.g., MRSA POA versus HA-MRSA).

***Professional fee ratio.*** We used the concept and data of professional fee ratio (PFR) to examine how hospital costs are decomposed into facility-based and service-related components (Peterson, Xu, Florence, Grosse, & Annest, 2015). PFR is defined as the total cost of an admission as a function of the hospital facility cost for specific procedures and diagnoses. For example. PFR of 1.3 applies when a $130 of total cost contains both $30 of professional services (e.g., physician involved in care) and $100 of hospital facility cost. The cited study analyzed a retrospective cohort of 2004–2012 inpatient admissions and reported the estimates of PFR by various criteria, including major diagnostic category, diagnostic related group, clinical classification software, and ICD-9-CM diagnosis code (Peterson et al., 2015). We merged[37] this data with IP PUDF to assign PFR to each individual observation.

***Key dependent and independent variables.*** In Model 1, the presences of MSSA and MRSA acquired in hospitals (STAPH CAT=2 and 4 respectively) were considered as the two key dependent variables. Other category values (e.g., STAPH CAT=3 as MRSA present on admission) were excluded from consideration because they are less likely related to hospital structure and built environment. Patient-level room assignment (i.e., whether a patient stays in a private

[37] Because our data was coded with ICD-10-CM, we used MS-DRG as the merging variable.

room) and hospital-level private room percentages were considered as the key independent variables: the former was regarded as internal effect while the latter as external effect.

In Model 2, the three key dependent variables were considered, including inpatient length of stay (LOS), in-hospital death likelihood, and average Medicare payments (per patient and DRG). STAPH CAT was used as the key independent variable.

***Covariates.*** Medical burden and healthcare-access can vary. We sought to address shortcomings of administrative data and cross-sectional design and account for disproportionate conditions across patients (DiNardo, 2010; Harmon et al., 2000). Analyses 1 and 2 were both adjusted using patient age, race and ethnicity, admission sources, admission types, procedure classes, private room medically required, ICU stay, and 29 Elixhauser comorbidity conditions. We also adjusted hospital-level covariates as fixed effects by including rural location, teaching facility, major therapeutic procedures (Edelsberg et al., 2009; Panlilio et al., 1992; Wakefield et al., 1987), nurse-to-patient ratio (Afif et al., 2002; Hugonnet et al., 2006; Penoyer, 2010), uninsured and Medicaid patients[38], occupancy rates, and physical space per bed (O'Neill et al., 2018).

Our choice of risk adjusting covariates is consistent with validated risk-adjustment models of MRSA (Callejo-Torre et al., 2016) which confirmed significant and independent risk factors of MRSA include patient age, patient gender, severity of medical burden[39], previous

[38] as a proxy indicator of safety net hospitals (Kovner & Gergen, 1998; G. M. Lee et al., 2012)
[39] measured by Acute Physiology, Age, Chronic Health Evaluation III (APACHE III) score

antibiotic treatments, transferred patients, and local skin infections. Note that all these variables except skin infections and medical burden severity were controlled in our models. To properly adjust individual medical burden, we adjusted Elixhauser comorbidity conditions[40].

**Statistical analysis.**

***Analysis for Model 1 (Analysis 1).*** Descriptive statistics are presented to compare patient characteristics by individual private room assignments (private room assigned vs not) and by hospital groups. Hospital groups are identical with Groups 1-3 detailed in Chapter III: (1) Group 1 hospitals (900,340 patients from 113 facilities) contain fewer than 62% private patient rooms (PPRs) among all patient rooms; (2) Group 2 hospitals (1,154,687 patients from 114 facilities) contain 62%-82% PPRs; and (3) Group 3 hospitals (615,828 patients from 114 facilities) are those where more than 82% of patient rooms are PPRs. Patient characteristics compared in the descriptive analysis include race/ethnicity, gender, procedure classes, disease severity, and length of stay.

A multivariate statistical model to predict the risk of developing staph infections during hospitalizations were developed by utilizing logistic regressions. To minimize heteroskedastic bias, M-estimators were used to calculate confidence intervals (Huber, Lechner, & Wunsch, 2013). Any model predictors were considered as statistically significant if type-1 error is less probable than 5%.

[40] And for this reason, we could not include skin infections because of collinearity. Moreover, we believe Elixhauser conditions to serve an equivalent or even better control than APACHE III score – we could not test this because APACHE III was impossible to obtain in our IP PUDF database.

***Analysis for Model 2 (Analysis 2).*** Descriptive statistics were used to summarize patient characteristics of each Staph condition (STAPH CAT=1,2,3, and 4) and non-Staph controls (STAPH CAT=0). We then conducted the multivariate analysis using propensity-score matching (PSM) approaches to examine the attributable impacts of staph infections on healthcare outcomes of interest.

PSM was used in Analysis 2 because ordinary regressions are limited to handle critical statistical challenges usually observed in the context of hospital-acquired infections. These limitations are possibly caused by hidden variables, selection bias, and endogeneity. (A. G. Barnett et al., 2009; De Angelis et al., 2011b; Nelson, Samore, et al., 2015a) To allow enough flexibility for the analysis, we generated comparable cohort groups by matching the nearest neighbors to each patient in the HA-MRSA cohort (of the smallest size among all the conditions). For better matching accuracy, we applied caliper[41] of 0.2[42] to guarantee that matched patients did not largely differ from the target HA-MRSA patients.

Welch's t-tests (also known as unequal variance t-tests) were conducted over matched cohorts to get attributable outcomes and evaluate statistical significances. Generalized linear regression model with log-link was applied to matched samples (all cohorts combined) for multivariate analysis purposes. Note that all these tests and regressions were processed over the weighted samples with frequency weights derived by the matching software.

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[41] Caliper means the maximum tolerated difference as a function of standard deviation.
[42] This is from the conclusions of Austin (2011) based on intensive numerical simulations regarding various matching methods and their performances.

Analyses 1 and 2 were processed with Stata software, version 13.0. Propensity score matching in Analysis 2 was done with PSMATCH2 Stata add-on module revised in 2018 (originally released in 2003) (Leuven & Sianesi, 2018).

**Results**

**Analysis 1.**

Tables 11 and 12 present descriptive characteristics of 2,670,855 patients categorized by patient room assignment and by hospital Group. Multivariate analyses of individual and hospital-wide effects of private rooms predict both internal and external effects as well as possible interactions between these (Table 13). These include a respective 23% and 20% reduced risk to develop HA-MSSA and HA-MRSA for patient assigned a private room and similar risk reductions among patients using hospitals with higher proportions of private rooms. The protective external effects were maximized in Group 3 hospitals, showing a respective reduction of MSSA and MRSA risks by 27% and 32% from the baseline (Group 1). It is worth noting that all the internal, external, and interaction effects were statistically significant (all p-values less than 0.05). We estimate that combining all private rooms effects could drive a cumulative 38% and 52% risk reduction for HA-MSSA and HA-MRSA respectively.

Patient characteristics associated with higher risk of HA-MSSA include younger ages (β's < -0.56 for aged $18^{+}$ in comparison with the baseline of underaged group; p≤0.001), male gender (female β=-0.542; $p<0.001$), more procedures received (βranged from 0.126 to 0.277 depending on procedure classes, $p<0.001$), and ICU stay (β=1.332; $p<0.001$). Patient-level risk predictors of HA-MRSA may include the followings: non-Hispanic African American race

(β=0.105; *p*=0.002), urgent or emergency admission (β=0.033; *p*=0.027), transfer from other hospitals (β=0.039; *p*=0.012), more procedures received (βvaried from 0.156 to 0.275 depending on procedure classes, p≤0.024), and ICU stay (β=1.101; *p*<0.001) (Table 13).

Model 1 also indicates that the effects of comorbidity intensively varies. Predicting conditions for HA-MSSA include alcohol abuse (β=0.407; *p*<0.001), deficiency anemias (β=0.296; *p*<0.001), drug abuse (β=0.465; *p*<0.001), electrolyte disorders (β=1.006; *p*<0.001), neurological disorders (β=0.713; *p*=0.001), paralysis (β=0.673; *p*=0.001), and pulmonary circulation diseases (β=0.354; *p*=0.052). By comparison, more Elixhauser conditions were associated with higher risk of HA-MRSA, including the followings: deficiency anemias (β=0.327; *p*<0.001), rheumatoid arthritis (β=0.470; *p*=0.003), congestive heart failure (β=0.350; *p*<0.001), chronic pulmonary disease (β=0.334; *p*<0.001), drug abuse (β=0.545; *p*<0.001), liver disease (β=0.271; *p*=0.015), electrolyte disorders (β=0.636; *p*=0.001), neurological disorders (β=0.589; *p*<0.001), obesity (β=0.375; *p*<0.001), paralysis (β=0.725; *p*<0.001), pulmonary circulation disease (β=0.532; *p*=0.001), solid tumors (β=0.350; *p*=0.013), and weight loss (β=0.378; *p*<0.001).

Hospital-level risk predictors (as fixed[43] effects) were examined in Model 1. While some disparity between HA-MSSA and HA-MRSA were observed, it is worth noting that there are common consistent predictors for higher risk of HA-Staph infections: public hospitals (β's=0.648 and 0.300; *p*<0.001 and *p*=0.012), percentages of major therapeutic procedures relative to total procedures in hospitals (β's=0.027 and 0.021; p's<0.001 both), and percentages of uninsured

[43] These variables remain fixed among patients in the same hospital.

and Medicaid patients (β's=0.012 and 0.013; p's<0.001 both). Similarly, common protective predictors were identified as the followings: higher nurse-to-patient ratio (β's=-1.292 and -1.445; p's<0.001 both) and larger physical space per bed (β's=-0.032 and -0.021; *p*=0.048 and *p*<0.001).

Table 11: Patient characteristics by patient room assignment

| Variable | Bay rooms (*n*=1,373,633) | Private rooms (*n*=1,297,222) |
|---|---|---|
| Age category (col %) | | |
| Younger than 18 | 30.70% | 2.66% |
| 18-44 | 19.03% | 37.42% |
| 45-64 | 21.83% | 25.77% |
| 65-74 | 12.82% | 15.89% |
| 75 or more | 15.61% | 18.26% |
| Female gender (%) | 51.98% | 63.77% |
| Race and ethnicity (%) | | |
| NH White | 44.05% | 52.26% |
| NH Black | 12.93% | 12.81% |
| NH Asian | 2.38% | 2.07% |
| NH Other | 6.60% | 6.18% |
| Hispanic | 34.03% | 26.69% |
| Urgent or emergency admission (%) | 56.11% | 68.26% |
| Admission source (col %) | | |
| No transfer | 55.50% | 71.14% |
| Transfer from Clinics | 10.07% | 22.91% |
| Transfer from Hospitals | 4.31% | 3.71% |
| Transfer from SNF ICF ALF | 27.55% | 0.42% |
| Transfer from another HC facility | 1.25% | 0.86% |
| Other | 1.32% | 0.97% |
| Procedures by class (mean) | | |
| Minor Diagnostic | 0.364 | 0.305 |
| Minor Therapeutic | 0.783 | 0.786 |
| Major Diagnostic | 0.015 | 0.026 |
| Major Therapeutic | 0.363 | 0.673 |
| Private room medically required (%) | 0.79% | 1.95% |
| ICU stay during hospitalization (%) | 34.28% | 13.83% |

| | | |
|---|---|---|
| Elixhauser mortality score (mean, pts) | 2.93 | 3.12 |

Table 12: Patient characteristics by hospital group

| Variable | Group 1 hospitals (*n*=900,340) | Group 2 hospitals (*n*=1,154,687) | Group 3 hospitals (*n*=615,828) |
|---|---|---|---|
| Age category (col %) | | | |
| Younger than 18 | 19.79% | 18.83% | 9.85% |
| 18-44 | 30.40% | 29.13% | 22.22% |
| 45-64 | 22.91% | 21.92% | 28.39% |
| 65-74 | 12.33% | 13.67% | 18.41% |
| 75 or more | 14.56% | 16.46% | 21.12% |
| Female gender (%) | 57.60% | 59.50% | 54.60% |
| Race and ethnicity (%) | | | |
| NH White | 38.31% | 48.24% | 61.86% |
| NH Black | 12.25% | 13.42% | 12.76% |
| NH Asian | 2.20% | 2.74% | 17.43% |
| NH Other | 5.24% | 7.17% | 1.33% |
| Hispanic | 42.00% | 28.43% | 6.62% |
| Urgent or emergency admission (%) | 60.31% | 62.21% | 64.11% |
| Admission source (col %) | | | |
| No transfer | 62.10% | 62.64% | 65.42% |
| Transfer from Clinics | 15.03% | 15.62% | 19.44% |
| Transfer from Hospitals | 4.24% | 3.39% | 4.85% |
| Transfer from SNF ICF ALF | 15.63% | 16.90% | 7.81% |
| Transfer from another HC facility | 1.42% | 0.61% | 1.38% |
| Other | 1.59% | 0.83% | 1.10% |
| Procedures by class (col %) | | | |
| Minor Diagnostic | 0.320 | 0.313 | 0.399 |
| Minor Therapeutic | 0.749 | 0.832 | 0.748 |
| Major Diagnostic | 0.018 | 0.020 | 0.026 |
| Major Therapeutic | 0.748 | 0.026 | 0.614 |
| Private room medically required (%) | 0.90% | 1.94% | 0.92% |
| ICU stay during hospitalization (%) | 23.51% | 24.09% | 26.06% |
| Elixhauser mortality score (mean, pts) | 2.60 | 2.99 | 3.71 |

Table 13: Logit regression results regarding nosocomial MSSA and MRSA risks

| Variable | HA-MSSA infection | | | | HA-MRSA infection | | | |
|---|---|---|---|---|---|---|---|---|
| | Adj. OR Exp *β* | *p* | Lower *β* | Upper *β* | Adj. OR Exp *β* | *p* | Lower *β* | Upper *β* |
| PPR assigned "*Internal effect*" | 0.77 | 0.000 | -0.30 | -0.23 | 0.80 | 0.000 | -0.23 | -0.22 |
| Hospital PPR Category (ref: Group 1) "*External effect*" | | | | | | | | |
| Group 2 (61.6%-82.9%) | 0.75 | 0.008 | -0.49 | -0.08 | 0.76 | 0.010 | -0.48 | -0.06 |
| Group 3 (>82.9%) | 0.73 | 0.011 | -0.55 | -0.07 | 0.68 | 0.003 | -0.64 | -0.13 |
| Interaction between internal and external effects | | | | | | | | |
| PPR assigned at Group 2 hospitals | 1.11 | 0.039 | 0.01 | 0.21 | 0.85 | 0.000 | -0.24 | -0.09 |
| PPR assigned at Group 3 hospitals | 1.11 | 0.015 | 0.02 | 0.19 | 0.88 | 0.046 | -0.24 | 0.00 |
| Age category (ref: younger than 18) | | | | | | | | |
| 18-44 | 0.57 | 0.001 | -0.90 | -0.22 | 1.31 | 0.323 | -0.26 | 0.80 |
| 45-64 | 0.52 | 0.000 | -1.02 | -0.31 | 1.15 | 0.600 | -0.39 | 0.68 |
| 65-74 | 0.48 | 0.000 | -1.10 | -0.36 | 1.22 | 0.479 | -0.35 | 0.75 |
| 75 or more | 0.35 | 0.000 | -1.44 | -0.67 | 1.45 | 0.185 | -0.18 | 0.91 |
| Female gender | 0.58 | 0.000 | -0.69 | -0.40 | 0.70 | 0.000 | -0.49 | -0.21 |
| Race and ethnicity (ref: NH White) | | | | | | | | |
| NH Black | 0.81 | 0.030 | -0.41 | -0.02 | 1.11 | 0.002 | 0.04 | 0.17 |
| NH Asian | 0.88 | 0.621 | -0.61 | 0.37 | 0.72 | 0.257 | -0.89 | 0.24 |
| NH Other | 1.01 | 0.915 | -0.24 | 0.27 | 1.27 | 0.036 | 0.02 | 0.47 |
| Hispanic | 0.98 | 0.837 | -0.18 | 0.15 | 0.86 | 0.087 | -0.34 | 0.02 |
| Urgent or emergency admission | 0.98 | 0.812 | -0.22 | 0.17 | 1.03 | 0.027 | 0.00 | 0.06 |
| Admission source (ref: no transfer) | | | | | | | | |
| From Clinics | 0.74 | 0.016 | -0.54 | -0.06 | 0.93 | 0.553 | -0.30 | 0.16 |
| Transfer from hospitals | 0.89 | 0.298 | -0.35 | 0.11 | 1.04 | 0.012 | 0.01 | 0.07 |
| Transfer from SNF ICF ALF | 0.34 | 0.000 | -1.55 | -0.60 | 0.88 | 0.658 | -0.70 | 0.44 |
| Transfer from another HC facility | 1.20 | 0.400 | -0.24 | 0.60 | 0.62 | 0.127 | -1.10 | 0.14 |
| Other | 0.94 | 0.837 | -0.71 | 0.57 | 1.07 | 0.819 | -0.51 | 0.65 |
| Procedures (by class) | | | | | | | | |
| Minor Diagnostic | 1.22 | 0.000 | 0.18 | 0.22 | 1.18 | 0.000 | 0.14 | 0.19 |
| Minor Therapeutic | 1.32 | 0.000 | 0.26 | 0.29 | 1.32 | 0.000 | 0.26 | 0.29 |
| Major Diagnostic | 1.13 | 0.147 | -0.04 | 0.28 | 1.18 | 0.024 | 0.02 | 0.31 |
| Major Therapeutic | 1.13 | 0.000 | 0.10 | 0.15 | 1.17 | 0.000 | 0.14 | 0.18 |
| Elixhauser comorbidity condition | | | | | | | | |
| AIDS | 0.77 | 0.462 | -0.94 | 0.43 | 1.50 | 0.164 | -0.17 | 0.98 |
| Alcohol abuse | 1.50 | 0.000 | 0.19 | 0.63 | 1.03 | 0.811 | -0.24 | 0.31 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Deficiency Anemias | 1.35 | 0.000 | 0.15 | 0.44 | 1.39 | 0.000 | 0.18 | 0.47 |
| Rheumatoid arthritis/collagen vas | 1.19 | 0.351 | -0.19 | 0.53 | 1.60 | 0.003 | 0.16 | 0.78 |
| Chronic blood loss anemia | 0.65 | 0.073 | -0.90 | 0.04 | 0.91 | 0.637 | -0.51 | 0.31 |
| Congestive heart failure | 1.06 | 0.495 | -0.11 | 0.23 | 1.42 | 0.000 | 0.19 | 0.51 |
| Chronic pulmonary disease | 1.09 | 0.345 | -0.09 | 0.26 | 1.40 | 0.000 | 0.18 | 0.49 |
| Coagulopathy | 1.08 | 0.422 | -0.11 | 0.27 | 1.13 | 0.214 | -0.07 | 0.31 |
| Depression | 1.01 | 0.960 | -0.21 | 0.22 | 1.07 | 0.499 | -0.14 | 0.28 |
| Diabetes w/o chronic cc | 0.79 | 0.025 | -0.45 | -0.03 | 1.12 | 0.246 | -0.08 | 0.30 |
| Diabetes w/ chronic cc | 1.06 | 0.509 | -0.12 | 0.24 | 1.05 | 0.632 | -0.14 | 0.23 |
| Drug abuse | 1.59 | 0.000 | 0.20 | 0.73 | 1.72 | 0.000 | 0.25 | 0.84 |
| Hypertension | 1.10 | 0.256 | -0.07 | 0.26 | 0.98 | 0.772 | -0.19 | 0.14 |
| Hypothyroidism | 0.93 | 0.539 | -0.29 | 0.15 | 0.84 | 0.118 | -0.38 | 0.04 |
| Liver disease | 0.89 | 0.338 | -0.35 | 0.12 | 1.31 | 0.015 | 0.05 | 0.49 |
| Lymphoma | 1.32 | 0.256 | -0.20 | 0.76 | 1.00 | 0.991 | -0.55 | 0.55 |
| Fluid and electrolyte disorders | 2.73 | 0.000 | 0.85 | 1.17 | 1.89 | 0.000 | 0.48 | 0.79 |
| Metastatic cancer | 0.91 | 0.603 | -0.44 | 0.26 | 1.06 | 0.752 | -0.29 | 0.40 |
| Other neurological disorders | 2.04 | 0.000 | 0.56 | 0.87 | 1.80 | 0.000 | 0.43 | 0.75 |
| Obesity | 0.93 | 0.447 | -0.26 | 0.11 | 1.45 | 0.000 | 0.21 | 0.54 |
| Paralysis | 1.96 | 0.000 | 0.47 | 0.87 | 2.06 | 0.000 | 0.53 | 0.92 |
| Peripheral vascular disease | 0.79 | 0.046 | -0.47 | 0.00 | 1.11 | 0.333 | -0.10 | 0.31 |
| Psychoses | 0.88 | 0.426 | -0.46 | 0.19 | 1.27 | 0.121 | -0.06 | 0.54 |
| Pulmonary circulation disease | 1.42 | 0.052 | 0.00 | 0.71 | 1.70 | 0.001 | 0.21 | 0.86 |
| Renal failure | 1.00 | 0.986 | -0.19 | 0.19 | 1.00 | 0.983 | -0.18 | 0.18 |
| Solid tumor w/out metastasis | 0.79 | 0.199 | -0.58 | 0.12 | 1.42 | 0.013 | 0.07 | 0.63 |
| Peptic ulcer Disease x bleeding | 0.90 | 0.638 | -0.53 | 0.32 | 0.97 | 0.891 | -0.43 | 0.37 |
| Valvular disease | 1.13 | 0.364 | -0.14 | 0.37 | 0.88 | 0.327 | -0.39 | 0.13 |
| Weight loss | 1.17 | 0.103 | -0.03 | 0.34 | 1.46 | 0.000 | 0.20 | 0.56 |
| Hospital ownership (ref: for-profit) | | | | | | | | |
| Public hospitals | 1.91 | 0.000 | 0.42 | 0.88 | 1.35 | 0.012 | 0.07 | 0.53 |
| Non-profit hospitals | 1.33 | 0.001 | 0.12 | 0.45 | 1.12 | 0.182 | -0.05 | 0.28 |
| Rural location | 0.55 | 0.029 | -1.14 | -0.06 | 1.32 | 0.129 | -0.08 | 0.63 |
| Teaching facility | 1.06 | 0.525 | -0.11 | 0.22 | 1.05 | 0.000 | 0.04 | 0.05 |
| (log) Nurse-to-Patient ratio | 0.27 | 0.000 | -1.92 | -0.66 | 0.24 | 0.000 | -2.10 | -0.79 |
| Major therapeutic procedures (%) | 1.03 | 0.000 | 0.02 | 0.04 | 1.02 | 0.000 | 0.01 | 0.03 |
| Uninsured and Medicaid patients (%) | 1.01 | 0.000 | 0.01 | 0.02 | 1.01 | 0.000 | 0.01 | 0.02 |
| Occupancy rates (%) | 1.01 | 0.096 | 0.00 | 0.02 | 1.01 | 0.016 | 0.00 | 0.02 |
| (log) Average physical space per bed | 0.97 | 0.048 | -0.06 | 0.00 | 0.98 | 0.000 | -0.03 | -0.02 |

* McFadden's adjusted pseudo R2 = 0.179 (HA-MSSA) and 0.210 (HA-MRSA)

**Analysis 2.**

Analysis 2 examined how healthcare outcomes relate to and differ by staph infection types. Table 14 presents descriptive characteristics of patients (the same sample size as Analysis 1) categorized by staph infection type. Table 15 presents patient characteristics of matched cohorts. Our unadjusted results presented in Table 16 show that any kind of staph infections – regardless of methicillin-sensitivity and no matter whether they are acquired in hospitals – increased length of stay, in-hospital death risk, and Medicare payment. Both MSSA and MRSA were linked to more serious outcomes when those infections were developed during hospitalization. Compared to the baseline (no staph infection), HA-MSSA and HA-MRSA groups showed roughly four times higher payments ($33k and $39k respectively; baseline=$9.4k), 5 times longer stays (24.9 and 25.2 days respectively; baseline=5.1 days), and a 9 times higher in-hospital death rate (12.7% and 14.1% respectively; baseline=1.5%). It is worth noting that with any measure, the following inequalities hold consistently: (1) staph infections acquired in hospitals are associated with worse outcomes in comparison with those present on admissions; and (2) MRSA is associated with worse patient outcomes than MSSA.

After Staph cohorts are matched based on propensity scores, the differences in healthcare outcomes become smaller but still meaningful. Compared to Medicare payments at the baseline (no staph infections; Mean payment= $17,766; 95% CI= [$16,938, 18,635]), MRSA POA[44], HA-MSSA, and HA-MRSA caused excess costs by +$4.2k, +$6.6k, and +$12.1k

[44] Present on admission

respectively (all p's lower than 0.001). Similarly, staph infections increased inpatient length of stays by an additional 2-9 days: +1.8 days for MSSA POA, +2.0 days for MRSA POA, +8.6 days for HA-MSSA, and +8.9 days for HA-MRSA respectively (baseline = 9.2 days; all significant and $p<0.001$). Only HA-MSSA and MRSA significantly increased in-hospital death risk: +4.04%p for HA-MSSA ($p=0.002$) and +4.83%p for HA-MRSA ($p<0.001$).

Table 14: Patient characteristics by staph cohort (unmatched)

| Variable | No Staph | POA-MSSA | HA-MSSA | POA-MRSA | HA-MRSA |
|---|---|---|---|---|---|
| Age category (col %) | | | | | |
| Younger than 18 | 16.49 | 3.20 | 8.16 | 2.68 | 4.48 |
| 18-44 | 27.66 | 23.74 | 23.19 | 22.3 | 17.47 |
| 45-64 | 23.42 | 32.08 | 37.76 | 36.9 | 33.38 |
| 65-74 | 14.58 | 16.01 | 18.15 | 18.37 | 20.63 |
| 75 or more | 17.86 | 13.97 | 12.74 | 19.75 | 24.03 |
| Female gender (%) | 58.30 | 37.24 | 34.01 | 42.62 | 39.56 |
| Race and ethnicity (col %) | | | | | |
| NH White | 47.81 | 51.35 | 47.98 | 55.09 | 50.7 |
| NH Black | 13.3 | 11.62 | 14.57 | 13.33 | 17.23 |
| NH Asian | 30.05 | 30.77 | 29.37 | 26.01 | 24.19 |
| NH Other | 2.36 | 1.11 | 1.75 | 0.97 | 1.16 |
| Hispanic | 6.47 | 5.15 | 6.33 | 4.6 | 6.72 |
| Urgent or emergency admission (%) | 62.73 | 85.7 | 77.87 | 85.43 | 78.05 |
| Admission source (col %) | | | | | |
| No transfer | 62.27 | 78.06 | 72.01 | 78.54 | 70.87 |
| Transfer from Clinics | 16.24 | 11.79 | 9.38 | 10.89 | 11.28 |
| Transfer from Hospitals | 4.14 | 6.80 | 10.37 | 6.65 | 10.24 |
| Transfer from SNF ICF ALF | 14.02 | 0.61 | 4.27 | 1.25 | 3.79 |
| Transfer from another HC facility | 1.09 | 1.65 | 2.75 | 1.61 | 1.62 |
| Other | 1.23 | 1.09 | 1.22 | 1.07 | 2.16 |
| Procedures by class (mean count) | | | | | |
| Minor Diagnostic | 0.352 | 0.582 | 1.844 | 0.536 | 1.625 |
| Minor Therapeutic | 0.815 | 1.346 | 4.028 | 1.33 | 3.776 |
| Major Diagnostic | 0.021 | 0.043 | 0.087 | 0.04 | 0.085 |
| Major Therapeutic | 0.526 | 0.909 | 1.586 | 0.771 | 1.631 |

| | | | | | |
|---|---|---|---|---|---|
| Private room medically required (%) | 1.41 | 1.77 | 1.75 | 2.09 | 2.39 |
| ICU stay during hospitalization (%) | 25.44 | 33.17 | 75.51 | 34.02 | 72.64 |
| Elixhauser mortality score (mean pts) | 3.30 | 5.45 | 11.41 | 5.75 | 11.76 |

Table 15: Patient characteristics by staph cohort (matched)

| Variable | No Staph | POA-MSSA | HA-MSSA | POA-MRSA | HA-MRSA |
|---|---|---|---|---|---|
| Age category (col %) | | | | | |
| Younger than 18 | 3.21 | 3.36 | 6.22 | 3.21 | 3.26 |
| 18-44 | 13.60 | 15.64 | 22.15 | 16.59 | 17.34 |
| 45-64 | 34.32 | 36.47 | 33.99 | 32.63 | 34.33 |
| 65-74 | 23.61 | 20.63 | 19.58 | 22.00 | 20.69 |
| 75 or more | 25.25 | 23.90 | 18.06 | 25.57 | 24.38 |
| Female gender (%) | 37.06 | 40.3 | 38.69 | 39.13 | 39.78 |
| Race and ethnicity (col %) | | | | | |
| NH White | 52.78 | 52.98 | 50.53 | 51.42 | 52.11 |
| NH Black | 15.48 | 16.31 | 17.00 | 18.79 | 16.37 |
| NH Asian | 22.67 | 23.61 | 25.80 | 22.00 | 23.94 |
| NH Other | 1.17 | 0.86 | 1.06 | 1.56 | 1.06 |
| Hispanic | 7.90 | 6.24 | 5.61 | 6.23 | 6.51 |
| Urgent or emergency admission (%) | 80.29 | 79.17 | 76.32 | 79.56 | 79.57 |
| Admission source (col %) | | | | | |
| No transfer | 73.03 | 70.06 | 71.32 | 70.21 | 72.1 |
| Transfer from Clinics | 8.84 | 12.09 | 10.93 | 11.55 | 11.36 |
| Transfer from Hospitals | 11.49 | 9.88 | 9.41 | 10.82 | 10.04 |
| Transfer from SNF ICF ALF | 2.74 | 2.88 | 4.70 | 3.67 | 2.73 |
| Transfer from another HC facility | 1.49 | 2.02 | 1.37 | 1.92 | 1.58 |
| Other | 2.42 | 3.07 | 2.28 | 1.83 | 2.2 |
| Procedures by class (mean) | | | | | |
| Minor Diagnostic | 1.462 | 1.37 | 1.766 | 1.4 | 1.427 |
| Minor Therapeutic | 3.271 | 3.153 | 3.887 | 3.144 | 3.384 |
| Major Diagnostic | 0.087 | 0.074 | 0.068 | 0.069 | 0.084 |
| Major Therapeutic | 1.524 | 1.543 | 1.65 | 1.426 | 1.505 |
| Private room medically required (%) | 1.87 | 1.72 | 1.36 | 1.46 | 2.55 |
| ICU stay during hospitalization (%) | 61.76 | 53.93 | 74.5 | 55.36 | 71.91 |
| Elixhauser mortality score (mean, pts) | 12.65 | 11.35 | 11.33 | 12.08 | 11.21 |

Table 16: Mean healthcare outcomes by staph cohort (unmatched results)

| Staph cohort | Charges (USD) | | | Medicare payment (USD) | | | LOS (day) | Mortality |
|---|---|---|---|---|---|---|---|---|
| | Total | Facility | Professional | Total | Facility | Professional | | |
| No Staph | 55,803 | 46,314 | 9,489 | 9,416 | 7,815 | 1,601 | 5.1 | 1.50% |
| MSSA POA | 96,595 | 84,044 | 12,551 | 15,269 | 13,285 | 1,984 | 9.3 | 3.23% |
| HA-MSSA | 374,621 | 325,844 | 48,777 | 32,623 | 28,375 | 4,248 | 24.9 | 12.70% |
| MRSA POA | 99,976 | 87,267 | 12,709 | 15,140 | 13,215 | 1,925 | 9.5 | 3.70% |
| HA-MRSA | 431,752 | 375,422 | 56,330 | 38,972 | 33,887 | 5,085 | 25.2 | 14.10% |

Table 17: Adjusted (matched) results of hospital cost and relative differences by staph cohort

| Staph cohort | Adjusted cost (USD) | | | Relative to C1 | | Relative to C5 | |
|---|---|---|---|---|---|---|---|
| | Mean | Lower | Upper | Delta | *p* | Delta | *p* |
| No Staph (C1) | 20,058 | 19,123 | 21,039 | | | 13,612.91 | 0.000 |
| POA-MSSA (C2) | 21,255 | 20,278 | 22,279 | 1,196.72 | 0.094 | 12,416.20 | 0.000 |
| HA-MSSA (C3) | 27,547 | 26,213 | 28,950 | 7,489.11 | 0.000 | 6,123.80 | 0.000 |
| POA-MRSA (C4) | 24,780 | 23,705 | 25,904 | 4,721.89 | 0.000 | 8,891.02 | 0.000 |
| HA-MRSA (C5) | 33,671 | 31,409 | 36,096 | 13,612.91 | 0.000 | | |

Table 18: Adjusted (matched) results of inpatient length of stay and relative differences by staph cohort

| Staph cohort | Adjusted LOS (day) | | | Relative to C1 | | Relative to C5 | |
|---|---|---|---|---|---|---|---|
| | Mean | Lower | Upper | Delta | *p* | Delta | *p* |
| No Staph (C1) | 9.2 | 7.2 | 11.2 | | | 8.9 | 0.000 |
| POA-MSSA (C2) | 11.0 | 9.0 | 13.0 | 1.8 | 0.000 | 7.2 | 0.000 |
| HA-MSSA (C3) | 17.7 | 15.7 | 19.8 | 8.6 | 0.000 | 0.4 | 0.520 |
| POA-MRSA (C4) | 11.2 | 9.2 | 13.2 | 2.0 | 0.000 | 6.9 | 0.000 |
| HA-MRSA (C5) | 18.1 | 16.1 | 20.1 | 8.9 | 0.000 | | |

Table 19: Adjusted (matched) results of mortality risk and relative differences by staph cohort

| Staph cohort | Adjusted Mortality (%) | | | Relative to C1 | | Relative to C5 | |
|---|---|---|---|---|---|---|---|
| | Mean | Lower | Upper | Delta | *p* | Delta | *p* |
| No Staph (C1) | 9.5% | 7.8% | 11.1% | | | 4.83% | 0.000 |
| POA-MSSA (C2) | 10.0% | 8.2% | 11.8% | 0.52% | 0.676 | 4.31% | 0.002 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| HA-MSSA (C3) | 13.5% | 11.5% | 15.5% | 4.04% | 0.002 | 0.79% | 0.582 |
| POA-MRSA (C4) | 10.2% | 8.4% | 12.0% | 0.71% | 0.566 | 4.12% | 0.003 |
| HA-MRSA (C5) | 14.3% | 12.3% | 16.3% | 4.83% | 0.000 | | |

Table 20: Matched regression results for adjusted hospital costs

| Variable | β | Exp (β) | *p* | Lower | Upper |
|---|---|---|---|---|---|
| Staph infection category (ref: No Staph) | | | | | |
| POA-MSSA | -0.101 | 0.904 | 0.037 | -0.196 | -0.006 |
| HA-MSSA | 0.176 | 1.192 | 0.000 | 0.082 | 0.270 |
| POA-MRSA | -0.020 | 0.980 | 0.690 | -0.119 | 0.079 |
| HA-MRSA | 0.280 | 1.323 | 0.000 | 0.171 | 0.388 |
| Hospital ownership (ref: For-profit hospitals) | | | | | |
| Public hospitals | 0.119 | 1.126 | 0.048 | 0.001 | 0.237 |
| Not-for-profit hospitals | 0.075 | 1.078 | 0.062 | -0.004 | 0.154 |
| Rural location | -0.370 | 0.691 | 0.000 | -0.513 | -0.226 |
| Teaching facility | 0.156 | 1.169 | 0.000 | 0.079 | 0.232 |
| (log) Nurse-to-patient ratio | -0.454 | 0.635 | 0.005 | -0.773 | -0.135 |
| Major therapeutic procedures (%) | 0.020 | 1.021 | 0.000 | 0.015 | 0.026 |
| Medicaid + Uninsured (%) | 0.000 | 1.000 | 0.665 | -0.002 | 0.003 |

* McFadden's adjusted pseudo R2 = 0.191

**Discussion**

**Externality of private rooms.**

Our findings from Model 1 supports our key aim to identify indirect benefits, or "positive externalities" driven by private rooms' protections against cross-transmission of staph infection.

Our results revealed that more private rooms in hospitals could reduce the risk of HA-MSSA and MRSA infections by up to 34%. Note that this external effect worked separately from the

benefit due to private room assignment (i.e., "internal" effect), which contributed to reduce infection risks by 20-23%. Figure 6 summarizes how infection risks can vary across patients with 6 different situations (combinations between two room types and three different hospital groups).

Our Model 1, specifically regarding internal effects, is in line with previous findings regarding general benefits of private rooms regarding HAI-safety in the literature such as higher hand hygiene compliance (Borg et al., 2008; Salge et al., 2017), superior aerial control (King et al., 2015), better staff communication (Bartley & Streifel, 2010), and lower nursing loads (Borg, 2003; Dancer et al., 2006). Our results are also consistent with a private room's impact on MRSA reductions empirically assessed by the most-cited previous studies (Bracco et al., 2007; Levin et al., 2011; Teltsch et al., 2011)[45] while countering generalizability concerns and other common limitations using richer data samples of IP PUDF. Although our findings from Model 1 should be further validated[46], we strongly believe that they could add the missing piece of hospital-wide private room effects ("externality") to the literature.

Similar to our observations in prior study of CLABSIs[47], interaction between the internal and external effects seem to exist (O'Neill et al., 2018). When there are all or zero private rooms, the likelihood of a patient to be assigned a private room is also 100% or 0% without any

[45] Our results are generally smaller than these studies, largely because (1) we decomposed private room effects into internal and external aspects, and (2) the mentioned studies examined ICU while ours focused on acute beds.
[46] Current literature cannot do this because, to best our knowledge, no previous study examined hospital-wide private room effects distinctly.
[47] Central-Line Associated Blood Stream Infections

ambiguity. However, if private and bay rooms are mixed, say 50-50, how to assign patients to each room type depends on clinical or operational decisions from hospital staffs (physicians and nurses), which results in higher freedom of degree. While efficient hospital bed allocation has been discussed in the literature (Dumas, 1984; He, Madathil, Oberoi, Servis, & Khasawneh, 2019; Mackay & Millard, 1999; Schmidt, Geisler, & Spreckelsen, 2013), hospitals seem to handle limited resources inconsistently, which means that a similarly-conditioned patient can be assigned to a private room in one hospital while the patient should stay in a bay room in another similar hospital. To summarize, our results of significant interactions in Model 1 clearly indicate that there exists an inter-dependence between the both effects to a certain extent. However, readers should also be cautious in that such dependence may reflect hidden or unmeasurable causal factors. Without knowing each hospital's room/bed assignment rule, it may be difficult to differentiate multiple underlying mechanisms behind such dependence and non-linearity. Future studies should verify them with a more detailed data set.

As hypothesized, we found that patients assigned to bay rooms can reduce their MRSA risk by going to better hospitals (i.e., Group X to Y when Y>X) (Figure 7). It is worth noting that marginal reductions with regard to moving to higher-tiered groups indicate two noticeable remarks: (1) risk reduction for bay-room patients is higher when they move to Group 2 from Group 3 than to Group 1 from Group 2, which is largely because safety benefits of hospitals would follow the diminishing marginal rate of return regarding private room percentage, and (2) bay-room patients can enjoy even more benefit than private-room patients when they move to Group 3 hospitals (12% of risk reduction for bay-room patients vs 9% for private-room

patients; $p<0.001$). The latter point is due to interactions between internal and external effects of private rooms and is also consistent with our analogy of "herd-immunity" using infectious disease in a vaccinated society as discussed in Chapter I. We strongly believe that HA-MRSA risk of bay-room patients asymptotically converge to the same level of MRSA risk of private-room patients, though this may need to be verified by time-series analyses with multi-year data set.

Figure 6: HA-Staph risk comparison across different combinations between hospital groups and room assignments (normalized: 100% as the most dangerous combination)

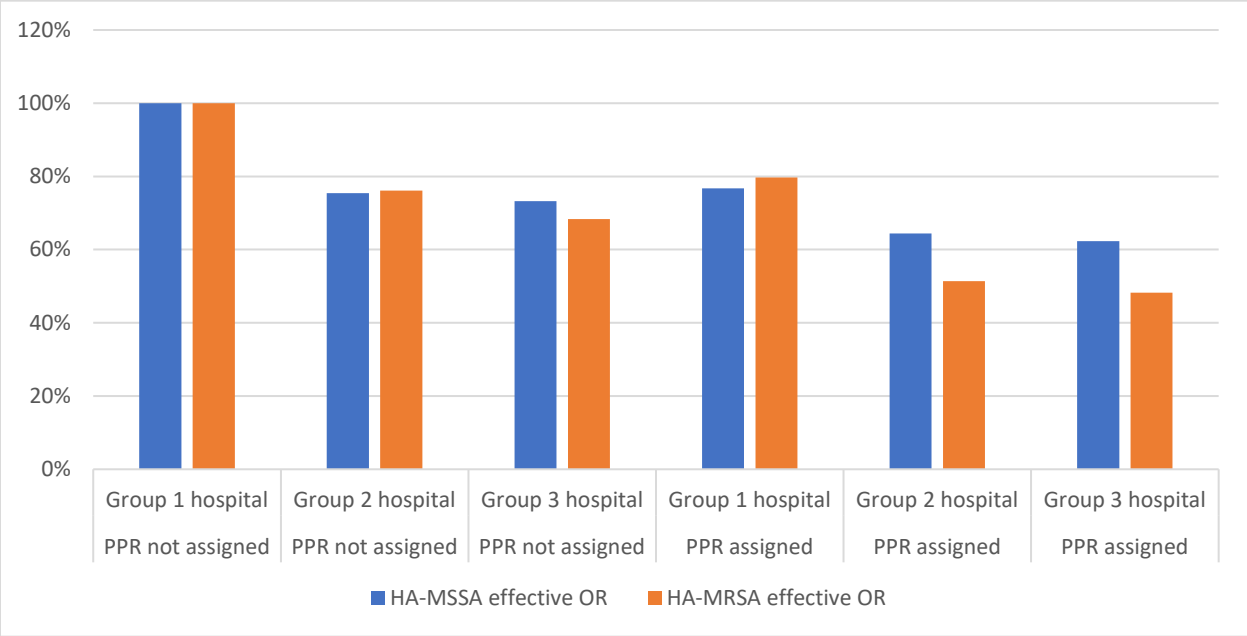
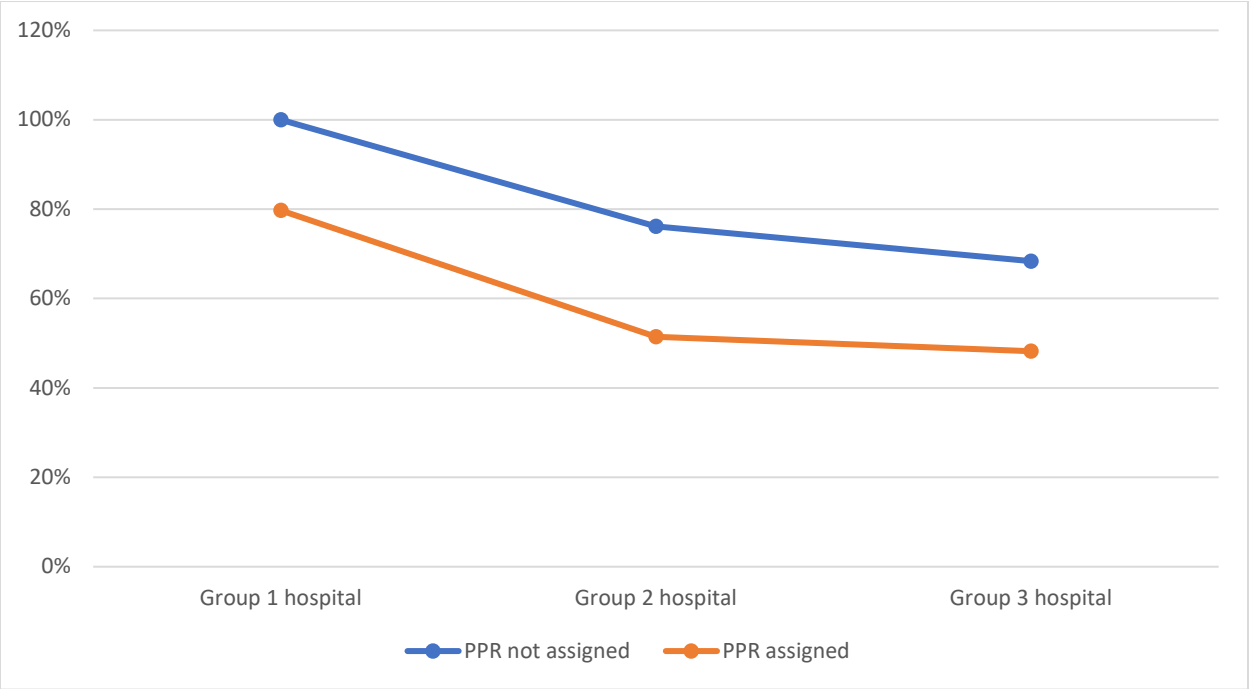


Figure 7: HA-MRSA risk comparison between PPR assigned and not with regard to hospital groups (normalized)




**Cost and outcome impacts.**

As discussed earlier, we believe charges might be inappropriate cost measure for HAIs, mainly due to huge within- and between- hospital variances in the US healthcare system. This is empirically verified by our data. For all Texas inpatients in the fiscal year 2016, patient charges exceed average Medicare payments by more than 300% at the median (i.e., charges being 4 times Medicare payments) and 1200% at the 95th percentile. For the matched samples, the variance gets much larger: charges being 7 times larger than Medicare payments at the median and 28 times at the 95th percentile. Our validation is consistent with the recent finding that the charges of the top 50 hospitals are about 10 times higher than their Medicare-allowable costs (Bai & Anderson, 2015).

To get more practical estimates of hospital costs, our measure of Medicare payments should be properly adjusted to give a more realistic estimate of actual costs, which Medicare payments largely fall short of in most hospitals. According to a recent survey (American Hospital Association, n.d.-b), the Medicare payment rate represents approximately 89% of a hospital's actual costs. Equivalently, average hospital costs are 1.13 times (inverse of 89%) higher than average Medicare payments. Thus, hospital costs can be assessed if the multiplier of 1.13 is applied to our regression predictions of Medicare payments. Using this approach, staph infections add an attributable cost per case of $1,197 for MSSA POA ($p$=0.094; not statistically significant), $4,721 for MRSA POA ($p$<0.001), $7,489 for HA-MSSA ($p$<0.001), and $13,612 for HA-MRSA ($p$<0.001) (Figure 8). Our estimates are generally smaller than previous cost findings from US studies (Cosgrove et al., 2005; S. P. Kim et al., 2012; Nelson, Samore, et al., 2015a; R. J. Rubin et al., 1999). However, with serious challenges of methodological differences (e.g., matched versus not), smaller sample sizes (including single-site studies), and problematic costing measures (i.e., patient charges being used by all the cited studies), directly comparing our results with cost literature may introduce another bias.

Defining various categories in staph infections could reveal impacts attributable to antibiotic resistance as well as nosocomial onset. We found that the most meaningful burdens of antibiotic resistance are cost-related relative to other outcomes measured such as LOS and in-hospital mortality. Antibiotic resistance increased hospital cost an average of 18% above baseline per patient (equivalent to +$3,500) when infections were not nosocomial (not statistically significant; $p$=0.226), and 31% (equivalent to +$6,100) for hospital-acquired

infections ($p$=0.015). This discrepancy between nosocomial and non-nosocomial cases may not be surprising because antibiotic resistance developed by Staph bacteria has been known to cause more problems in hospital settings due to various reasons including intensive uses of antibiotics (Ducel et al., 2002; Lin et al., 2015; Ventola, 2015). However, our analysis could not verify antibiotic resistance impact on LOS and in-hospital deaths (p-values all exceeding 0.5). It is possible that the statistical insignificancy might be a result of our use of ICD-10-CM to identify drug resistance. ICD-9-CM, the previous version of ICD, has been criticized for its low accuracy in detecting drug-resistant infections (Burnham, Kwon, Babcock, Olsen, & Kollef, 2017; Thorpe, Joski, & Johnston, 2018): there are approximately 8 or more undiagnosed antibiotic-resistant infections for every one identified via ICD-9-CM codes (Burnham et al., 2017). While ICD-10-CM may outperform the legacy coding system in many aspects, accuracy and validity for identifying antibiotic resistance remains unverified to date. Inherent limitations of IP PUDF data, including ICD codes that could mis-identify antibiotic-resistant infections as antibiotic-treatable ones, have the potential to allow underestimates of resistance-attributable effects.

Compared with antibiotic-resistance, nosocomial onset of staph infections showed more dramatic differences with important implications for healthcare priority setting. Nosocomial MRSA increased patients' hospital costs by 29% (equivalent to +$8,900; $p$<0.001), inpatient stays by 19% (equivalent to +6.9 days; $p$<0.001), and in-hospital death risk by +3.6%p (in absolute difference; $p$=0.022). Nosocomial MSSA also resulted in +$6,300 in costs ($p$<0.001), +6.8 days in LOS ($p$<0.001), and +3.1%p in death risk ($p$=0.030). While reducing HAIs and lowering inappropriate antibiotic uses in hospitals are both important, analytical limitations for

the former is a challenge to reliable comparison. On the other hand, our findings around the protections private patient rooms allows against HAIs are robust and substantial, and provide strong support for healthcare agencies, policy makers, and others to prioritize investments in the built environment.

To our knowledge, this thesis study is the first examination of how hospital costs could be decomposed into facility-based and service-related aspects. Figure 9 presents the result of decomposition after applying PFRs for each corresponding MS-DRG in our 5 Staph cohorts. Mean PFRs range from 1.134 (MRSA POA) to 1.158 (No staph infections), with statistically significant distinction between each category (Welch's t-test p-values lower than 0.05). It is worth noting that costs due to staph infections are dominated by facility-based elements rather than professional services (87-88% of total costs). This may imply that Staph patients need more hardware resources such as better patient rooms, longer room stays, and/or costlier diagnostic/therapeutic technologies (Grundmann et al., 2006). Note that our results of longer adjusted[48] LOS may partly demonstrate that staph infections increase LOS by +2-9 days compared to the baseline.

[48] Adjustments done via matching

Figure 8: Mean costs and confidence intervals by staph infection cohort

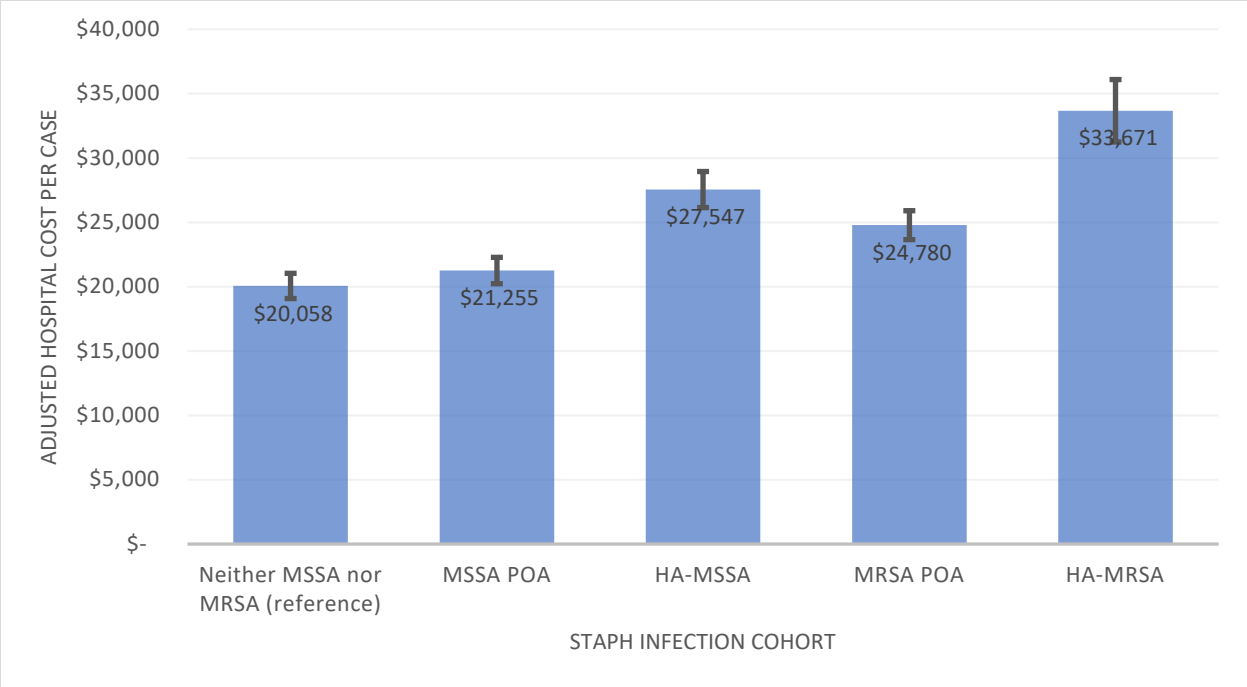
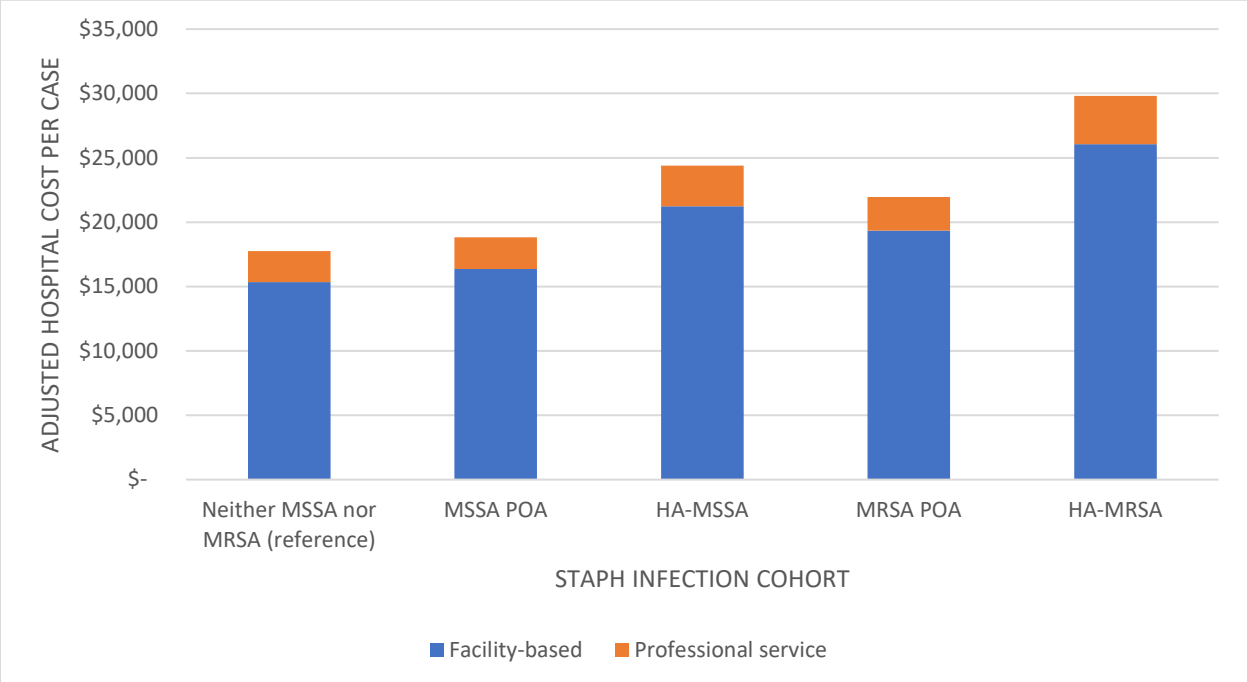



Figure 9: Decomposed mean costs by staph infection cohort



**Antibiotic resistance in staph infections.**

While our results indicate that the impact of antibiotic resistance in staph infections is not substantial at least in the short run, we believe that this issue should not be overlooked, as such resistance may cause long term critical effects on patients (Ventola, 2015). Our data show that, in Texas, resistance-gained staph infections already exceed half of the diagnosed cases. Considering concurrent overuses of antibiotics in US hospitals (CDC, 2017; Ventola, 2015), the time trend is expected to keep increasing.

Interestingly, with the aid of newly defined STAPH CAT variable in this study, we could analyze patient-level risk factors or predictors of MRSA in comparison with MSSA, from both general and nosocomial infections' perspective. Our unadjusted analyses indicate that the risk of antibiotic resistance, as measured by the ratio of MRSA to MSSA, significantly (Chi-square test P-value lower than 0.05) differ across different groups characterized as the followings: (1) Those aged 75 or more had 90% higher chance of antibiotic resistance of staph infections, compared to underaged group; (2) females showed 30% higher risk of antibiotic resistance than males; (3) African-American races and White races (both non-Hispanic origins) race and ethnicity presented 39% or 30% respective higher risk of resistance than Hispanic origins; and (4) patients transferred from skilled nursing facilities showed the most drastic level of resistance (MRSA incidence more than doubled MSSA incidence), hugely differed from patients referred from clinics (90% higher risk). Admission types and ICU experiences did not significantly affect this risk. Even after restricting within nosocomial infections, the categories of age, gender, race and ethnicity were significantly associated with the antibiotic resistance. Note

that, for general inpatients, MRSA incidence is 30% higher than MSSA, and for nosocomial staph infections, MRSA incidence was very close to MSSA incidence.

As presented in Table 21, our multivariate results adjusted for comorbidity conditions detailed and reiterated our unadjusted results. The risk of antibiotic resistance was significantly higher in the following groups: aged 75 or more (63% higher risk than the underaged), African-American (9% higher risk than White and 22% higher risk than Hispanics), female (17% higher risk than male), and transfers from skilled nursing facilities (38% higher risk than no transfer and 46% higher risk than clinic referrals). There can be various explanations of such discrepancy. For example, female was more associated with antibiotic resistance than male possibly because for some woman-specific infections, there may be higher chance of receiving antibiotic treatments. A study from the CDC[49] found that about 4 in 10 women with urinary tract infections during early pregnancy filled a prescription for antibiotics (nitrofurantoin or trimethoprim-sulfamethoxazole) (Ailes, 2018). Also, the fact that transferred from skilled nursing facility, intermediate care facility, or assistant livings were associated significantly higher risk of antibiotic resistance is in line with recent examinations. CDC recently identified the most common prescribing problems in nursing homes as using antibiotics in inappropriate ways (used when not needed, wrong drugs chosen, and/or wrong dose or duration) (CDC, 2017). CDC's medical examinations confirmed the followings (CDC, 2015): (1) 11 percent of nursing home residents were on antibiotics on any single day; (2) every three antibiotic

[49] Centers for Disease Control and Prevention

prescription was for the treatment of urinary tract infections; at least half of these prescriptions were for either the wrong drug, dose, or duration; and (3) 38 percent of orders for antibiotics lacked documentation of one or more important prescribing elements.

Our results were also consistent with three conditions that are inherently less risky than other comorbidity conditions: alcohol abuse, fluid and electrolyte disorders, and valvular diseases. First, most antibiotic medications are packaged with a warning to avoid alcohol during treatments for various reasons (i.e., heavy drinking may impair immune system function) (National Institute on Alcohol Abuse and Alcoholism, 2014; Weathermon & Crabb, 1999). Second, current practice guideline generally does not recommend using antibiotics for valve-related conditions such as mitral valve prolapse (Nishimura et al., 2008). Third, use of antibiotics is often limited by associated renal toxic effects (e.g., decreased glomerular filtration rate), which may reduce antibiotic uses for fluid and electrolyte disorders (Pazhayattil & Shirali, 2014).

Table 21: Logit regression results for MRSA presence among staph infections and nosocomial staph infections

| Variable | MRSA relative to staph infection | | | | MRSA relative to HA-staph infection | | | |
|---|---|---|---|---|---|---|---|---|
| | Adj. OR | *p* | Lower | Upper | Adj. OR | *p* | Lower | Upper |
| Age category (ref: younger than 18) | | | | | | | | |
| 18-44 | 1.16 | 0.016 | 1.03 | 1.32 | 1.22 | 0.314 | 0.83 | 1.81 |
| 45-64 | 1.07 | 0.258 | 0.95 | 1.22 | 1.29 | 0.207 | 0.87 | 1.93 |
| 65-74 | 1.35 | 0.000 | 1.18 | 1.54 | 1.56 | 0.039 | 1.02 | 2.39 |
| 75 or more | 1.63 | 0.000 | 1.43 | 1.86 | 2.91 | 0.000 | 1.88 | 4.49 |
| Race and ethnicity (ref: NH White) | | | | | | | | |
| Black | 1.09 | 0.011 | 1.02 | 1.16 | 1.21 | 0.127 | 0.95 | 1.53 |
| Hispanic | 0.87 | 0.000 | 0.83 | 0.91 | 0.89 | 0.270 | 0.73 | 1.09 |
| Asian | 0.80 | 0.027 | 0.66 | 0.98 | 0.79 | 0.462 | 0.41 | 1.49 |
| Other | 0.88 | 0.006 | 0.80 | 0.96 | 1.12 | 0.498 | 0.80 | 1.57 |
| Female gender | 1.17 | 0.000 | 1.12 | 1.23 | 1.10 | 0.287 | 0.92 | 1.31 |
| Admission source (ref: no transfer) | | | | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 2 From Clinics | 0.92 | 0.017 | 0.87 | 0.99 | | | | |
| 3 Transfer from hospitals | 0.96 | 0.344 | 0.89 | 1.04 | | | | |
| 4 Transfer from SNF ICF ALF | 1.38 | 0.001 | 1.14 | 1.68 | | | | |
| 5 Transfer from Another HC fac | 0.89 | 0.135 | 0.76 | 1.04 | | | | |
| 6 Other | 0.93 | 0.480 | 0.77 | 1.13 | | | | |
| Comorbidity | | | | | | | | |
| AIDS | 1.18 | 0.106 | 0.97 | 1.43 | 1.13 | 0.778 | 0.48 | 2.64 |
| Alcohol abuse | 0.72 | 0.000 | 0.65 | 0.80 | 0.62 | 0.003 | 0.45 | 0.85 |
| Deficiency Anemias | 1.05 | 0.027 | 1.01 | 1.10 | 1.10 | 0.312 | 0.92 | 1.31 |
| Rheumatoid arthritis/collagen vas | 0.91 | 0.055 | 0.82 | 1.00 | 0.98 | 0.931 | 0.63 | 1.52 |
| Chronic blood loss anemia | 1.05 | 0.616 | 0.88 | 1.25 | 1.76 | 0.046 | 1.01 | 3.07 |
| Congestive heart failure | 1.15 | 0.000 | 1.08 | 1.21 | 1.22 | 0.051 | 1.00 | 1.50 |
| Chronic pulmonary disease | 1.30 | 0.000 | 1.23 | 1.37 | 1.32 | 0.008 | 1.07 | 1.61 |
| Coagulopathy | 0.86 | 0.000 | 0.80 | 0.92 | 0.94 | 0.541 | 0.75 | 1.16 |
| Depression | 1.16 | 0.000 | 1.09 | 1.23 | 1.12 | 0.420 | 0.86 | 1.45 |
| Diabetes w/o chronic complications | 1.10 | 0.003 | 1.03 | 1.17 | 1.38 | 0.012 | 1.08 | 1.78 |
| Diabetes w/ chronic complications | 0.88 | 0.000 | 0.84 | 0.93 | 0.99 | 0.956 | 0.79 | 1.25 |
| Drug abuse | 1.19 | 0.000 | 1.08 | 1.30 | 1.14 | 0.468 | 0.80 | 1.63 |
| Hypertension | 0.97 | 0.301 | 0.93 | 1.02 | 0.91 | 0.353 | 0.75 | 1.11 |
| Hypothyroidism | 1.04 | 0.245 | 0.97 | 1.11 | 0.87 | 0.322 | 0.65 | 1.15 |
| Liver disease | 1.00 | 0.981 | 0.92 | 1.08 | 1.36 | 0.037 | 1.02 | 1.81 |
| Lymphoma | 1.06 | 0.606 | 0.86 | 1.30 | 0.73 | 0.381 | 0.35 | 1.49 |
| Fluid and electrolyte disorders | 0.86 | 0.000 | 0.82 | 0.90 | 0.72 | 0.000 | 0.61 | 0.86 |
| Metastatic cancer | 0.87 | 0.056 | 0.76 | 1.00 | 1.39 | 0.130 | 0.91 | 2.13 |
| Other neurological disorders | 1.07 | 0.024 | 1.01 | 1.14 | 0.95 | 0.577 | 0.79 | 1.14 |
| Obesity | 1.03 | 0.332 | 0.97 | 1.08 | 1.61 | 0.000 | 1.29 | 2.01 |
| Paralysis | 1.39 | 0.000 | 1.28 | 1.50 | 1.01 | 0.929 | 0.80 | 1.28 |
| Peripheral vascular disease | 1.06 | 0.058 | 1.00 | 1.13 | 1.45 | 0.005 | 1.12 | 1.88 |
| Psychoses | 1.26 | 0.000 | 1.15 | 1.40 | 1.15 | 0.499 | 0.77 | 1.70 |
| Pulmonary circulation disease | 1.03 | 0.708 | 0.89 | 1.19 | 1.13 | 0.581 | 0.73 | 1.76 |
| Renal failure | 1.10 | 0.002 | 1.04 | 1.17 | 1.01 | 0.906 | 0.80 | 1.29 |
| Solid tumor w/out metastasis | 0.90 | 0.108 | 0.80 | 1.02 | 1.76 | 0.009 | 1.15 | 2.70 |
| Peptic ulcer Disease x bleeding | 0.96 | 0.659 | 0.79 | 1.16 | 0.90 | 0.693 | 0.52 | 1.55 |
| Valvular disease | 0.79 | 0.000 | 0.72 | 0.86 | 0.73 | 0.050 | 0.53 | 1.00 |
| Weight loss | 1.12 | 0.000 | 1.06 | 1.20 | 1.32 | 0.009 | 1.07 | 1.62 |

* McFadden's adjusted pseudo R2 = 0.125 (all) and 0.109 (nosocomial only)

**Comparison with the hospital model developed previously.**

Like our study detailed in Chapter III, the study in Chapter IV also serves as an underlying support for evidence-based designs. The biggest difference is increased detail and degree of freedom. For example, the hospital model detailed in Chapter III can predict MRSA reductions based on hospital parameters, but not end outcomes attributable to MRSA. Thus, for business

decisions where all considerations should be converted to calculable monetary quantity, the hospital model must rely on other supporting evidence (e.g., MRSA cost studies) to transform reduced infections to dollars saved. That often introduces various problems such as study population discrepancy or incompatible research design: challenges in synthesizing evidence are well documented for general data science (B. J. Becker et al., 2017, 2017; Cao, 2017) as well as for health service research area (Bravata, McDonald, Shojania, Sundaram, & Owens, 2005; Johnstone, 2004). By comparison, estimates from our Models 1 and 2 can be integrated more smoothly (i.e., identical data source and consistent variable setting) and utilized toward a "complete" cost-benefit analysis, in that together these models account for the entire cycle from private rooms to end outcomes (e.g., costs). As a practical application example of Models 1 and 2, we will conduct a Monte-Carlo simulation of cost-benefit analysis for two different hospitals in the subsequent chapter. Furthermore, Model 1 enables to analyze multi-dimensional nature of private rooms (i.e., internal, external, and interactive effects), which may shed a light on underlying mechanisms and pathways. Our hospital model (Chapter III) and patient model (Model 1 in Chapter IV) can mutually validate each other by aggregating patient-level outcomes (MRSA risk) by hospital and comparing with hospital-level estimates of MRSA incidence.

**Limitations.**

Our analyses and models detailed in this chapter still face methodological challenges. Hence, potential readers should raise cautions in interpreting and applying our results.

First, all the limitations discussed in Chapter III applies to this chapter: including estimation of private room percentages, cross-sectional study designs, and bias due to unmeasurable variables.

Second, potential misspecification can be a limitation in our matching approach. We largely relied on the assumption that all the relevant differences across staph infection categories were captured in model variables. In practice, staph infections might be caused by highly complicated interactions among various environmental, psychological, and structural factors (e.g. hygiene status of physicians, nurse quality, private patient rooms), which our administrative database (IP PUDF) could only assess to the limited extent. Although future studies should examine these with more detailed data, we did our best to use the most effective set of variables of IP PUDF to capture significant impacts on MRSA infections. Even if there were some misspecification error, we treated each complication in a consistent way. Therefore, we believe that relative differences would be still meaningful.

Third, the PFR approach is rather exploratory and still needs more verification and validation. We are particularly concerned that PFRs were originally calculated from commercial and Medicaid insurances – without including Medicare payments – in the original study (Peterson et al., 2015). A later special commentary in the same year indicated that PFRs for Medicare patients could be biased (De Lissovoy & Landon, 2015). For this reason, readers should carefully interpret our results regarding facility-related costs.

# CHAPTER V

# A SIMULATION STUDY OF THE COSTS AND BENEFITS OF PRIVATE HOSPITAL ROOMS SHOWING THE IMPORTANCE OF ORGANIZATIONAL CONTEXT

## Background

### Study purpose.

In recent years, there have been two general approaches to reducing hospital-acquired infections (HAIs; also known as *nosocomial infections*). The first is to change the behavior of physicians, nurses, and other healthcare providers in broad and sometimes subtle ways that yield better outcomes. The managerial tools employed to achieve better outcomes include performance feedback (Rosenthal, Guzman, & Pezzotto, 2003), physician-led multidisciplinary teams (Jain, Miller, Belt, King, & Berwick, 2006), and maintaining a safety culture (P. J. Pronovost et al., 2008). The second emphasizes standardizing best clinical practices for preventing infections. Examples of this approach include establishing protocols for hand hygiene compliance and the use of personal protective equipment, such as wearing a mask and latex gloves, or the management of multidrug-resistant infections (Siegel, Rhinehart, Jackson, & Chiarello, 2007; Siegel, Rhinehart, Jackson, Chiarello, et al., 2007). Despite these efforts, the overall rate of improvement over time in preventing nosocomial infections has slowed significantly since 2010. Between 2006 and 2010, nosocomial infections[50] decreased by up to

[50] As measured by nosocomial methicillin-resistant Staphylococcus aureus infections and nosocomial central-line associated bloodstream infections

41%. Yet from  2011 to 2015, there was only a 9% further decrease (Office of Disease Prevention and Health Promotion, n.d.). The diminishing yield from well-established interventions suggests that the 'low hanging fruit' of HAI reduction as currently understood may be dwindling, and that a rethinking of HAI management is key to renewed progress.

Due to the multifactorial nature of nosocomial infections, there is a consensus that no single intervention will be effective in reducing HAIs. Instead a multidimensional approach is needed, including an emphasis on the built environment. There have been many improvements in hospital design that are believed to reduce the risk of a HAI. These include improved ventilation systems, the use of antimicrobial surfaces, improved hand hygiene, and private hospital rooms along with private bathrooms. We paid a specific attention to the last element, private hospital rooms. In addition to expected improvement in patient safety, hospitals generally have a surplus number of beds (McDermott, Elixhauser, & Sun, 2017) and a declining patient census (American Hospital Association, 2019) in recent years. This can be another reason for hospitals to convert legacy bay rooms to private rooms (H. Chaudhury, Mahmood, & Valente, 2016). In practice, however, it is difficult to assess the incremental benefit of private room conversion relative to their cost, which stands as a critical barrier to important investments in the built environment as a major tool for infection control. Moreover, patient room design cannot be easily modified but must be planned, budgeted, and built into facilities many years before they are ever used, which cause methodological challenges in research. In this respect, our emphasis in this chapter will be on private hospital rooms and their potential "protective effects," including a consideration of selected unmeasured design features, such as

the age of the physical facility and renovation. Unfortunately, only a few studies have examined or investigated the return on investment (ROI) from improving the built environment (Sadatsafavi et al., 2016; Sadler et al., 2011; Shepley, Smith, Sadler, & White, 2014), and none have been performed for a new construction or at a large-sized renovation level. Therefore, the primary purpose of Chapter V is to investigate both the costs and benefits of a hospital renovation project to transform existing bay rooms into private rooms.

In Chapters 3 and 4 we demonstrated that nosocomial staph infections can be prevented at both the hospital and patient level, through two distinct effects of private rooms, including the protective effect of being assigned to a private room (the marginal effect), and the effect of selecting a hospital with mostly private rooms regardless of subsequent room assignment. The results reported in Chapters 3 and 4 reinforce growing evidence that PPR is one of the key elements in designing safer hospitals and healthcare facilities. We also estimated the attributable costs (along with other health outcomes) of nosocomial staph infections (Chapter IV). In the present chapter, we examine the financial costs and benefits of choosing an all-private room design. In terms of costs, we will consider both the capital investment (construction) costs, as well as the ongoing, variable costs, such as increased nurse staffing. The financial benefits will be realized primarily from preventing costly HAIs, such as CLABSI, MRSA, and MSSA.

Projected savings were primarily derived from expected HAI reductions. We used the statistical models developed in Chapter IV and our previous research on CLABSI to estimate ROI from such renovation projects.

**Empirical staffing model.**

We assume that hospitals with an all-private room design would require more nurses per bed than a comparable hospital with mostly bay rooms. Hospitals' possible concern is that, if more nurses are required after renovation to private rooms, the increased operational costs from additional nurse staffing may cause some hospitals to opt out an all-private room design. Note that renovation (to all-private room design) does not systematically change nurse-to-patient ratio[51]. Therefore, federal and state-regulations that mandate minimum nurse staffing levels do not enforce hospitals with an all-private room design to hire more nurses. Our hypothesis is that hospitals with mostly private rooms may require additional nurses per bed due to increased walking distances and workloads, as has been reported in the literature (Mooney, 2008; A. Moore, 2009; Young & Yarandipour, 2007). Patient rooms in an all-private room facility are typically designed to be so spacious that they resemble a hotel room (Figure 10) and typically include a fold out couch for family members. Thus, all-private room design makes patient care more challenging for nurses due to increased distances between rooms (Hendrich & Chow, 2008; Maben et al., 2016). This applies to both patients requesting help and nurses needing assistance from another staff member, particularly when timing should be taken into consideration (Flowers, 2008). It is generally agreed in the literature that nursing workloads are expected to be higher in private rooms than in bay rooms (Flowers, 2008;

[51] There can possibly come more incoming patients in better designed hospitals (e.g., better marketing potentials), which is not incorporated in this logic development due to unclear and indirect relationships.

Lawson, Phiri, & Wells-Thorpe, 2003; Maben et al., 2016). By contrast, a bay room may enable economies of scale that allow hospitals to employ fewer nurses.

An analysis of hospital workspace design must also consider the relationships between patient care, room design, and the nursing station, which have long been the core of nursing care activities in hospitals. The nursing station is a primary work area assigned to a specific unit and typically includes unit reception along the records storage and charting work areas (Gurascio-Howard & Malloch, 2007). The following elements are considered as critical issues in the nursing station and nurse labor efficiency: walking distances, accessibility, visibility, and supervision difficulty (Hamilton, 1993). More recently, and with the aid of information technologies, enterprising designers have downsized the traditional, centralized nurse stations (formerly the heart of a hospital unit; see left picture of Figure 11) and replaced it with smaller alcoves and workstations situated closer to patient rooms (Figure 11; right picture). This design, commonly known as decentralized nursing station, is considered better in several key criteria if stations are strategically situated: improved nurses' visibility, increased patient care time, reduced nurses' administration task, and lowered environmental noise level (Fay, Cai, & Real, 2019). Note that just as hospital design trends have shifted toward using an all-private room design, there has been a similar shift toward decentralizing nursing stations. Therefore, the hospitals built within the last decade are likely to have both private rooms and decentralized nursing stations. Studies in the literature have shown that decentralized nursing stations generally increase walking distance (Fay, Carll-White, Schadler, Isaacs, & Real, 2017; Gurascio-

Howard & Malloch, 2007; Pati, Harvey Jr, Redden, Summers, & Pati, 2015), which leads hospitals to hire more nurses and presumably offsets ROI (Gurascio-Howard & Malloch, 2007).

Despite the obvious, more subtle cost burdens from higher capital costs, increased nurse staffing, and other factors, private rooms (and all-private room design by extension) may provide benefits to nurses as well as to patients that are unrelated to improved infection control. Traditional bay rooms are often regarded as performance obstacles by nurses – insufficient workspace for completing paperwork (Gurses & Carayon, 2007), charting, and operating medical equipment (Varni et al., 2004). Nurses also see the benefit of an all-private room design in that unnecessary internal transfers can be reduced (Rashid, 2007). However, there are potentially negative perceptions toward private rooms as well – such as stress, isolated work environment, and decreased teamwork (A. Moore, 2009). Considered together, staffing issues in all-private room design might be complicated by various factors, which turned a design decision into a multi-dimensional problem that needs scientific and data-driven approaches.

Ideally, a fully specified causal model explaining both positive and negative aspects of nurse staffing would be the most useful for our cost-benefit analysis. Yet it is nearly impossible to find such a model in the extant, peer-reviewed literature. Perhaps the best available approach to counter these constraints would be to develop a prediction model that controls the hospital-to-hospital variation of staffing levels (quantities) and provides a fair comparative analysis among heterogenous hospitals. In other words, we aim to provide a statistical model predicting an appropriate staffing level (i.e., used in our cost-benefit analysis to assess labor

costs) given publicly-available information – drawn from the Texas inpatient database (IP PUDF) and the AHA hospital survey.

Figure 10: Typical bay room (left) and private room (right)


Figure 11: Centralized (left) and decentralized (right) nursing station(s)


**Methods**

**Data sources.**

The Texas Inpatient Public Use Data File (IP PUDF) for the FY[52] 2016 (Texas Department of State Health Services, 2017) serves as our primary data source to obtain patient

[52] Fiscal Year

demographics and diagnoses. Hospital parameters such as nurses and licensed beds were accessed via the American Hospital Association (AHA) annual survey (AHA, n.d.).

**Target infections.**

For this analysis, we focused on three conditions – two staph infections, methicillin-resistant Staphylococcus Aureus (MRSA) and methicillin-sensitive Staphylococcus Aureus (MSSA), and central-line associated bloodstream infection (CLABSI). These were prioritized (compared to other HAIs) because of their seriousness (high incidence and greater medical/economic impact) in Texas hospitals (CDC, 2016). We only considered a nosocomial onset (hospital-acquired), as the focus of this thesis is prevention of HAIs and its relationship with the built environment.

**Underlying models.**

To assess acquisition risks of nosocomial MRSA and MSSA in private and bay rooms, we used our patient-level infection incidence logit model described in Chapter IV. The outcome of interest was the risk of developing HA[53]-MRSA and HA-MSSA, and inputs are individual (patient-level) private room assignments, hospital-wide private room percentages, and other relevant covariates. Attributable costs of HA-MRSA and HA-MSSA were drawn from our cost model (also described in Chapter IV), based on the controlled analyses where patient characteristics were matched across different Staph cohorts.

[53] Hospital-Acquired

We used our two previously described models to evaluate HA-CLABSIs (O'Neill et al., 2018). These assess acquisition risk, with the first based on patient room assignments and the other based on hospital's private room percentages. Attributable costs per each HA-CLABSI case were drawn from a systematic review in the literature (Scott, 2009).

As noted, a well specified analysis must include information about how many additional staff members (nurses) are required in all-private room design relative to alternatives. However, to our knowledge, there is no peer-reviewed model suited for our needs and data. Thus, we developed a cross-sectional regression model to assess staffing quantity based on hospital characteristics[54], including private room percentages, licensed beds, average physical space (per bed), percentages of the uninsured and Medicaid-insured patients, teaching facility, and hospital ownership.

**Simulation structure.**

***Consistency.*** Our simulation structure is consistent with similar cost-benefit analyses in the literature (Sadatsafavi et al., 2016; Shepley et al., 2014) in terms of the choice of input and outcome measures, and analysis timeline, with major exceptions of our analysis utilizing representative data and focusing on nosocomial Staph and central line infections.

***Hospitals.*** It is desirable to provide a comparison of settings where the potential savings from the prevention of HAIs are likely to differ significantly. Because our dataset includes more

[54] Input variables were chosen based on (1) high correlation ($r>0.7$) with full-time equivalent (FTE) nurses and (2) low correlations ($r<0.4$) among input variables to reduce collinearity.

than 300 hospitals, we selected two representative hospitals to illustrate how the financial benefits of the all-private room design may depend on multiple hospital-level characteristics such as organizational parameters (number of licensed beds, nurse staffing, private rooms as percentage, hospital ownership, etc.); patient demographics (race and ethnicity, age, comorbidities, etc.); and hospital location (located in rural areas vs. urban areas). To that end we evaluated two facilities: John Peter Smith Hospital in Fort Worth, Texas (also known as JPS Hospital; henceforth referred to as "Hospital A" in this study) and Hill Regional Hospital in Hillsboro, Texas ("Hospital B"). Hospital A is characterized by a lower percentage of private rooms (38%), and is a public, safety-net, large (537 licensed beds) teaching facility where more nosocomial infections are occurring. Hospital B is largely the opposite – for-profit, rural, and smaller (58 licensed beds) hospitals with higher percentage of private rooms (59%). Nosocomial infection incidence is much lower in Hospital B. While more vulnerable populations (more African American and Hispanic patients and those with lower social and economic status) go to Hospital A, patients in Hospital B show a higher Elixhauser comorbidity score (3.3 vs 2.0; $p<0.001$).

***Input variables.*** We considered input variables largely from four aspects: construction, staffing, non-HAI revenue increase, and cost-savings from HAI reduction. The first two constitute the cost of this simulation while the last two define the benefit. Construction costs were estimated assuming no change in the number of beds in a hospital. Instead, we assumed that new private rooms will be constructed to replace existing beds in bay rooms. Admittedly, private rooms need more space per bed than bay rooms. The invariant area ratio between

private and bay rooms in hospitals was assumed[55] and calculated as 0.598 based on the Functional and Space Program report (Tarrant County Texas, 2014). We also used the average hospital facility construction cost rate per unit area ($429 per square feet in 2018 US dollar) (Sadler et al., 2011). Total construction cost required of an all-private room renovation was derived as a closed-form function of known quantities in our data sources, including total physical area, licensed beds, percentage of private rooms, and area ratio between private and bay rooms (Appendix II); we estimated a 10% standard error for construction costs. We also used the Functional and Space Program report to project potential revenue changes based on four scenarios representing broad combinations of payor mix changes and process improvements over time that cannot be attributed to reductions in nosocomial infections[56]. To extrapolate this estimation to other hospitals, we converted the results into a function of construction costs (ratio of increased revenue to construction cost), which ranged from 72.8% to 118.2% and incorporated these into our simulation using a four-state discrete probability distribution with equal chances (25%) for each outcome.

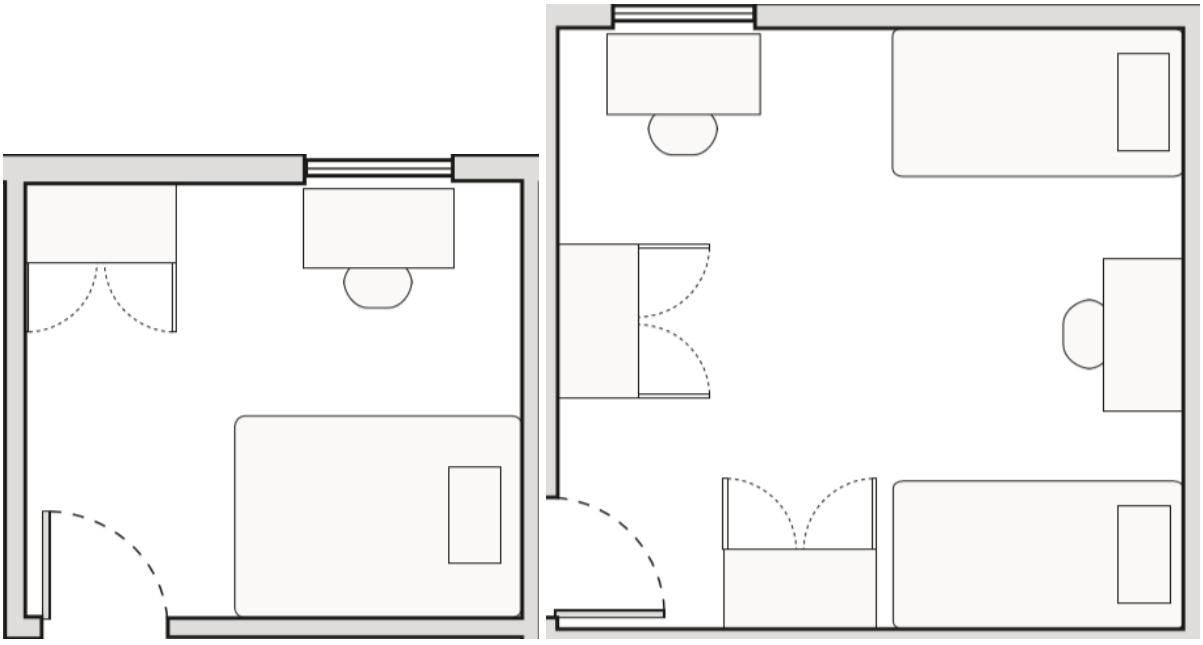
Potential change in nurse labor costs, such as ongoing variable costs, was estimated as a function of an additional full-time equivalent (FTE) nurses that all-private room design could require (as predicted by our multivariate model) and the median nurse annual salary in Texas in

[55] We admit that this is a strong assumption, mainly because of data limitation. See Limitations of this Chapter.
[56] Therefore, any benefits from this forecast are independently and additively included in our cost-benefit analyses.

2018 ($60,655 per year; the middle point between licensed practice nurses and registered nurses).

Finally, offsetting cost savings from reduction of nosocomial infections were considered. Cost savings were assessed by estimates for prevented infections multiplied by infection-attributable costs. Prevented infections were calculated by the difference between expected infections in current status (current mix between private and bay rooms) and those in all-private room design. Infection risks and costs were drawn from the statistical models as already discussed. Detailed justifications and operational steps of probability fitting for the above variables are explained in Appendix I.

Figure 12: Floor plans of typical private (left) and bay (right) rooms



***Outcome measures.*** We used standard methods to calculate the net present-value benefits (NPV) (Quah & Haldane, 2007; Sassone & Schaffer, 1978) for outcomes that accrue over time using 2.75% federal discount rate reported by the Federal Reserve for December 2018 (The Federal Reserve System, 2019). We followed well-established NPV calculations in the literature.

We acknowledge at least two major weaknesses of NPV measure in the context of this analysis. On one hand, the result may change as discount rates change. For example, the federal discount rate has become 3.0% since January 2019 – although we adhered to the original discount rate because it did not significantly change simulation results in this case. On the other hand, particularly for the purpose of comparative analysis, NPV is highly subjective to project scales (Ross, 1995). If the same project plan is doubled in both costs and benefits, NPV would also be doubled (i.e., NPV = $PV^{57}_{benefits}$ - $PV_{costs}$). Thus, any conclusions based on NPV may introduce unfairness when there are inherent volume differences. This concern applies to our Hospitals A and B.

To address these two issues, we used internal rate of return (IRR) as the primary outcome measure.[58] IRR is defined as a discount rate to make NPV of cash flows of the project to be zero. The same formula with NPV is used to calculate IRR – usually with iterative numerical computations. Using IRR can address the two main problems of NPV that were

[57] Meaning the present value of the sum of variables
[58] NPV is still calculated and reported as complementary measure.

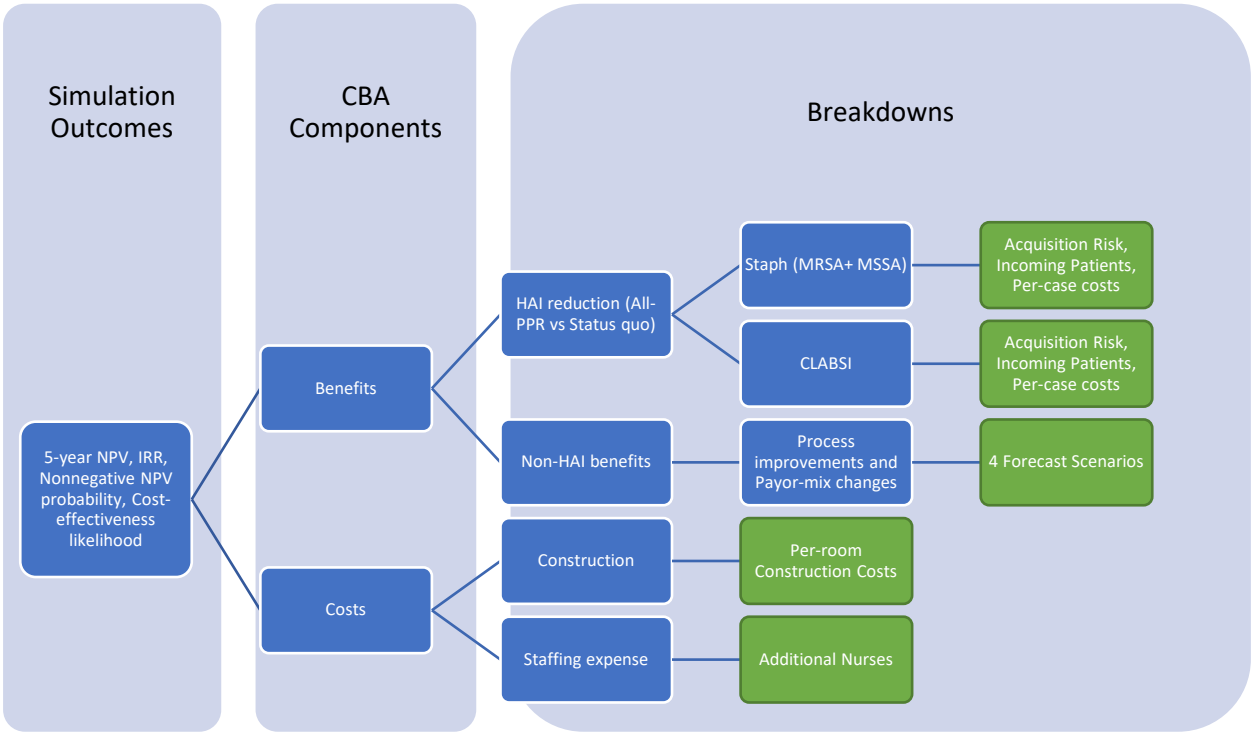
previously discussed. In addition, IRR is also considered as a standardized method in cost benefit analysis in every field (Quah & Haldane, 2007).

We calculated two additional outcomes of interest, the probability of non-negative NPV and the probability of cost effectiveness. The latter is defined as probability at which IRR exceeds the hurdle rate of cost effectiveness (5.9%) drawn from the weighted average cost of capital for hospitals and healthcare facility sector (The New York University Stern School of Business, 2019).

***Simulation method.*** We used the Monte Carlo method for our simulations. The Monte Carlo method (also known as the Monte Carlo experiment) is a computational algorithm producing repeated random generations to obtain numerical results, assuming that deterministic (in principle) problems are solvable using randomness (Kroese, Brereton, Taimre, & Botev, 2014). Cost-benefit is largely deterministic in principle – meaning that we can know the exact result when all relevant information is known with certainty and without bias. However, costs, revenues, and cost-saving effects from reduced HAIs are not available to measure to the extent that the solution is truly deterministic. In other words, all components needed to evaluate cost-benefit relationships are inherently random, and the Monte Caro approach can be suitable.

Our simulation generated random numbers for input variables over 5,000 repetitions[59], giving broad distribution of probable results rather than one or a few point estimates. The simulation assumed a five-year analysis timeline and inter-year independence among probabilities (i.e., Year 2 input variables are independent of Year 1 input variables). The resulting probability distribution for the simulation inputs and fitted optimal parameters are presented in the Results' section headed "Descriptions of Hospitals and Baseline Estimates".

Figure 13: Simulation structure




[59] The number of iterations in our simulation was determined to have the precision of order 0.5%; 1.110% for N=1,000, 0.495% for N=5,000, and 0.350% for N=10,000

***Sensitivity analysis.*** We evaluated our model's robustness to variation in key assumptions using one-way sensitivity analyses. This analysis considered variation in assumed construction costs, non-HAI benefits (i.e., expected revenue increases due to process improvements and payor mix changes), labor costs, and cost-saving amounts due to HAI reduction. IRRs estimated using a range of +/- 10% change to baseline assumptions (e.g., 10% increased construction cost as pessimistic assumption) as well as maximum tolerance borderline (i.e., the most pessimistic assumption that still ensure cost-effectiveness). In addition, elasticity and shadow prices were calculated and reported as comprehensive sensitivity measures. Input elasticity shows how IRR variable responds to a change in unit assumption changes (Bronfenbrenner, 1961). Shadow price is conceptually as well as operationally very similar, only differing in responses presented in absolute terms (%p difference) as opposed to relative terms (%) (Sassone & Schaffer, 1978). For example, if IRR changes by 2% (from 3% to 5%) in response to 1% assumption change, shadow price is 2%p (absolute change in IRR) and elasticity is 1.5 (i.e., relative change: 2%/3%=1.5).

***Software.*** We used Stata version 13.0 to complete all regression analyses (StataCorp, 2013). Probability fitting and Monte-Carlo simulations were obtained via Microsoft Excel (2016) and Real Statistics Resource Pack software (Release 5.4) (Zaiontz, 2018).

## Results

### Descriptions of hospital and baseline estimates.

Table 22 illustrates descriptive statistics for Hospitals A and B. As we intended, these two hospitals differ from each other in various aspects. Hospital A is publicly owned and located

in an urban area; relative to Hospital B it has more beds (537 vs 58 beds), a lower proportion of private rooms (38% vs 59%), a higher occupancy rate (71% vs 12%), higher nursing loads (nurse-to-patient ratio=0.7 vs 0.8), and higher nosocomial infection rates in all the three HAIs examined in this analysis. In addition, Hospital A sees more publicly insured patients and the uninsured as well as non-white patients, which are often associated with more vulnerable population. From these differences, the suitability[60] of all-private room design (renovation) is expected to be much higher for Hospital A than for Hospital B.

Based on the underlying model predictions with actual patient data from Hospitals A and B, we identified the optimal probability distributions and appropriate parameters fitted by those predictions (Table 23; also see Appendix I).

Required additional nurses in all-private room design were predicted by our multivariate staffing model presented in Table 24. Note that this staffing model was initially estimated with all Texas hospitals (*n*=201), not restricted within Hospitals A and B. After the model was developed, additional nurses needed were predicted from the model with corresponding hospital characteristics. We found that, after adjusting potential confounders, every 1% increase in private rooms required an average 0.4% more nurses (*p*=0.004). Other strong and significant predictors include licensed beds, average physical space, and portion of major therapeutic procedures (e.g., surgery) among whole procedures in hospitals. It is worth

[60] Suitability in this context should be interpreted as positive cost-saving effects.

mentioning that our staffing model could explain 79.6% of conditional variance among Texas hospitals.

Table 22: Comparison of characteristics between Hospitals A and B

| Variable | Hospital A | Hospital B |
|---|---|---|
| Ownership style | Public | For-profit |
| Teaching facility | Teaching hospital | Non-teaching hospital |
| Location | Urban | Rural |
| Licensed beds | 537 | 58 |
| Admitting inpatients | 28,621 | 1,248 |
| % Private rooms | 37.8% | 59.0% |
| Occupancy rate | 71.1% | 11.8% |
| Nurse FTE | 1379 | 60 |
| Nurse-to-patient ratio | 0.7 | 0.8 |
| Average physical space per bed (sqft) | 2,812 | 1,862 |
| % African American patients | 24.7% | 10.4% |
| % Hispanic patients | 36.3% | 15.8% |
| % Medicaid-insured and uninsured | 71.4% | 40.3% |
| Acquisition risk of HAIs: bay-room (per 100,000) | | |
| MSSA | 0.072% | 0.0008% |
| MRSA | 0.058% | 0.0023% |
| CLABSI | 0.590% | 0.560% |
| Acquisition of risk of HAIs: private room (per 100,000) | | |
| MSSA | 0.056% | 0.0006% |
| MRSA | 0.047% | 0.0018% |
| CLABSI | 0.460% | 0.442% |
| Expected suitability of All-private room renovation | High | Low |

Table 23: Baselines of parameters and their assigned probability distributions for Hospitals A and B

| Simulation parameter | Hospital A | | Hospital B | |
|---|---|---|---|---|
| | Baseline | Probability distribution | Baseline | Probability distribution |
| Annual patients | 28,621 | Normal (28,621 + 2018T, 354.7) | 1,248 | Normal (1248, 150.0) |
| MSSA acquisition risk | | | | |
| Status quo | | | | |
| PPR assigned | 0.056% | Gamma (3.90, 0.00014) | 0.001% | Gamma (1.92276, 0.000003) |
| PPR not assigned | 0.072% | Gamma (5.21, 0.00014) | 0.001% | Gamma (1.92277, 0.000004) |
| All-PPR | | | | |
| PPR assigned | 0.046% | Gamma (5.16, 0.00009) | 0.000% | Gamma (1.92276, 0.000003) |
| MRSA acquisition risk | | | | |
| Status quo | | | | |
| PPR assigned | 0.047% | Gamma (5.41, 0.00009) | 0.002% | Gamma (1.71466, 0.000010) |
| PPR not assigned | 0.058% | Gamma (5.44, 0.00011) | 0.002% | Gamma (1.71468, 0.000013) |
| All-PPR | | | | |
| PPR assigned | 0.029% | Gamma (5.37, 0.00005) | 0.001% | Gamma (1.71462, 0.000006) |
| CLABSI acquisition risk | | | | |
| Status quo | | | | |
| PPR assigned | 0.46% | Gamma (119.44, 0.00004) | 0.44% | Gamma (6.39, 0.00069) |
| PPR not assigned | 0.59% | Gamma (122.48, 0.00005) | 0.56% | Gamma (6.60, 0.00084) |
| All-PPR | | | | |
| PPR assigned | 0.25% | Gamma (53.12, 0.00005) | 0.25% | Gamma (3.65, 0.00070) |
| Costs of each incident of HA-CLABSI ($ k) | 15.65 | Lognormal (9.659, 0.354) | ← | |
| Costs of each incident of HA-MSSA ($ k) | 27.11 | Lognormal (10.2, 0.09) | ← | |
| Costs of each incident of HA-MRSA ($ k) | 33.14 | Lognormal (10.4, 0.10) | ← | |
| Additional construction costs of turning bay rooms to PPRs ($ mil) | 22.19 | Lognormal (16.9, 0.10) | 1.01 | Lognormal (13.8, 0.10) |
| Additional annual labor costs ($ mil) | 1.19 | Lognormal (14.0, 0.08) | 0.18 | Lognormal (12.1, 0.08) |
| Revenue increases (% of add. Construction cost) | 95.5% | 4-state discrete | ← | |

Figure 14: John Peter Smith Hospital in Fort Worth, TX (left; "Hospital A") and Hill Regional Hospital in Hillsboro, TX (right; "Hospital B")


Table 24: Logit regression results for predicting nurse staffing

| Variable | *β* | *p* | Lower | Upper |
|---|---|---|---|---|
| Private rooms (%) | 0.004 | 0.004 | 0.001 | 0.007 |
| (log) Licensed beds | 0.947 | 0.000 | 0.868 | 1.027 |
| (log) Average physical space per bed in sqft | 0.244 | 0.020 | 0.038 | 0.450 |
| Uninsured and Medicaid patients in hospitals (%) | -0.004 | 0.116 | -0.009 | 0.001 |
| Major therapeutic procedures in hospitals (%) | 0.010 | 0.003 | 0.003 | 0.016 |
| Teaching facility | 0.118 | 0.280 | -0.097 | 0.334 |
| Hospital ownership (ref: for-profit hospitals) | | | | |
| Public hospitals | 0.298 | 0.068 | -0.022 | 0.619 |
| Non-profit hospitals | 0.178 | 0.123 | -0.049 | 0.406 |

**Simulation results.**

As represented in Table 25, our simulations indicated that – despite variability in the estimates of costs and infection risks – the additional cost of private rooms, including both construction and labor costs, were largely offset by ongoing cost savings due to reductions in HAIs for suitable hospitals. In Hospital A (the "better" case for PPR/the built environment as a high value investment), five-year construction costs were projected to be 4.4 million US dollars

annually (95% CI = 3.8 to 5.1 million USD), with additional new expenses a predicted need to hire 19.6 more nurses every year at an additional ongoing costs of 1.2 million USD. Considering revenue forecasts based solely on improved efficiency and payor mix changes during a five-year window, new costs would exceed new revenue by 4.6 million USD. This is dramatically different when HAI prevention effects from private rooms are considered as offsetting benefits.

Compared to the current patient room-mix (combination of bay and private rooms), an all private-room design is estimated to prevent 118 nosocomial infections annually (equivalent to 461 infections for a five-year window, discounted by time value) and save 12 in-hospital deaths attributable to those infections annually (equivalent to 56 time-counted deaths for a five-year window). Means of annual prevention of target infection are specified in the following breakdown: (1) HA-CLABSI prevented by 99 (±1.2; 95% CI for means[61]) cases; (2) HA-MRSA infections prevented by 9.4 (±0.4) cases; and (3) HA-MSSA prevented by 10 (±0.5) cases. Due to these, Hospital A could avoid 8.9, 1.3, and 1.4 in-hospital deaths respectively.

Our simulation could show that such health benefits were translated into financial benefits (cost-saving effects), due to relative gains of attributable costs (i.e., additional costs of HAIs) not occurring after renovation. An all-private room design is predicted to not only cover new costs but to exceed these by an annual average 2.7 million USD (0.3, 0.4, and 2.0 million USD of respective cost savings from HA-MSSA, HA-MRSA, and HA-CLABSI reductions). All

[61] Note that CIs reported in this paragraph are CI for mean, not CI for raw variable. The former is related to standard error (sample size-dependent) while the latter is linked to standard deviation (sample size-independent). On the contrary, Table 25 reports (non-parametric empirical) CIs for raw variable.

elements taken into consideration, the five-year net present-value benefit was 5.8 million US dollars, with IRR being approximately 11%. Note that this cost-saving effect from HAI reduction is ongoing (i.e., safety gain remaining persistently) unlike one-time or time-limited costs (i.e., after a five-year window, there will be no additional costs). In other words, expanding the time window (i.e., a hospital building life cycle is generally considered to be 20-40 years) can boost net benefits and investment returns. However, we adhere to reporting five-year results to provide readers more conservative estimations.

Hospital B (the "worse" case for PPR/built environment investments), on the other hand, would fare much less well with an all-private room design scenario. HAI reduction cost-saving is estimated to total 0.21 million USD with nearly indiscernible prevention effects and even less – 0.1 million USD net benefit during the five-year time window. Even taking volume difference into account (i.e., Hospital B is 89% smaller than Hospital A in terms of beds), IRR was 5.5% which was still slightly lower than the industry average return of 5.9%.

The empirical[62] distribution of IRRs among 5,000 simulated trails are presented in Figure 15. The results largely reiterate our findings. The curve for Hospital A looks less smooth than that of Hospital B, possibly due to spurious correlation among randomly generated variables in non-linear transformation (i.e., IRR calculations have no closed-form solutions) (J. Kim & Alger,

[62] IRR distribution was plotted with the set of actually simulated point results.

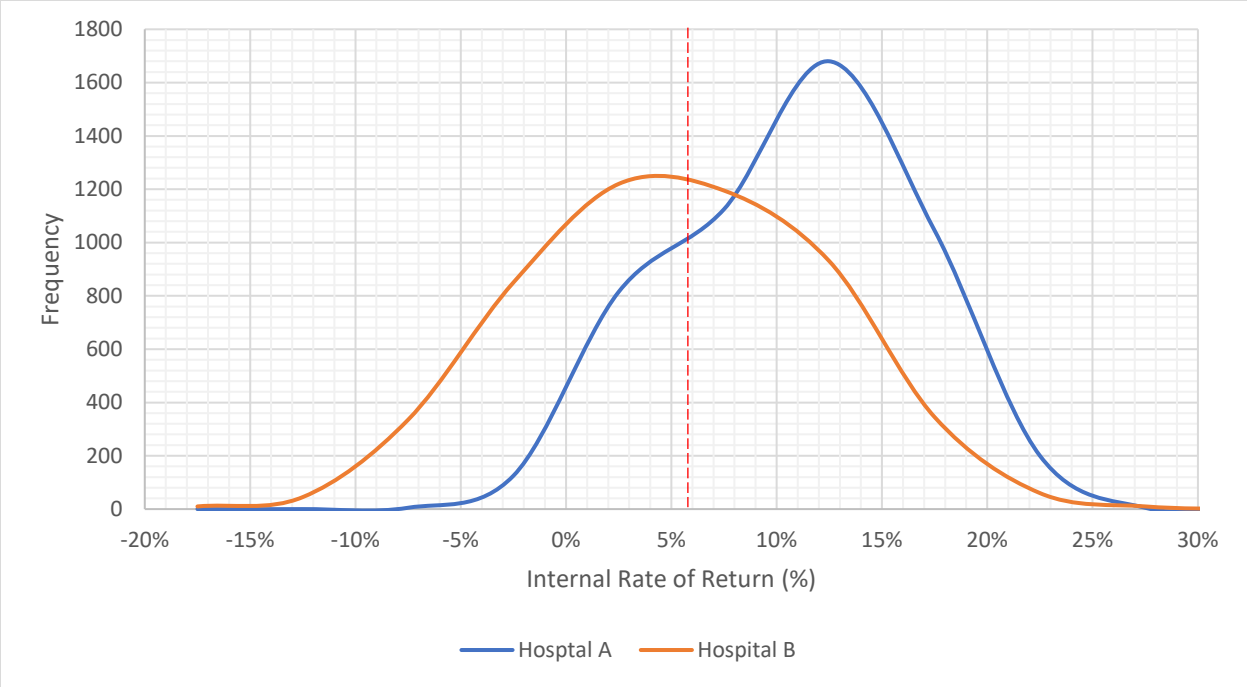
2001; Phillips, 1986), as inflection points[63] changed each set[64] of different simulations. Hospital B was relatively less affected because infection-related random variables could not meaningfully impact IRR calculations. While the generated IRRs seemed to follow normal distribution[65], our normality test indicated that they were not normally distributed (all p-values less than 0.007), even with testing under frequently used transformations. (including log, inverse, square, square root, etc.)

[63] a point of a curve at which a change in the direction of curvature occurs (e.g., changing first-order derivatives around IRR=2.8% for Hospital A)
[64] One set of simulation equals 5,000 repetitions that are separately conducted.
[65] With means being 11.0% (Hospital A) and 5.5% (Hospital B), and standard deviations being 4.9% (Hospital A) and 5.9% (Hospital B)

Table 25: Means and simultaneous confidence intervals of simulation results (*n*=5,000)

| Variable | Hospital A | Hospital B |
|---|---|---|
| Annual benefits from HAI reductions ($ mil) | | |
| HA-MSSA | 0.30 (0.03-0.72) | 0.05 (0.05-0.06) |
| HA-MRSA | 0.36 (0.03-0.76) | 0.07 (0.06-0.08) |
| HA-CLABSI | 2.00 (0.93-3.54) | 0.09 (0.01-0.20) |
| *3 HAIs combined* | 2.65 (1.00-5.03) | 0.21 (0.12-0.34) |
| Prevented HAIs (annual; # events) | | |
| HA-MSSA | 10 (1-25) | 0 (0-0) |
| HA-MRSA | 9 (1-21) | 0 (0-0) |
| HA-CLABSI | 99 (68-131) | 3 (0-7) |
| Avoided deaths (annual; # events) | | |
| HA-MSSA | 1 (0-3) | 0 (0-0) |
| HA-MRSA | 1 (0-3) | 0 (0-0) |
| HA-CLABSI | 9 (6-12) | 0 (0-1) |
| *3 HAIs combined* | 12 (6-18) | 0 (0-1) |
| Increased revenues (annual; $ mil) | 4.60 (3.22-6.15) | 0.21 (0.14-0.28) |
| Annual projection of construction costs ($ mil) | 4.44 (3.82-5.12) | 0.20 (0.17-0.24) |
| Annual staffing expenses ($ mil) | 1.19 (1.04-1.35) | 0.18 (0.16-0.21) |
| Nurse increases in FTEs (annual) | 19.6 (17.2-22.2) | 3.0 (2.7-3.4) |
| Annual net benefit (time-unadjusted; $ mil) | 1.62 (-0.65-4.71) | 0.03 (-0.07-0.18) |
| Net present-value benefit (all year; $ mil) | 5.73 (-0.94-12.03) | 0.08 (-0.26-0.45) |
| Internal Rate of Return (%) | 10.95 (1.28-19.69) | 5.45 (-6.18-16.20) |
| Nonnegative NPV likelihood (all year; %) | 90.3 | 63.8 |
| Cost-saving likelihood (all year; %) | 78.3 | 46.0 |

Figure 15: Distribution of internal rates of return (*n*=5,000)




**Sensitivity analysis.**

Table 26 illustrates our results of sensitivity analyses examining the potential impact of different assumptions on IRRs. The results are presented as relative changes as well as the borderline value (threshold) of the parameter that would place the investment at the border of risk neutrality[66], where hurdle rate was defined as 5.9% for hospital and healthcare facility sectors (The New York University Stern School of Business, 2019). We found that the simulation results were most sensitive to assumptions regarding construction costs for both hospitals. If construction costs turn out 10% higher than we assumed, Hospital A's mean IRR would drop

[66] Readers can regard these values as conceptual break-even points to ensure positive market risk-adjusted returns (benefits starting to exceed the sum of actual and opportunity costs).

down to 7.4%, although that degraded result remain cost-effective. Not until construction costs exceed 115% of that assumed would we predict an IRR that is not cost effective for Hospital A. At the same time, the initially cost-ineffective case of Hospital B would turn into a worthy investment where construction costs could be lowered by 1.2% or more. Calculating elasticity and shadow price further revealed that all four parameters of the sensitivity test were more sensitive in Hospital B than in Hospital A. This is also supported by empirical distributions of IRRs (Figure 15), as Hospital B's IRRs are more dispersed and have fatter "tails". Thus, small changes of parameters are more likely to affect IRR. Our results also suggest that, although assumptions on HAIs can impact IRR to some extent, they're inelastic enough to be supported by HAI models developed in the previous chapter (i.e., lower threshold of confidence interval of infection risks or costs would not flip cost-effectiveness of all-private room renovation).

Table 26: Sensitivity analysis results

| Hospital | Testing parameter | IRR when 10% more optimistic (IRR %) | IRR when 10% more pessimistic (IRR %) | Input Elasticity of IRR | Shadow price in IRR% | Cost-saving borderline (Relative to original input) |
|---|---|---|---|---|---|---|
| A | Construction costs | 15.1% | 7.4% | 3.55 | 0.4% | 14.65% |
| | Non-HAI benefits | 13.8% | 8.0% | 2.67 | 0.3% | -16.80% |
| | Staffing expenses | 11.7% | 10.2% | 0.69 | 0.1% | 65.00% |
| | HAI-cost reductions | 12.6% | 9.3% | 1.52 | 0.2% | -29.25% |
| B | Construction costs | 9.3% | 2.1% | 6.62 | 0.4% | -1.21% |
| | Non-HAI benefits | 8.5% | 2.3% | 5.76 | 0.3% | 1.40% |
| | Staffing expenses | 8.2% | 2.6% | 5.10 | 0.3% | -1.60% |
| | HAI-cost reductions | 8.6% | 2.2% | 5.92 | 0.3% | 1.36% |

## Discussion

### Good and bad cases.

At their best, all-private room hospital design not only work effectively but are likely to drive sufficiently large reductions in nosocomial infections to offset to newly required construction and operating costs and provide substantial net increased revenue. In the best case scenario the financial feasibility of private-room conversion was substantial, and likely to exceed the current average 5.9% return on investment in the US sector of healthcare facilities and hospitals (The New York University Stern School of Business, 2019). Our Monte-Carlo cost-benefit analysis indicated 78% of chance that the investment return rate would exceed 5.9%, with a less than 10% chance for NPV to fall below zero. In this circumstance, even without the addition to health benefit such as saved lives, all-private room design is a justifiable option even from a purely financial perspective.

On the other hand, our work shows that all-private room design may be cost-ineffective for hospitals likely to see lower gains in associated benefits. There are many reasons for this, including lower staffing efficiency (like many small-volume hospitals), patients with inherently lower risk of developing staph infections or CLABSIs, non-teaching facility, or an already decent environment. Hospital B was intentionally chosen to have such characteristics to quantitatively demonstrate our idea, and as we expected, anticipated return for Hospital B underperformed the industry average. More importantly our analyses predict a 36% of chance for major losses – negative NPV – with an all-private room renovation in a “Hospital B” setting.

Our work adds important nuance to consideration of how and where investment in PPR/the built environment may be warranted. Previous cost-benefit analyses and relevant studies extrapolated one-hospital predictions to the entire spectrum of hospitals, an approach that cannot discriminate different level of risks across various hospitals. Even conducted with representative data and models, the best result expected from such an approach is the middle point between those like Hospital A and Hospital B, which has clear limitations in practical applications.

**Why simulation matters.**

With simple calculations (i.e., no probability distribution and numerical simulation unemployed) with point estimates from underlying models, respective returns on investment (ROIs) for Hospitals A and B could be obtained as 12.2% and 5.2%. We found the differences of +1.2% and -0.25% for Hospitals A and B between the expected returns calculated with the deterministic approach and those calculated with the probabilistic approach. From a decision-theoretical perspective, the expected value of outcome estimates from probabilistic analysis such as the Monte-Carlo simulation, rather than the deterministic point estimates, is the relevant figure of merit (Stinnett & Mullahy, 1998). Another advantage of the simulation approach is that once random samples from the probability distribution of IRR are generated, additional questions about the economic value or the financial risk of the investment can be answered, due to the ability of having “intervals” to analyze the higher-order moments such as variance, kurtosis, and skewness.

For example, Hospitals A and B differ in the likelihood of renovation success. Hospital A was 90.3% likely to have positive net present value in the five-year projection window while Hospital B failed to do so with only 63.8% probability. Regarding cost-effectiveness of the whole investment, an interesting contrast can be drawn by comparing ROI distributions. Where industry average ROI is approximately 5.9% which is regarded as a hurdle rate (lower boundary) of cost-effective investments., our results indicate respective cost-effective probabilities of Hospitals A and B were 78.3% and 46%.

**Sensitivity and face validity.**

Admittedly, simulation results are subjective and often sensitive to how underlying parameters are assumed. While we believe that this study utilized the best estimates available from the publicly available data, it is possible that data limitations challenge the integrity of our models. For example, our inputs regarding construction costs might be less robust than infection risks and treatment costs which were identified from the actual patient data. Compared to the latter, the former is closer to an educated guess, which may introduce higher variation in the reality. In this respect, we made significant effort to assure realistic assumptions for multiple ways.  First, our sensitivity analysis indicated that among the factors investigated, the financial plausibility of private rooms was mostly sensitive to construction costs (Table 26), which was in line with our intuitive concern described above. If construction costs change by

+1%, ROIs would respond by 3.6% relatively and +0.4%p absolutely.[67] With 10% more pessimistic assumption in construction costs (i.e., 1.1 times the originally assumed costs), ROI of Hospital A would go down to 7.4% as opposed to the original 11.0%. Hospital B with the same assumption would have 2.1% ROI. Note that Hospital A remains cost-effective (ROI>5.9%). Our results show that, while the degree of ROI changes according to assumption, the key conclusion of cost-effectiveness (cost-saving or not) would not change until 14.7% more pessimistic assumption in the most sensitive input parameter (construction costs). This implies that our models are robust over a relatively wide range of key assumptions. We also had the opportunity to validate our assumptions against reality –in 2018, Tarrant County voters supported a 800 million US dollar bond for JPS Hospital ("Hospital A"), with a pass rate higher than 82% (Ranker, 2018). The raised funds will be used to add a new patient tower as well as to renovate the existing facility with a modern design. This directly shows a sufficiently high perceived need for better design in built-in environments of healthcare facilities that taxpayers and government are willing to pay the costs. Therefore, an all-private room renovation project is not an abstraction or a thought experiment, but a real and current consideration for healthcare systems in Texas and likely beyond. Both the face validity and relevance of our work is also reinforced by our communication with experts from various fields, including a public

[67] Readers should be aware of the difference in absolute and relative changes in IRR. IRR is inherently defined as time-discount rates, and usually presented as percentages. In the context of sensitivity analysis, we have different "percentages" showing the ratio between original and changed values. We adhere to using the term "percent (%)" to report relative changes and "percent point (%p)" to present absolute changes. For example, if the original IRR is 20% and the changed IRR is 22%, the absolute change would be +2%p (i.e., the difference between 22% and 20%) while the relative change would be +10% (i.e., 2% is one tenth of the original IRR of 10%).

safe-net hospital in Fort Worth, Texas, and a healthcare-facility construction firm in Dallas, Texas and our careful review and use of two published official documents: the Tarrant County functional and space program (Tarrant County Texas, 2014) and the Texas hospital utilization and financial trends (Texas Department of State Health Services, 2018).

**Contrast to previous findings.**

Our model represents an advance over previous studies in the literature. It can predict the benefits of the all-private room design, based on the characteristics of an individual hospital. By contrast, previous cost-benefit analyses extrapolated the results of a single hospital to the entire spectrum of hospitals. At the same time, recent peer-reviewed reports of a cost-benefit simulation with similarities to ours noted much higher ROIs (IRR=56%, 95% CI=25%-87%) (Sadatsafavi et al., 2016). We believe this is more a function of basic differences in the project's outcome measures, including a different set of HAI of interest, and that our work includes some important improvements relative to Sadatsafavi's.

First, although their work was published recently, the underlying model was drawn from an old analysis (Bracco et al., 2007) of pre-2005 data. This has potential to inflate estimates of nosocomial infection acquisition risks relative to more recent epidemiology, and in turn inflating the value of interventions that drive risk reductions. For example, HA-MRSA acquisition risk was assumed 0.4% in Sadatsafavi's, which is not only 5 times higher than our data, but also far from present HAI statistics (Office of Disease Prevention and Health Promotion, n.d.) National snapshots point out that nosocomial infection risks have been decreasing over the years, potentially due to better practices and interventions. Between 2008 and 2014, CLABSIs

and MRSA infections were reduced by 50% and 36% respectively. Using the most recent data possible is the best way to prevent overestimations of a cost-saving effect. While one may raise the same question toward our study (i.e., 2016 data may also be outdated for use post-2019), the statistics show that nosocomial infection incidences became relatively stable after 2011, and lead us to believe our estimates are a more realistic and accurate reflection of current conditions. Second, the analysis structure may be less suitable than ours for large-scale renovations and new facility constructions in the US in several aspects: (1) study samples were from the Canadian population, which may differ from US patients in important ways including demographics, comorbidities, and healthcare accesses (Allen, 2006); (2) only eight ICU beds were considered in the simulation, which can introduce a significant bias in extrapolating to a larger scale (i.e., our Hospital A has more than 500 beds) or less sick population (i.e., ICU patients versus general inpatients); and (3) staffing elements were not considered in the benchmark potentially due to its small-scale nature despite consensus that staffing is one of the core considerations in evidenced-based architectural design for hospitals (Aiken et al., 2012; Gibson, 2007; Seelye, 1982; Weinstein, Stone, Pogorzelska, Kunches, & Hirschhorn, 2008).

**Limitations.**

As with any such work ours has limitations such as its cross-sectional study design and the complexities of private room identifications in administrative data discussed elsewhere in this work. Two additional potential limitations warrant additional consideration. First, it must be noted that CLABSI costs were derived from different data and may be inconsistently comparable to MRSA and other HAI costs. Still, underlying statistical models and probability

distribution fittings of incidence probabilities (Staph infections and CLABSIs; conditioned by private and bay rooms respectively) were based on the Texas IP PUDF. The same database was also used to estimate attributable per case costs of staph infections. Thus, those statistical inferences have high compatibility and link without serious methodological challenges. However, we used CLABSI-attributable cost estimates from a systematic review in the literature (Scott, 2009). This can introduce two challenges in the context of our simulation: (1) an underlying analysis is outdated (base studies conducted before 2003) (Hu, Veenstra, Lipsky, & Saint, 2004); and (2) generalizability of the results to Texas inpatient population remains questionable. However, assuming good internal validity of the systematic review and underlying studies, as they were from either high-authority federal organization (CDC) or a well-regarded peer-reviewed journal (Clinical Infectious Disease), it is more likely that cost estimates from more recent data become higher due to costlier technologies and treatments in general. Underestimation in infection costs reduces benefits of our cost-benefit analysis because lower costs reduce cost-saving effects. Therefore, we believe that this does not change the key direction of our findings. Furthermore, flexibility of our simulation models will enable future studies to improve our findings by conducting CLABSI cost studies with the same database used in this thesis[68].

[68] We did not analyze CLABSI costs because we want to focus on MRSA and staph infections throughout this thesis.

Second, some of our simulation variables, specifically non-infection related ones[69], were assessed under strong assumptions. For example, construction costs for renovation were calculated as the product of average construction cost rate per area and additional area required to transform a bay room to a private room. This estimation process implicitly relies on homogeneous hospital room structure (i.e., area ratio between private and bay room does not change hospital to hospital). Actual design decisions for private rooms may involve numerous factors (F. Becker & Parsons, 2007; Chan, 2000; Ellison et al., 2014; Joseph & Rashid, 2007; Olsson & Hansen, 2010), which may cause larger variance in construction costs than we assumed (i.e., 10% of mean as a standard deviation). While the data available as of this thesis do not fully resolve such ambiguity, the problem is largely mitigated by our sensitivity analysis. Our results indicate that 15% higher construction costs would not change key judgements. Other variables were even more inelastic in relation to assumption changes. In this respect, our analyses remain conservative even with limited data.

Third, it is possible to question our homogeneous ROI hurdle regardless of business ownership style (e.g., nonprofit hospitals vs for-profit hospitals). The topic of proper ROI targets for nonprofit versus for-profit hospitals has been viewed from economic, accounting, and financial perspectives (Center for Health Care Stategies, 2007; Reinhardt, 2000; Wedig, Hassan, & Sloan, 1989). While we believe separate costs of capital could be more ideal, a consistent

[69] In the context of this study, infection-related variables consist of infection acquisition risks for staph infections and CLABSIs, and infection-attributable costs.

approach to estimate for-profit and nonprofit hospitals is yet to be established (Conrad, 1984; Heutel & Zeckhauser, 2014; Reinhardt, 2000; Valvona & Sloan, 1988; Wedig et al., 1989). Note that our approach is to demonstrate how a cost-saving effect of HAI preventions could offset incremental costs of an all-private room renovation relative to status quo rather than to make an actual judgement call to invest. It is also worth mentioning that in our analysis, a for-profit hospital was outperformed by a nonprofit hospital. With additional consideration of accounting benefits such as tax exemption (Herring, Gaskin, Zare, & Anderson, 2018; Reinhardt, 2000), the gap would be likely widened – our analysis results would largely remain valid. Nonetheless, we recommend readers aware of heterogenous business nature across different hospitals.

**Implications.**

Regardless of all such limitations, this thesis demonstrates a potentially high ROI in private rooms compared with open-bay rooms, which are still commonplace in many large legacy hospitals and healthcare facilities (e.g., public safety-net hospital). In addition, our study shows the feasibility of objective evaluation based on decision-theoretical principles, along with full characterization of uncertainty, in informing investment decisions.

Our findings notwithstanding, facility design and operations are adjuncts, no substitutes, for good hospital practices around controlling nosocomial infections. More thoughtful hospital design should support good hospital practices such as better care coordination, staff-to-staff as well as staff-to-patient communication, and cleaner and quieter hospitalization experience (i.e.,

this is one of the metrics evaluated in HCAPHPS[70] and associated with reimbursements). Our results provide new evidence for a more holistic approach to infection control, and just as importantly that this can be cost-effective as well. It is still worth noting that the choice of patient room type is not the only source of improvement in hospital performance, and other questions such as medical technology, staff training, and disinfection practices can be consistently integrated into our simulation model to evaluate costs and benefits once such data become available.

While there have been significant reductions of hospital-acquired infections in US hospitals, there is still considerable room for improvement – and hospital design is a recognized factor. Economic evaluation regarding financial implications plays a huge role in the approval process for decisions made by both hospital boards and policy makers. However, the decision-making process is suboptimal in terms of lacking objectivity and transparency. Our analysis model demonstrates that objective evaluation is possible by making use of transparent data (e.g., publicly available large database). Hospital boards that are considering building a new hospital can use our models and simulation approach to evaluate the "business case" for the all-private room design. While construction costs are higher for the all-private room design, these costs can be offset by the ongoing savings, in both US dollars and lives, from the prevention of hospital-acquired infections.

[70] the Hospital Consumer Assessment of Healthcare Providers and Systems

In addition, our analyses reinforce that there is no single universal answer regarding whether all-private room design is appropriate. As in all healthcare outcomes are highly dependent on individual and specific conditions, and these must be reflected in and carefully considered in any analysis. Our Hospital B result demonstrates that there are clear boundaries beyond which PPR and other design features are not simply cost-ineffective but overall ineffective, with no appreciable reduction in health risk. Different situations across hospitals may result in varying success or failure in applying even "inherently good" design. From a policy perspective, the best policy can be making hospitals responsible for additional costs associated with preventable nosocomial infections and safety-harming factors, which would create financial incentives for providers to perform a comprehensive implementation of evidenced-based managements and design. Such policy (as a form of incentives or penalties) must account for hospital-to-hospital differences and should be evidence-based. This study also demonstrates that, if good design (all-private room hospital) is adopted for places in need, it can result in solidly high ROI.

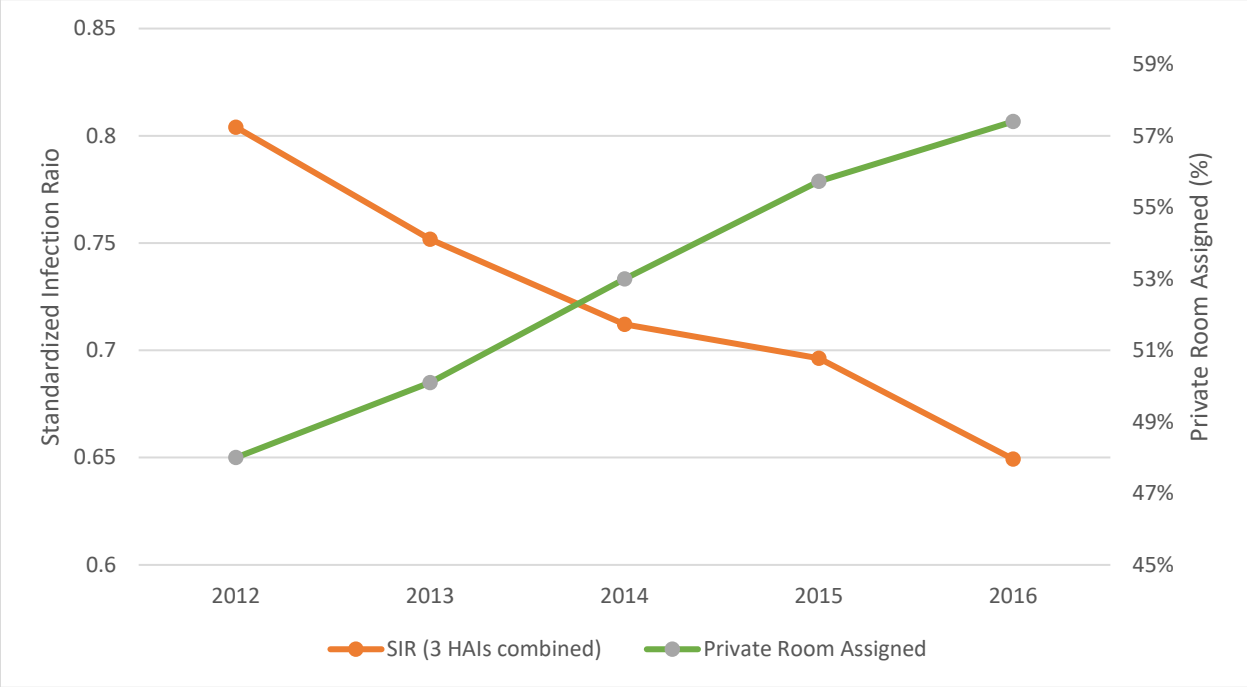
It is worth mentioning that this analysis can be expanded to statewide or even potentially to national-wide, so that relevant policies can be quantitatively evaluated. The steps in our simulation structure can repeatedly apply to any other hospitals in Texas with zero change in modeling and variable configurations. At the end of this iteration, each Texas hospital will have distributions of cost, benefit, and cost-benefit measures. The group of these estimations can be used to evaluate the effectiveness of a "policy case". For example, policy makers can see statewide gains such as total deaths avoided if (hypothetically) all-private room

renovations are mandated for all legacy hospitals. With this expansion, it is also possible to identify risk factors of low value renovation (i.e., project ROI not meeting the industry average), which can shape relevant policies more targeted and more efficient. Our statewide unadjusted results indicated the following estimations. Among approximately two million inpatients (those stayed in ICU units only excluded; 57% stayed in private rooms while 43% in bay rooms), HA-MRSA, HA-MSSA, and HA-CLABSI occurred to 949, 1329, and 316 patients respectively, which possibly accounted for 183, 171, and 49 in-hospital deaths. These infections were also associated with 45, 54, and 16 million dollars of respective Medicare reimbursements, which we consider a proxy of hospital costs. Extrapolating private rooms' per-patient incidence, death rate, and reimbursement average to entire state inpatient population, significant gains are expected: prevented infections (370 HA-MRSA, 338 HA-MSSA, and 104 HA-CLABSI), 160 deaths avoided (60, 82, and 18 deaths due to HA-MRSA, HA-MSSA, and HA-CLABSI), and 40 million US dollars of Medicare reimbursements saved (15, 22, and 4 million US dollars from HA-MRSA, HA-MSSA, and HA-CLABSI)[71]. The time trend of aggregated HAI observations and private room assignments reiterates this policy implication. Figure 16 was complied with Texas HAI data drawn from NHSN[72] HAI progress reports during the fiscal year 2012 to 2016 (CDC, 2018a)[73]

[71] Admittedly these figures did not control hospital-specific situations, thus might contain selection or other biases. We believe that this is worthy of more in-depth analyses, potentially as our next project.
[72] National Healthcare Safety Network
[73] As discussed in Chapter III, the current US surveillance HAI measure does not cover MRSA non-bloodstream infections and MSSA infections. Due to this limitation, we took weighted averages of CLABSI and MRSA bloodstream infections as proxy estimates, with respective weights of 1/3 and 2/3.

and our private room assessments[74] based on IP PUDF for the same period, which presents a clear association between reduced HAIs and increased private room assignments.

Figure 16: Statewide trend of HAIs and private room utilizations in recent years (FY2012-2016)




[74] Conditioned by (1) 2 or more days stay, (2) acute-care hospital, and (3) ICU-only patients excluded.

## CHAPTER VI

## SUMMARY OF FINDINGS, MANAGERIAL IMPLICATIONS, CAVEATS, AND FUTURE DIRECTIONS

### Background

As explained previously, the multifactorial nature of hospital-acquired infections makes them difficult to address with any single intervention. While HAI control has been improved through clinical practices, such as hand hygiene compliance, and use of personal protective equipment, US control targets remain largely unmet[75] (Office of Disease Prevention and Health Promotion, n.d.). It is plausible that the built environment may interact with HAI risk, and other improvements in hospital design may play a significant role in reducing "never events" Unfortunately, the relationship between HAI risk and various physical design features remains poorly understood. Substantial incentives for HAI control exist, including "value-based purchasing" and other quality related elements of Medicare reimbursement. A better understanding of the role of facility design for improving patient safety and optimizing reimbursement is especially needed nowadays.

We sought to address this knowledge gap through an analysis of the common HAI, Staphylococcus aureus (Staph) infections, with a specific focus on methicillin-resistant Staphylococcus aureus with hospital onsets. Among all HAIs, HA-MRSA is worth investigating

[75] For example, Healthy People 2020 aims to reduce central line infections down to 0.25 Standardized Infection Ratio (SIR) by 2020 while 2014 SIR was reported being 0.5. A similar gap was identified with methicillin-resistant staph infections (i.e., 2020 target = 6.56 infections per 100,000 population; 2014 report = 17.3 infections per 100,000 population) (Office of Disease Prevention and Health Promotion, n.d.).

further for a number of reasons: (1) it is one of the costliest and most dangerous human pathogens causing HAIs; (2) it is recognized as a major HAI by federal and state governments and impacts public reporting and reimbursement; and (3) evidence is inconclusive (regarding associations between MRSA and outcomes), sparse (regarding environmental and structural predictors of MRSA), and methodologically limited (most reports stem from small, non-representative samples or low-validity secondary data, as illustrated in Tables 1 to 3).

Our previous work in this area focused on Central-Line Associated Bloodstream Infections. The findings demonstrated that private rooms are associated with HAI control, suggesting these as part of the built environment may be an important part of coordinated approach to reduce HAI risk. This thesis extends these findings and applies lessons learned to address the methodological shortcomings of administrative data. Our aim is to fill existing gaps around how the built environment interacts with HAI risk in the inpatient setting as well as the potential value of risk management through facility design. Ultimately this work will facilitate practical improvements in both management and policy.

**Re-evaluation of the Specific Aims Outlined Previously**

**Aim 1 (Chapter III).**

***Specific Aim Re-described.*** We aimed to develop hospital-level predictive models that link the effect of facility design to HA-MRSA reductions and hospital cost. Based on representative large data, this work examined the association between facility design, primarily focusing on patient rooms, and HA-MRSA infections. We examined the rate and attributable impact of HA-MRSA infections at the hospital level, hospital cost (measured by Medicare

reimbursement), and the relative value of investment in facility constructions or renovations relative to HAI control.

***Study purpose.*** In Chapter III, we suggested a feasible public reporting measure based on structural components. This measure addressed practical questions of HAI safety effects raised in construction projects and business plans such as "How many nosocomial infections can be actually prevented?". We examined how design factors could relate to HA-MRSA, developed a statistical model to predict HA-MRSA incidence at a hospital level, and paid a specific attention to the effect of private patient rooms on HA-MRSA incidence.

***Findings.*** For 341 Texas hospitals during the fiscal year 2016, across different hospital groups (categorized by private rooms in hospitals), we observed a significant variation in many hospital characters (ownership types, publicly insured or uninsured patients, racial patient-mix, average medical burden, nurse staffing, dominant procedure class, and physical occupancy). Our adjusted multivariate model revealed that each 1% increase of private room among all rooms was associated with 0.8% reduction of HA-MRSA infections ($p<0.001$) and confirmed significant hospital-to-hospital variation in organizational variables.

Our predictions were consistent with estimates predicted by the Standardized Infection Ratio model currently used by the CDC. The improved diagnostic power (more cases identified) but remained compatibility combinedly suggested the proportion of private rooms in an inpatient facility as a robust indicator for better protection against HAI; required reporting of this metric would not only be informative but robust – it is transparent, easily confirmed, and static. And due to this reason, the present thesis urges hospitals to publicly disclose how many

private rooms they contain. We verified that "safer" hospitals were associated with having mostly private rooms. To help patients make better informed decisions in choosing places to get care, patients and their families should be able to access such an easy-to-understand indicator like percentage patient rooms, which can ultimately result in big public health gains. Chapter III also implied that governments, relevant authorities, and interested parties should expand a MRSA surveillance measure to cover a more comprehensive set of whole infections, as opposed to a narrowed definition of bloodstream infection. We verified that an expansion of MRSA definitions did not critically affect surveillance consistency.

**Aim 2 (Chapter IV).**

***Specific aim re-described.*** We examine the effects of 'positive externalities' of private rooms relative to HA-MRSA risk at the patient level. Positive externality in this context was defined as indirect hospital-wide effects on patients regardless of assigned room types. The hypothesis for this aim was that the patients' benefits due to PPR are decomposed into individual (direct) and hospital (indirect) effects. This implies that, even if a patient is assigned to a bay room, this patient would be safer against HA-MRSA compared to the equivalent patient assigned to non-PPR at a 'worse' hospital (i.e., lower percentage of private rooms), other factors being equal.

***Study purpose.*** We explored nosocomial staph infections and related conditions at the patient level, particularly focusing on the patient's perspective of a full pathway from private rooms to end healthcare outcomes, as specified with the two following objectives: (1) an integrated statistical model to simultaneously evaluate internal and external effects and predict

the risk of nosocomial staph infections (both HA-MRSA and HA-MSSA); and (2) estimates of the attributable impacts of staph infections on three major healthcare outcomes: in-hospital death risk, inpatient length of stay, and hospital costs.

***Findings.*** In analysis of 2,670,855 Texas inpatients during the fiscal year 2016, our multivariate analysis confirmed both hospital-independent effect of private rooms as well as room-independent (hospital-wide) effect of private rooms. These two effects together could drive a cumulative 38% and 52% risk reduction for HA-MSSA and HA-MRSA respectively. As expected, we found that HA-MSSA and HA-MRSA worsened healthcare outcomes for patients; we also found substantial related operational impacts for hospitals, including four times higher costs. Using matched cohorts via propensity score, our analysis pointed out specific attributable outcomes due to HA-MSSA and HA-MRSA: for each patient, HA-MRSA was associated with an excess $12,100 cost, 8.9 more days of stay, and 4.8% higher mortality risk. HA-MSSA was also impactful, though associated with less severe outcomes ($6,600 more costs, 8.6 more days of stay, and 4% higher mortality risk).

Our analyses in Chapter IV had a very important implication: hospitals with fewer private rooms should try their best to convert existing bay rooms to private rooms. We verified indirect effects of private rooms, showing that even patients who stayed in bay rooms could benefit increased safety due to higher percentage of private rooms. According to our analyses, the benefit of a process improvement (patients assigned to private room) could be disproportionately maximized when a better facility design (hospitals having mostly private rooms) is combined. Moreover, our cost analysis showed that the costs of invasive staph

infections (both MRSA and MSSA) was mostly (approximately 90%) explained by facility costs rather than professional fees, which also provided a strong support for hospitals and policy makers to prioritize investments in the built environment in fighting against HAIs.

**Aim 3 (Chapter V).**

***Specific aim re-described.*** We developed a probabilistic cost-benefit analysis simulation model and applied the simulation model for actual hospitals to test the practical application of our methods. Such a CBA would help hospitals judge how investments in the built environment may be justified by cost-saving benefits from reduced HAIs. We expanded our focus from HA-MRSA to include HA-MSSA and HA-CLABSI as well. This allowed a more fully capture the potential value of HAI control.

***Study purpose.*** We investigated both the financial costs and benefits of choosing an all-private room design in comparison with current room-mix. Projected savings were primarily derived from expected reductions in hospital-acquired infections. We also developed an empirical staffing model to predict additional nurse staffing required to an all-private room design.

***Findings.*** Renovation to all-private room design was meaningfully more cost-effective for a larger, public, safety-net hospital (Hospital A[76]) than a smaller, rural, for-profit hospital (Hospital B[77]). This demonstrates that the benefits of an all-private room design will vary

[76] John Peter Smith (JPS) Hospital in Fort Worth, TX
[77] Hill Regional Hospital in Hillsboro, TX

substantially based on hospital and patient characteristics. Despite variability in the estimates of costs, and infection risks, the additional costs of private rooms – including both fixed (construction) and variable (labor) costs – were largely offset by ongoing cost savings due to preventions of HAIs (i.e., annual cost-saving effect reached up to $2.7 million). The mean internal rate of return (IRR) over 5-year analysis period was 11% for Hospital A and 5% for Hospital B. For Hospital A, and an all-private room design was predicted to prevent 12 patient deaths per year due to lower HAI risk.

Our results implied that hospitals and policy makers should not only make their best effort to increase private hospital rooms but also evaluate each facility renovation project or each private room-related policy in a scientific and quantitative way. While private rooms were costlier than bay rooms to build and operate, they were more effective in avoiding costs associated with nosocomial infections and providing substantial health protections including saved lives. These two aspects (costs and benefits) should be examined to figure out overall cost-effectiveness. Our analysis, by showing two contrasting examples, demonstrated how these can be simulated with known (publicly available) parameters, without being trapped in practical uncertainties. Our statewide unadjusted results suggested that, if all-private room design was mandated for all Texas hospitals (not only for new facilities), the state could expect overall 45 million US dollars of costs saved and 160 deaths avoided due to prevention of HAIs – substantial gains by all means.

Importantly, we also found that hospitals treating vulnerable populations enjoy a higher ROI as well as ongoing cost-saving with an all-private room design. This huge potential

contribution to the community should not be overlooked in valuing construction and renovation projects of safety-net hospitals.

## Strengths of the Present Thesis

### Focuses on evidence-based design.

Evidence-based design in healthcare industry is defined as any decision about the built environment of hospitals being based on scientific research creating the most efficient outcomes. This concept has attracted huge attention of general public and experts from various fields and become the fastest growing trend in healthcare, due to the expected values added to hospitals – including enhanced patient safety, reduced medical errors, decreased patient need for medication, reduced staff injuries, and increased staff efficiency through improved workflow (F. Becker & Parsons, 2007; Gamble, 2010). The multifactorial nature of nosocomial infections has even further emphasized the importance of such evidence-based approaches. Unfortunately, there was not enough "good evidence," and available reports reflect weak external validity from smaller sample sizes and potential confounding issues. Other peer-reviewed studies based on administrative data introduced their own problems, such as validity issues related to outdated data.

This work fills important gaps. Its focus on private rooms as a core design element and examination of the value proposition for HAI control are especially important. Our methods were robust and inclusive – we examined more than 200 hospitals and 3 million hospitalized patients to develop predictive models for the three largely distinct pathways: from patient room to nosocomial infection (Chapters 3 and 4), from nosocomial infection to attributable

outcomes (Chapter IV), and from patient room to overall cost-saving effect (Chapter V). Our mixed-effect models adjusted patient demographics as well as hospital characteristics to reduce confounding bias (models developed in Chapter IV and applied to cost-benefit analysis in Chapter V). The use of the most recent ICD-10-CM coded data throughout this thesis is expected to increase validity to a significant extent, considering superior coding details and better coding practices (i.e., presumably better software and closer connection with electronic medical records). We also separated direct and indirect effects of patient rooms on health outcomes – called "internal" and "external" effects of private rooms – which increased the explaining power of our analyses and proposed a new perspective to analyze the context (Chapter IV). Furthermore, we sought to maximize translations from knowledge to practice by suggesting an application example in Chapter V: probabilistic cost-benefit analysis for two real hospitals.

**Internal and external compatibility.**

Though we include three distinct studies, these are inherently cohesive. Patching different study findings to generate a new model is not unusual in scientific research, but different study designs and incompatible data sources (in terms of both population and data collection timing) often introduce validity and reliability issues – particularly in the health service study area (Bravata et al., 2005; Johnstone, 2004). This is much more well controlled in this work – each examined the same study population as well as the same data collection period, and variable definitions are highly consistent.

We used a publicly available data source, and others using our methods with the same data can easily replicate and validate our findings. Moreover, as we did in this thesis, if a data source and variable definition are consistent with our design, investigators can integrate our models and results as a part of newer studies. This potentially benefits not only academic researchers but also those in non-academic fields (e.g., business analysts) who are usually limited to access research-purpose data.

Our analysis framework and model definitions were largely independent from data sources and their organization. Thus, the threat of lacking external validity due to outdated data collection years or Texas-specific results (for the purpose of applications to other non-Texas states) can be disarmed without much difficulty – only needing to update results by re-applying our methods and frameworks to a newer or more appropriate data source with zero or minimal changes.

**Advanced analytical methods used.**

In addition to the use of large and representative data set, we utilized statistical and analytical methods to extract maximum information from our rich data and rule out various noises. The rigorous use of such tools enabled us to obtain the prediction accuracy close to experimental designs, which was inherently impossible for this thesis for ethical, financial, and practical reasons (Chapter II).

In Chapter III, we used the Predictive Margins to assess a marginal (incremental) risk regarding the portion of private rooms in a hospital. This method allowed us to plug in different levels of private rooms in a hospital, leave all other covariate the same ("Ceteris paribus"),

predict MRSA risk, and average the results. Compared to traditional unadjusted approaches (e.g., scatter plot between private rooms and MRSA risk), our method could reduce bias caused by confounders. In Chapter IV, we used the Propensity Score Matching to assess attributable impacts of staph infections on healthcare outcomes. This approach has been used in medical studies to compare treatment and control groups to reduce selection bias from non-identical sampling. We creatively considered "presences of staph infection" as a selection factor and "relevant end outcomes (costs, LOS, and mortality risk)" as outcome variables, which allowed us to apply this method for our data. As a result, our prediction could rule out selection bias (caused by typical confounders such as comorbidities) more effectively than otherwise. In Chapter V, we used the Monte-Carlo Simulation along with additional sensitivity analysis to achieve realistic results based on uncertainly known inputs. This allowed us to figure out cost-saving effects as a continuum rather than an on-an-off oversimplification. We could also examine financial plausibility of different situations, which would not be as accurate as our work if deterministic approaches based on point estimates were used (traditional approach).

It is worth mentioning that we made our best effort to find the most optimal method for each study, which was proven and well discussed regarding its analytical performance in statistical and mathematical literature. And all the methods we used resulted in accurate predictions as a quasi-experimental approach, which potential state holders would enjoy as a "better" evidence.

## Limitations of the Present Thesis

### Cross-sectional designs.

We utilized cross-sectional design for 1 year of Texas inpatient data, mainly due to data limitation. Starting from October 1, 2015, inpatient hospital procedure coding changed to ICD-10-CM for diagnosis and ICD-10-PCS for therapeutic procedures, which introduced incompatibility in terms of infection assessments between pre-fiscal year (FY) 2016 and post-FY 2016 data. Given our focus on practical applications along with our concerns regarding known limitations of ICD-9-CM such as low validity of MRSA assessments, we found post-FY 2016 data more suitable for this thesis.

We highly recommend potential readers to interpret our findings with caution. Predicted benefits are better understood as a comparative result (i.e., hospital to hospital variation) rather than an absolute effect, though that extrapolation is possible. But it implicitly presumes that, to completely rule out biases, (1) hospital variations are sufficiently captured in control variables in the models and (2) time-variant changes (e.g., policy, regulation, etc.) are not present. This means that a certain risk of prediction errors would be unavoidable in applying our findings to practical projects, although our results were taken in very conservative ways. Fortunately, as detailed and shown in Chapters 3-5, our study and analysis frameworks are organized so flexibly that we will be able to expand this thesis to multi-year longitudinal analyses, once newer data are applied.

**Measure limitations.**

There is no known standardized measure of reporting private rooms in a hospital in either relative or absolute quantity. Due to this data limitation, a private room percentage of each hospital was inferred based on charge data – possibly affected by room utilizations and occupancy. While (1) our models adjusted occupancy and relevant covariates and (2) charge-based room assessments were still meaningful to the context of the present thesis, in that only actually assigned rooms were focused, we would like future research to verify the robustness of our findings if actual figures of private room data are applied.

Multiple and complicated interactions may exist among patients, staffs, facilities, and nosocomial infections. The nature of hospital structure and design always imposes unidentified confounders on researchers because some interactions among core elements often introduce unwanted and unmeasurable offsetting endogenous effects. For example, hospitals treating a dangerous population (increased risk of infection) may concentrate on in-hospital safety more (decreased risk). It is possible that this mutually-countering interaction may result in higher variation of analyses and predictions.

The primary focus of this thesis is private rooms and their protective effects on preventing nosocomial infections. Yet, there are many other potential benefits of private rooms, including patient privacy, reduced errors, increased nurse and patient satisfaction, etc. (Habib Chaudhury et al., 2005, 2006; Huisman et al., 2012; Reiling et al., 2008) Hospital designs involve many other important elements beside private rooms (e.g., patient and staff flow) (Gamble, 2010; Hicks, McGovern, Prior, & Smith, 2015; Joseph & Rashid, 2007; Olsson &

Hansen, 2010). Future research should extend our analysis to include a broader and comprehensive scope of the built environment and patient safety.

**Use of administrative Data and ICD-10-CM in identifying MRSA.**

Administrative data have been often criticized as questionable reporting accuracy. Especially, diagnostic and surgery information assessed via ICD-9-CM codes were challenged due to their low sensitivity or low positive predictive value regarding MRSA infections. Although we decided to opt out ICD-9-CM and opt for newer ICD-10-CM, which could increase data validity (through more robust coding definition, coding practice improvement, and more intuitive user interfaces of latest software), the data quality of ICD-10-CM in the context of HAI is still in doubt from a conservative perspective. At this point, we were unable to fully justify our use of ICD-10-CM administrative data because of lacking validation studies about this coding version. Instead, we examined how hospital-level MRSA cases identified by ICD-10-CM differed from laboratory-confirmed MRSA bloodstreams at the hospital level in CMS Hospital Compare database and observed disparity in absolute quantities (inherently unavoidable due to different MRSA definitions) but high correlations between the two assessment methods. Therefore, for the specific needs of this thesis, we regarded our administrative data as “sufficiently validated” in terms of MRSA identification. However, we still recommend readers not to overinterpret our assessments but to consider them as a solid “indicator or proxy” to true MRSA cases and relevant outcomes.

## Recommendations

### Policy: safety-related public reporting.

Despite nearly universal consensus over the importance and effectiveness of public reporting of patient safety indicators, safety-related reporting measures – specifically regarding staph infections – are subject to critical biases. As demonstrated in Chapter III, the current US MRSA surveillance measure (bloodstream infections) cannot comprehensively cover various routes of infections such as pneumonia due to MRSA, which might be potentially problematic in generating unintended consequences (Kavanagh et al., 2017; Schuts et al., 2016; Winters et al., 2016). Our findings provide evidence that expanding MRSA surveillance is not only possible with current administrative data but also likely to remain consistent with other measures.

Quantifying the protective effects of private rooms on nosocomial infection risk underscores the need for enhanced hospital disclosure of their proportion of private rooms. Our findings suggest that important public health gains are possible given smarter hospital choices by patients. (i.e., they can recognize “better” hospitals easily.) With such transparent information in the healthcare industry and market, hospitals would be more accountable for better hospital designs by themselves to survive in competitions. Moreover, unlike process measures such as incidence, short-term invariability of private rooms (as a characteristic of structure measure) will make hospitals extremely hard to manipulate, falsify, or underreport.

Consistent with previous reports for antibiotic overuses and antimicrobial stewardship policies (CDC, 2015; Pogorzelska-Maziarz et al., 2015; Schuts et al., 2016), we found hospital-wide antibiotic resistance levels were significantly associated with the conditional incidence of

MRSA among staph infections. This suggests methicillin-resistance rate (i.e., the ratio of MRSA to staph infections) as a useful and robust indicator for inpatient antibiotic resistance and overuse. Traditionally, antibiotic overuses are assessed mostly from outpatient prescriptions, which has inherent limits in inpatient research and surveillance (Gerber et al., 2010; Ventola, 2015). We believe that using MRSA as "bellwether" has potential to overcome such limitations.

**Management: evidence-based renovation of legacy hospitals.**

Private rooms are now considered as the minimum standard for newer hospitals. Still, legacy hospitals such as rural or safety-net hospitals contain many bay rooms. This may impose greater risk of nosocomial infections and relevant disadvantages on patients who are limited to choose such hospitals for geographical or financial reasons. Our findings suggest important opportunities for such hospitals should they choose to proactively renovate their facilities and build safer environments. Our cost-benefit analysis method and framework can be used to evaluate business cases and renovation projects in a more evidence-based way, which ultimately may suggest that the cost for such renovation may be offset by safety benefits and reimbursement gains obtained from prevented nosocomial infections.

**Research: possible derivatives of this thesis**

We found that effectiveness of private rooms in hospital design is sensitive to multiple hospital characteristics and patient-mix. We focused on an all-private room design as one design target, but hospitals under certain situations (e.g., smaller for-profit hospitals) may find investment and labor costs too overwhelming even after considering safety gains.

Our methods suggest the opportunity to evaluate specific hospital characteristics to determine an optimal number and percentage of private rooms at the single facility level. Taken together with concerns regarding private rooms – such as supervision required for falls in patients (Habib Chaudhury et al., 2005; Taylor, Card, & Piatkowski, 2018), nurses preferring combined design of private and bay rooms (Hendrich & Chow, 2008; Maben et al., 2016), and/or some patients reporting loneliness (Pease & Finlay, 2002; Reid, Wilson, Anderson, & Maguire, 2014) – pros and cons of mixed-room design (having both private and bay rooms) are worthy of in-depth investigations, along with determinations of "optimal" ratio of private rooms to bay rooms. The present thesis would contribute to such research as a good starting point.

During data analyses, we found that our data set was richer than we originally assumed, with potential to possibly address many urgent public health and healthcare issues. Disproportionate risk of antibiotic resistance between urban and rural populations was one such opportunity identified. Our preliminary analysis suggested that the risk of gaining methicillin-resistance as opposed to methicillin-treatability is significantly higher in people living in rural areas and people going to rural hospitals. Potential interactions, as well as inter-age-cohort disproportionateness (i.e., underaged inpatients in rural area/hospitals having drastic risk level of bacteria gaining resistance) were also confirmed. The results were highly consistent across several statistical models differing in adjustment of confounders. We believe that this research topic deserves to more thorough analysis, and as a clear next step of this thesis, we

are currently working on testing whether our preliminary findings remain consistent across various conditions, ruling out spurious data abnormalities.

## APPENDIX I

## DISTRIBUTION FITTING FOR INPUT VARIABLES

### Determination of Probability Distribution

We first examined whether variables were normally distributed by using Shapiro-Wilk test (Shapiro & Wilk, 1965) and Shapiro-Francia test (Shapiro & Francia, 1972), both of which are well-established and verified to outperform other statistical tests for normality in terms of statistical power (Razali & Wah, 2011). Our test results indicated that annual incoming patients were normally distributed ($p>0.1$ in both test) after adjusting time trends (yearly changes) but other variables (infection risks, costs, and nurse staffing) were not ($p<0.001$). Thus, this analysis assigned normal distribution for annual incoming patients.

Then, we considered two major probability distributions often used to fit bell-shaped data distribution with abnormal kurtosis and skewness: gamma and log-normal distributions. While these two probability distributions are known to be more similar than different in the context of probability fitting (Jones, 2009; Nixon & Thompson, 2004), there has been a good consensus that gamma distributions work better for log-skewed data (i.e., log-normal, by definition, works better if logs of a variable is more normally distributed), supported by both theoretical and empirical evidences (Faddy, Graves, & Pettitt, 2009; Jones, 2009; Schulz &

Griffin, 1999). We found that our cost variables[78] were distributed log-normally (i.e., normality tests resulting in $p>0.05$ at best after log-transformations) but distributions of infection risks were log-skewed. For this reason, we assigned log-normal distributions for cost variables and gamma distributions for infection acquisition risks.

**Detailed Operations of Distribution Fitting**

For normal and log-normal distributions, fitting process is straightforward, as these distributions are determined by two easily calculable parameters: mean and standard deviation. The difference between these two is which of raw or log-transformed values are used in computations.

To determine optimal parameters for gamma distributions, we used maximum likelihood estimator (MLE) of scale and shape parameters of gamma distribution. We closely followed computational operations (Zaiontz, 2017) with Microsoft Excel add-on package (Zaiontz, 2018). The overall process was consistent with peer-reviewed discussions (Husak, Michaelsen, & Funk, 2007; Schlain et al., 2010) and implementation with a different computer software (Ricci, 2005).

MRSA acquisition risk is used as a detailed example of gamma fitting steps. A hospital given (suppose it has N patients), we first predicted MRSA acquisition risks, conditioned by (1) a patient assigned to a private room with current percentage of hospital-level private rooms, (2)

[78] Note that the distribution of construction costs was assumed (as opposed to fitting) to be consistent with the literature. We were not able to access enough number of data points.

a patient assigned to a bay room with current hospital-level private rooms, and (3) all-private room design (as a hypothetical situation; a patient assigned to a private room as the sole option). 3N values were obtained (i.e., N values for each of 3 conditions). Then, shape and scale parameters of gamma distribution for each condition were determined with Excel as described in the above paragraph.

It is worth mentioning that we used predicted values to assess risks (for patients assigned to private and bay rooms) rather than actual incidence. This is mainly because of variable compatibility. Our simulation requires randomly generated probability for all-private room design, which is inherently virtual and thus should be calculated in a predictive way. Using real incidence may introduce unwanted incompatibility issues in comparing or taking differences (i.e., real probabilities for current design vs predicted probabilities for all-private room design). In addition, by using predicted values, probability fitting process achieves higher reliability due to larger sample sizes. Using real incidences only allows K (K<N) samples for private rooms N-K samples for bay rooms.

## APPENDIX II

## ALGEBRAIC DERIVATION OF CONSTRUCTION COST FORMULA

**Known Variables**

- A: Total physical area (in square feet)
- B: Total licensed beds
- x: Percent private rooms (%)
- C: Area ratio constant b/w private and bay rooms = 0.598
- R: Construction cost rate (per a square foot)

**Unknown Variables**

- $n_1$ = # Private rooms
- $n_2$ = # Bay rooms

**Derivation Steps**

The construction cost needed is the following:

$$\mathrm{R}\left\{\frac{Ax}{n_1} - \frac{A(1-x)}{2n_2}\right\}$$

Note that $\frac{Ax}{n_1} - \frac{A(1-x)}{2n_2}$ is a per-bed area difference between private and bay rooms.

From the definition of the C variable:

$$\frac{Ax}{n_1} \Big/ \frac{A(1-x)}{n_2} = C$$

$$\frac{n_2 x}{n_1(1-x)} = C$$

$$n_2 = \frac{C n_1 (1-x)}{x}$$

$$n_1 + 2n_2 = B$$

$$n_1 + \frac{2C n_1 (1-x)}{x} = B$$

$$n_1 = \frac{x}{(1-2C)x + 2C} B \, , \; n_2 = \frac{C(1-x)}{(1-2C)x + 2C} B$$

$$R\left\{\frac{Ax}{n_1} - \frac{A(1-x)}{2n_2}\right\} = \frac{AR}{B}\left(\left(2 - 2C - \frac{1}{2C}\right)x + 2C - 1\right)$$

Therefore, the construction cost needed can be fully assessed from measurable variables.

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