TOWARD A RESILIENT HEALTHCARE SUPPLY CHAIN – ESSAYS ON MANAGING HEALTH SYSTEMS, HOSPITALS, AND VACCINE DISTRIBUTION CHANNEL DURING PANDEMIC

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment to the requirements
for the degree of

Business Administration – Operations and Sourcing Management – Doctor of Philosophy

2022

ABSTRACT

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Hospitals across the country struggled to deliver care services in the context of increasing demand due to pandemic. Consequently, they struggled to manage the uncertainties of providing care services or to manage the vaccine distribution. This dissertation is structured into three essays to address these aspects.

When the pandemic started, healthcare practitioners struggled with uncertainties regarding the choice of correct treatment procedures and understanding the factors that determine the outcomes of such procedures. In the first essay, we consider the impact of health systems' choice of adopting service innovation (SI), their participation in community-based health information exchanges, and the geographical proximity of affiliated hospitals on their ability to lower ICU bed utilization. We found that adoption of the SI may help health systems to marginally decrease bed utilization. However, such benefit strengthens when these systems participate in a community HIE. Interestingly, our study finds that when a health system adopts SI, proximity of affiliated hospitals increases the health system's intensive care bed utilization.

During a pandemic, availability of vaccines is critical to combat adverse health consequences. Since December 14th, 2020, the policymakers scaled up the last-mile vaccine distribution to increase vaccine access to wider population. Vaccines are administered in facilities that differ in their capacity and the level of accessibility. New facilities are introduced over the course of time to provide the requisite capacity for vaccination. The second essay examines how

additions of such new facilities in a region impact the number of vaccines administered by existing facilities in that region. The essay also investigates the impact of the proximity of a vaccine provider to a vaccine hub on the number of vaccines administered by the provider. Our econometric results seem to suggest that addition of new vaccine providers contributes to the vaccination rates of existing providers in an area. We find that more accessible providers tend to distribute more vaccines in the population with the burgeoning vaccine provider ecosystem as compared to their less accessible peers.

As we moved past the first and second phase of the pandemic, the supply of medical and personal protection equipment (PPE) began to stabilize. However, bigger hospitals started bulking up their PPE inventory in the anticipation of uncertain future demand. The biggest healthcare supply chain concern is that the health systems may need to write off the excess inventory in case the demand never materialized, which entails higher inventory management costs and higher opportunity costs due to unused PPE. In the third essay, we look beyond health systems and examine how higher hospital bed occupancy increases PPE inventory levels. Further, based on our interviews with both supply chain and clinical professionals across several health systems, we investigate the effectiveness of the creation of the isolation wards in controlling the demand for PPE while informing on the trade-offs in hospital capacity management and clinical care. We conducted experiments using empirically grounded agent-based model of a typical Midwestern hospital operations during the recent pandemic to propose a framework that will help the hospitals to better manage the tradeoff of managing PPE inventory, providing faster care services and offering sufficient care capacity in the community.

This dissertation is dedicated to my wife, Shayonee, and my dogs, Phoebe and Jamie, who has made my life immeasurably better.

ACKNOWLEDGEMENTS

I am deeply grateful to my advisor and dissertation chair, Anand Nair, for his patience, guidance, and empathy throughout my time at Michigan State University. I have grown immensely over the past five years working with him, both as an academic and as a person. He has provided a level of support few could match, and none could surpass.

I am also grateful to my dissertation committee members Ranjani Ananthakrishnan, Vedat Verter and Jason Miller. Without them, this research would not be possible. Their constant positivity, wisdom, and willingness to share their time will forever inspire me.

I would also like to thank the other faculty and PhD students who have supported me during my time at Michigan State University and have made my time here so memorable. Especially Dustin Cole and Zhenzhen Yan with whom I have shared this journey start to finish. This journey would not have been so fun without them.

Finally, I would like to acknowledge my parents Bidyut and Sunanda for being there for me, for listening to my rants and more importantly guiding me for the last thirty-five years to be the person I am today. I would also like to thank my extended family Chandan and Nandini to enliven my mood when I felt low.

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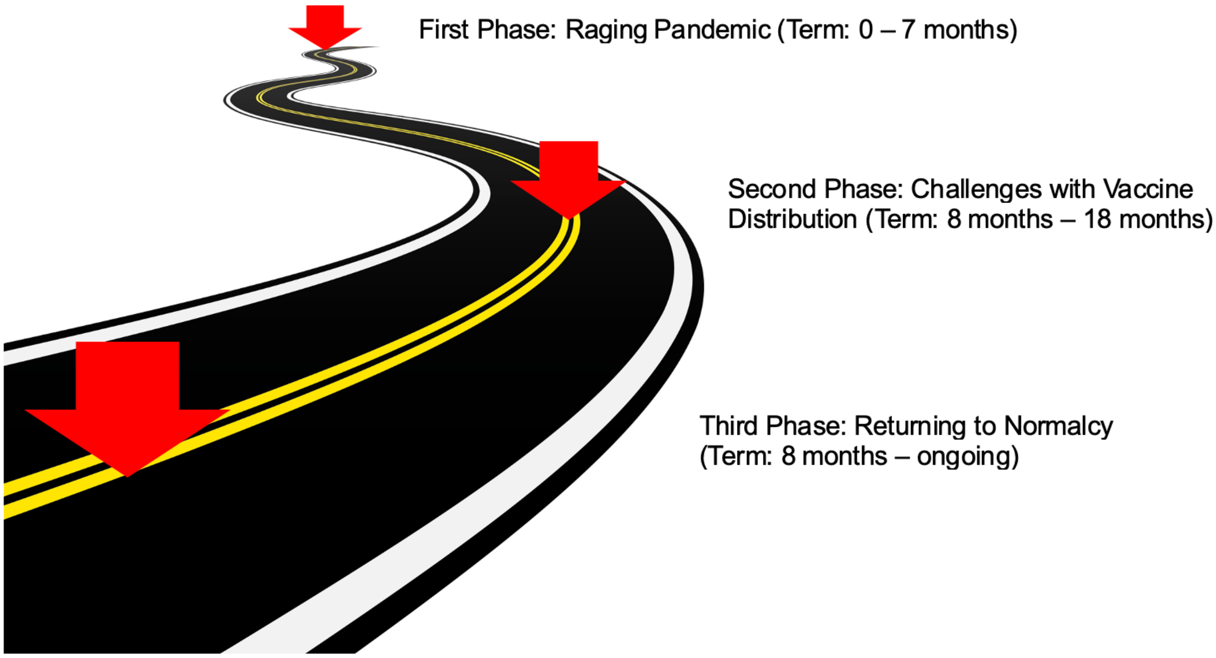
1. Chapter 1: Introduction and Research Motivation

> "Uncertainty creeps into medical practice through every pore. Whether a physician is defining a disease, making a diagnosis, selecting a procedure, observing outcomes, assessing probabilities, assigning preferences, or putting it all together, he (or she) is walking on very slippery terrain" ~ Eddy (1984)

Amid an already complex healthcare environment undergoing significant transformation, the public health emergency ushered in by COVID-19 pandemic upended care delivery and limited the speed at which organizations could transition toward value-based care models, digitization and enhance consumer experience. Care services were trying to make sense of emerging and incomplete data to guide resources required by patients, confused by the additional uncertainty as to whether subsequent peaks in COVID-19 patient hospitalization may be expected. Unfortunately, this is not the last pandemic that we have survived. Marani et. al. (2021) suggests a 38% probability that a person will experience an extreme novel pandemic in their lifetime. On the other hand, on a much smaller scale, the advent of epidemics from new viruses in different parts of the world is extremely common. Hence, it is required to develop a body of knowledge that may help us to remain better prepared and to develop a more resilient healthcare supply chain on the face of the uncertainties that the next pandemic/epidemic may bring. My dissertation aims to contribute toward developing that body of knowledge by better understanding the changing landscape of care processes that healthcare industry had experienced as it evolved through different phases of the pandemic.

The evolution of healthcare services through the pandemic can be broadly categorized into three distinct but sometimes overlapping phases as depicted in Figure 1.1. Each of the three essays in the dissertation cater to uncover the challenges that each phase brings in. The first phase is when the pandemic had just begun, and healthcare industry started to grapple with overwhelming demand of care services. It quickly became evident to the healthcare practitioners that their daily operations had become unsustainable, and they needed quick and fundamental changes to the care processes to accommodate the surging care demand. The objective of the healthcare industry quickly evolved from providing value-based care to hedging the risks of denying the sick patient the required care services. During this period, the healthcare practitioners started to adopt different care processes with little clinical evidence that those novel processes might work to heal patients quicker and enable the health providers to manage their service capacity better. In the first essay, my objective is to provide an operational framework that seeks to connect disparate healthcare practitioners from different organizations or across different institutions of the same organization so that information flow may improve. Our baseline research question seeks to understand whether adoption of the novel service procedure enables the healthcare organizations to provide care capacity in the community. Henceforth, the study has considered two distinct information streams – an external collaboration mechanism modeled by the intervention of participation in community health information exchange initiatives and an internal information and resource sharing mechanism modeled by the geographical structure of the health systems.

Figure 1.1 Phases of the Evolution of Healthcare Services during the COVID-19 Pandemic



Results from the econometric analysis offer implications for both theory and practice. The first essay seeks to contribute to three distinct streams of literatures. First, the study informs the service innovation literature that relates to implementation of the novel procedure. The results of the study suggest that health systems that adopted the novel procedure during the uncertain times presented by the pandemic may be able to lower the intensive care bed utilization due to pandemic related hospitalizations. Second, we contribute to the understanding of the impact of health information exchange on hospital resource utilization. The results of the study show that by participating in an information exchange coalition, health systems were able to reduce the intensive care bed occupancy. The study uses tenets of organizational information processing theory (OIPT) to further understand the level of uncertainties that a novel service procedure. Consequently, we find that information sharing coalitions provide the health systems the required structure for learning spillovers which aid healthcare organizations to manage the uncertainties around the novel procedure more efficiently and hence enhance the impact of adoption of novel procedure on the bed occupancy. Third the study contributes to the geographical proximity literature within an overarching theoretical framework provided by OIPT. Our results show that health systems that have affiliated hospitals in proximity tend to manage their bed occupancy poorly when novel service procedures are implemented. The essay also provides a more robust understanding of the novel processes that the healthcare administrators may pursue during a pandemic and enables them to develop policies that may make the new care processes more efficient.

The second phase of the pandemic has been characterized by introduction of the COVID-19 vaccines and by the definition of the mass vaccination process. The initial phase of the pandemic entails a lot of uncertainties. However, after about 8 months into the pandemic the quick invention of the m-RNA vaccines provided a moment of relief to the humankind and medical fraternity alike. However, the definition and establishment of the supply chain to distribute the vaccines in public proved to be the nightmarish experience for the policymakers and healthcare community. When the distribution started, people were waiting in line for hours to get their jabs or driving hundreds of miles to get their first vaccines[1]. However, as the vaccine yield gradually stabilized, the policymakers started to increase the vaccine provider infrastructure with a goal to inoculate 70% of the population by July 4, 2021. Such rapid vaccine infrastructure scale-up in a region may impact the vaccination rates of the incumbent providers in that region. This is an important consideration since it provides information on the effectiveness of the expansion plan for administering vaccines. On one hand, if addition of new vaccine providers reduces vaccines administered by incumbent facilities, there is a substitution effect as also evidenced in the retail context. From a policy perspective this reduces the efficacy of newly added facilities in increasing the overall vaccination levels in a region. In the second essay of the dissertation, I investigate how

[1] https://www.washingtonpost.com/lifestyle/travel/covid-get-vaccine-road-travel-/2021/04/08/5675e0f8-9631-11eb-b28d-bfa7bb5cb2a5_story.html

additions of new facilities in a region impact the number of vaccines administered by existing facilities in that region. Given the diversity of the vaccine providers that range from those with higher capacity (e.g., hospitals) to those with lower capacity (e.g., pharmacies), it is also important to understand if these vaccine providers differ in terms of the relative impact on their vaccine administration levels with the introduction of new facilities in the region. Hence, in this study, we further investigate whether relative accessibility of the different vaccine providers enables them to accrue additional benefits from the systemic vaccine infrastructure ramp-up process.

The study and results provide significant contributions to the theory. The findings contribute to the OM literature related to the downstream vaccine supply chains that has primarily looked at the allocation and administration of vaccines in the context of external uncertainties caused by an ongoing pandemic. The study provides novel empirical evidence that addition of new providers in the area increases the inoculation rate of the incumbent provider as it contributes to the collaborative vaccine provider ecosystem. The study also makes significant contribution to the stream of literature that has investigated the role of service accessibility in the health care context. The findings contribute to the extant research by showing that higher accessibility of health care providers often comes with a tradeoff of not having enough infrastructure to treat a high volume of patients. However, in the context of uncertainties introduced by a raging pandemic, accessibility of vaccine providers enables them to appropriate maximum leverage from collaborative vaccine ecosystem to inoculate more people. To the best of my knowledge, this is a novel finding that provides empirical evidence of how different providers offering varying levels of healthcare service accessibility achieve different positive externalities of a burgeoning vaccine provider ecosystem, and how this affects the inoculation rate of a vaccine provider.

The third phase of the pandemic is characterized by the efforts that hospital put to return to normalcy. After grappling with uncertainties over a period of 7 months hospitals gained a lot of knowledge how to manage their care processes. Gradually they evolved and learned to co-exist with the pandemic. Over the time the supply of critical medical equipment has also stabilized. Quickly, the hospitals started to experience another challenge. They realize over the initial phase of the pandemic that they have amassed huge inventories of PPE equipment of limited shelf-life in the anticipation of surging demand. Bigger and more powerful hospitals and health systems tend to bulk up on such inventories leaving the smaller health providers like nursing homes, long term care facilities and smaller hospitals struggling to procure this critical equipment. They tend to bulk up on more PPE inventories as their bed occupancy level increases, which leads to a very unsustainable situation for the hospitals. To control the demand of these equipment, these hospitals implement different policies. In my third dissertation essay, I investigate the effect of creation of the isolation wards on the way the hospital manages the demand of PPE inventory. However, such effect may come at a cost of deteriorating clinical performance. The study further investigates the tradeoffs of creating such isolation wards on the clinical performance and the capacity of care services that the hospital intends to offer in the population.

This essay contributes to the resource "de-pooling" literature. The effects of resource/capacity de-pooling on organization performances are ambiguous. Though the consensus suggests that resource de-pooling decreases resource utilization some studies in the healthcare management domain has demonstrated that de-pooling of resource has increased the service capacity of the organization. However, understanding of how resource de-pooling impacts different aspects of hospital performance is not well known. Our study informs that capacity de-pooling by means of creation of isolation wards enables the hospital to provide care service by holding lower inventory levels. However, that comes at a tradeoff. The hospitals end up rejecting more patients due to the de-pooling of the hospital beds.

2. Chapter 2: Managing Intensive Care Capacity with Service Innovation, Information Exchange Coalition, and Geographical Proximity of Affiliated Hospitals

2.1. Introduction

SARS-CoV-2 has wreaked havoc on human life infecting 219 million people and killing more than 4.55 million people worldwide by 25th September 2021. Health systems responding to the pandemic struggled to manage intensive care unit (ICU) beds. A New York Times article (Conlen et. al., 2021) reports that over 20% of the hospitals in the country experienced at least 95% ICU bed utilization in the week ending 31 December 2020 and, on average, 77% ICU beds were occupied nationwide as compared to 67% ICU bed occupancy in 2010[2]. Hospitals are struggling to manage their ICU bed capacity even after 20 months of the onset of the COVID-19 pandemic[3]. As ICU beds were critical to treat not only patients suffering from acute post COVID-19 complications but also for patients needing other emergency acute care services (e.g., cancer, stroke, cardiac arrhythmia), the pandemic has severely restricted the capacity of hospitals to deliver intensive care services to patients. Health care practitioners (HCPs) had to make hard choices regarding whom to allocate services (Mack, 2020). Besides, the number of usable ICU beds are limited by the number of nursing staff members available to tend to intensive-care patients (Conlen et. al., 2021), which further constricts the intensive care capacity of health systems. Hence, it is immensely important for health systems to manage their capacity to provide intensive care services to patients in need and effectively manage ICU bed utilization. In this study we consider the COVID-19 pandemic as a context of extreme uncertainty in demand and examine factors that can help health systems manage their intensive care bed capacity.

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[2] https://www.sccm.org/Blog/March-2020/United-States-Resource-Availability-for-COVID-19
[3] https://www.nytimes.com/interactive/2021/09/14/us/covid-hospital-icu-south.html

In the context of increasing demand of COVID-19 related hospitalizations and chances of the spread of virulent infections, hospitals would want to keep pandemic related ICU bed utilization as low as possible to ensure that ICU beds are available for patients admitted with COVID-19 related complications. To manage both patient care quality and capacity, health systems have been introducing service innovations. The convalescent plasma therapy (CPT) is one such service innovation that has been adopted and implemented by health care organizations in the aftermath of COVID-19 after the Food and Drug Administration (FDA) cleared the path for the treatment on 3rd April 2020 under extended access programs (EAP). In this study, we consider the CPT as a service innovation in which people who've recovered from COVID-19 donate blood, which is then processed to remove blood cells leaving behind plasma and antibodies to the virus. The plasma is then administered to people with the virus to boost their ability to fight the virus[4]. The therapy calls attention to operational and logistical considerations, such as choosing the right donor who is willing to donate plasma, apheresis[5] center capacity, storage and transportation of plasma concentrate, and testing for adequate antibody concentration (Sahu et. al., 2020). An effective service delivery process is needed that is contingent upon the operational decisions taken by different health systems.

The extant literature on service innovation offers mixed results of the impact of service innovation on organizational performance (Fang et al., 2008; Neely, 2008; Suarez et al., 2013). Existing literature cites several implementation obstacles including lack of attention from top management, deficiencies in organizational design and information technology, the lack of an appropriate culture, and insufficient capabilities for service management (Tong et. al., 2016;

[4] https://www.mayoclinic.org/tests-procedures/convalescent-plasma-therapy/about/pac-20486440

[5] Apheresis is the medical procedure that encompasses collection of whole blood from donor/patient and separation of the blood into individual components – red and white blood cells, platelets, and plasma – so that physicians can extract the required component/s

Kastalli and Looy, 2013; Gebauer et al., 2008). These operational and strategic challenges are due to the uncertainties associated with every step of administering the service innovation. The fact that very few health care practitioners have experience with managing the processes required for successfully administering service innovation associated with a newly introduced therapy during a pandemic adds to the uncertainties and risks of adopting service innovation such as the CPT. Organizational information processing theory (OIPT) suggests that under such circumstances, an organization will need more information to deliver the therapy successfully (Tatikonda and Rosenthal, 2000). Our research question caters to a baseline understanding of whether health organizations were able to work through the uncertainties to leverage the benefit of a potentially life-saving therapy. The first research objective of this study is to uncover the effect of the newly adopted service innovation (CPT), characterized by successful limited small-scale clinical trials and operational and logistical uncertainties, on the ICU bed utilizations due to COVID-19 hospitalizations, as measured by ICU COVID-19 patients to beds ratio.

As health systems continue to work through environmental uncertainties inflicted by the pandemic, they often rely on different information sharing structures. Adopting OIPT, we argue that health systems need more information to deliver innovative health care services during uncertainties and such information sharing structures enable them to acquire external and internal information to develop a knowledge-base that can be homogenously utilized across organizational units (Galbraith, 1973; Tatikonda and Rosenthal, 2000). In this study we explore how health systems leverage two information structures - participation in an information exchange coalition (external information sharing structure) and the geographical proximity of affiliated hospitals of a health system (internal information sharing structure) – to assuage uncertainties in delivering health care service.

Previous studies in health care operations management have stressed the importance of information exchanges among different entities in the health care industry (Ayer et. al., 2019; Dobrzykowski and Tarafdar, 2015). Most of the studies in OM consider health information exchange (HIE) initiatives within a health system or a hospital (e.g., Ayer et. al. 2019, Walker 2018, Dobrzykowski and Tarafdar 2015). During the COVID-19 pandemic, to combat the high health care demand, peer organizations connected with each other to understand the best practices of delivering health services. Consequently, to share clinical and procedural information, they organically came together and created information exchange coalitions that are similar to community HIEs. Institutionalization of such external information sharing structures is often strongly encouraged, incentivized (e.g., by CMS), or even mandated by the federal government. Extant literature focusing on HIEs comprising of multiple health systems has reported ambiguous effect on patient outcome (Everson, 2017). Some studies have shown a positive impact on the number of procedures performed (e.g., Atasoy et al. 2021) and financial performance (Frisse and Holmes 2007; Frisse et. al. 2012). On the other hand, studies have also reported that community HIEs do not significantly transform patient care and hospital capacity utilization (Vest 2009).

The need for information exchange coalitions gains prominence during a pandemic when health systems implement novel treatment procedures that lack suitable clinical evidence of effectiveness and has many operational and logistical uncertainties associated with execution. For example, during the second half of 2020, blood banks across the U.S. faced severe plasma shortages[6]. In such circumstances, an information exchange coalition may enable hospitals to locate reliable source to procure the plasma in order to continue offering the service innovation. Besides, such a coalition provides important process related information that can help participating

[6] https://www.nbcnews.com/health/health-news/desperate-scramble-covid-19-families-vie-access-plasma-therapy-n1183946

hospitals to improve clinical treatment (Tucker et. al., 2007). OIPT suggests that availability of information, as provided by an information exchange coalition, can ameliorate the risks and uncertainties of organizational tasks related to new service implementation (Galbraith, 1973). A coalition provide information about best practices to all participating organizations, which enables "organic" organizational approaches for the successful execution of uncertain tasks (Tatikonda and Rosenthal, 2000). These external information sharing structures, however, require resource deployment on the part of health systems to an address tasks such as routine data uploads, participating in knowledge sharing sessions and developing the right skillsets to analyze data from the information exchange initiative. These activities can put constraints on health systems' resources, especially during a pandemic. Building on extant literature and the precepts of OIPT, our second objective is to examine the direct effect of information exchange coalition on ICU bed utilization as well as its moderating role on the relationship between service innovation and ICU bed utilization.

Our third research objective is to examine the role played by the internal information sharing structure provided by the proximity of organizational units. Geographic proximity of affiliated units of an organization is known to play an important role in determining how organizations manage their resources and how it impacts performance (Howells, 2002; Knoben and Oerlemans, 2006; Letaifa and Rabeau, 2013). Studies report positive effect of geographic proximity, including information and resource sharing (Howells 2002), achieving economies of scope (Alcácer and Delgado 2016), and facilitating coordination and productivity (Giroud 2013). In the health care context, proximity enhances the spillover effect of patient health information exchanges for managing regional health care costs (Atasoy et. al. 2018) and mitigating inventory accumulation in hospitals (Zepeda et. al. 2016). Research has also pointed to the drawbacks of proximity of organizational units including increased competitive practices (e.g., refusal to share resources), interpersonal conflicts (Letaifa and Rabeau 2013), reduced interactive learning and innovation due to increased organizational control (Boschma 2005).

OIPT suggests that when organizations implement service innovation, especially during highly uncertain times, the internal information sharing structure provided by geographic proximity can help in managing informational needs associated with innovative service offerings (Tatikonda and Rosenthal, 2000). Nevertheless, to administer service innovation across multiple facilities of a health care system, geographic proximity can also induce frequent transfers of patients or physicians resulting in multiple handoffs in which process and clinical information may get either distorted or lost (Batt et. al., 2019) during pandemic. Such uncertainties may negatively impact the outcome of the service innovation as it increases the constraints associated with information processing (Tatikonda and Rosenthal, 2000). We investigate the effect of geographic proximity between affiliated hospitals in a health system on the system's ICU bed utilization as well as its moderating role on the relationship between service innovation and ICU bed utilization.

A panel dataset of 735 observations is carefully compiled to undertake this research investigation. We analyze the data using the difference-in-differences (DiD) approach with propensity score matching. The results show that health systems that adopted the service innovation were able to better manage their ICU bed capacity. Information exchange coalition and geographic proximity of affiliated hospitals in a health system also help with managing ICU bed utilization. We find that external information sharing structure provided by information exchange coalition helps health systems to better manage their ICU bed utilization when they administer service innovation. However, internal information sharing structures presented by geographic proximity coupled with administration of service innovation reduces the ability of health systems to manage ICU bed capacity.

The rest of the paper is organized as follows. In section 2 we review the literature and develop our hypotheses. We present our empirical strategy in section 3 that details the data collection efforts, intervention setting, and variables considered for this study. In section 4 we present our econometric approach, including the identification strategy and description of the quasi-experimental design using propensity score matching. The results and the robustness checks are presented in section 5 and in section 6 we discuss the implications of our study, limitations, and directions for future research.

2.2. Background and Hypothesis Development

2.2.1. Background

2.2.1.1. Service Innovation: The Case of the Convalescent Plasma Therapy

To understand what constitutes service innovation in the OM literature, we define service innovation as "an offering not previously available to a firm's customers resulting from the addition of a service offering or changes in the service concept that allow for the service offering to be made available" (Menor et. al. 2002; pg 138). More recent literature extends the definition and note that service innovation, in addition to the inherent newness, should provide benefit to the organization in the form of added value to its customers (Witell et. al., 2016; Toivonen and Tuominen, 2009). To characterize a new service offering as an innovation, we need to understand the process life cycle of how a service is developed and implemented. Fitzsimmons and Fitzsimmons (1999) and Menor et. al. (2002) suggest that the process steps following which a service innovation materializes can be broadly categorized into the planning and execution phases.

The planning phase encompasses design and analysis stages where decisions about market viability, internal resources and capabilities are considered. The execution phase includes development and launch stages that involve employing cross-functional efforts and key enablers, such as people, systems, and technology, to bring the service to fruition. The steps involve feedback mechanisms to improve the process and enhance the effectiveness of the service innovation.

Though the CPT is not new, and it has been used for decades to cure different viremia in patients, with new virus the effectiveness of the procedure and the related operational and logistical requirements may be different. Mayo clinic has been studying the CPT for many years and has used the therapy to treat infectious diseases. After the FDA cleared the path for the treatment of coronavirus disease (COVID-19) on 3rd April 2020 under extended access programs (EAP), Mayo Clinic coordinated the CPT across participating hospital systems to enable larger number of clinical studies. Health systems took autonomous decisions regarding whether to participate in such an initiative. It is important to note that the CPT is not merely a clinical innovation; participating in the initiative and adopting the CPT call for several operational decisions and coordination efforts among the team members engaged in the process. At the outset, health care system administrators are responsible for defining the financial requirements to introduce the treatment procedure. Tulchinshy and Varavikova (2014) notes that when new services are introduced in a health system, managers are responsible for developing the required processes, and defining the goals, priorities, and objectives of new services. As per the service life cycle model presented in Tulchinsky and Varavikova (2014), initially there is the process design phase that defines the economic and operational feasibility of the service and provides the service blueprints. The required resources, participants, partners and responsibilities are defined in this phase. After determining the process flow, health systems proceed to test the feasibility of the process and make necessary improvements. They generally start administering the procedure to a few patients and make changes along the way. Within the context of adoption of the CPT for treating COVID-19, as an example, Munson Health system initially administered the procedure to three patients at its affiliated hospitals. The health system sent patient reports to Mayo clinic to analyze the therapy's efficacy seven days after the patients had been treated[7]. Similar approach was adopted by other health systems as well. Depending on the results of the analysis at Mayo Clinic, hospital systems may make necessary changes before enrolling more patients in the program. This step is crucial as it is akin to the development and testing phase in the service innovation lifecycle where the service blueprint is implemented for the first time in practice (albeit at a small scale) to test the processes involved and to make any necessary changes for larger scale implementation.

After the service development phase, health systems launch the therapy for their patients. For example, by December 2020 Munson Health System had administered the CPT to more than 300 patients[8]. Hospital systems are entirely responsible for the execution of the novel therapy. The service blueprint of the procedure is presented in Figure 2.1. Health systems enrolled patients with severe cases of COVID-19 to receive the CPT. This required innovative ways in which health systems managed their service operations associated with delivering this therapy. The enrolled patients were screened for eligibility to receive the CPT transfusion under the criteria established by FDA EAP. The set of criteria established that the CPT can be administered to patients, at least 18 years old, with severe or immediate life-threatening COVID-19 disease and who have the ability or proxy ability to provide informed consent (Liu et al. 2020). Once patients were found fit

[7] https://www.record-eagle.com/collections/convalescent-plasma-study-underway-at-munson-hospitals/article_427854ee-8af9-11ea-896c-dbfcd46db45e.html
[8] https://www.record-eagle.com/collections/plasma-donations-still-sought-from-recovered-covid-19-patients/article_da6a118e-4aed-11eb-98ac-1f4f434971fe.html

for the CPT, as required by federal law (Code of Federal Regulations; 21CFR312.305 and 21CFR312.310), they met the expanded access use requirements as documented on FDA form 3926. The form was then submitted for each individual patient and reviewed and approved by FDA. Physicians then ordered suitable plasma. Due to the scarcity of plasma with required COVID-19 antibodies in the blood banks, hospital systems often invited their own patients, who were once treated for COVID-19 but were now cured of the viremia, to donate blood[9]. The liquid plasma extracted from the blood was then administered to a patient. Administering this process requires continuous improvement to address delays associated with various steps. In their continuous improvement efforts, health systems use several sources of information, such as feedback from Mayo clinic and best practices shared by the information exchange coalitions.

The inherent novelty of the CPT for treating COVID-19 and multiple steps to administer the process render the therapy to uncertainties and, consequently, require carefully coordinated operations and supply chain management practices to manage the service delivery process. Sahu et. al. (2020) notes that significant procurement related uncertainties exist in choosing the right donor willing to donate plasma as some donors may not have developed sufficient antibody titers in their blood. To make the matter worse, during the time when Mayo Clinic launched the expanded access program of the CPT, the blood banks in the country witnessed shortage in plasma supply, which severely constricted hospitals' ability to procure plasma. Apheresis center capacity may form a bottleneck due to the increasing demand for administering the CPT. During the apheresis process, safety precautions are required as there are additional risks of collateral infections such as allergic reaction, HIV, and hepatitis B and C[10]. To address these issues, prudent sourcing, operational and logistical decisions are needed. Additionally, the degree of immunity

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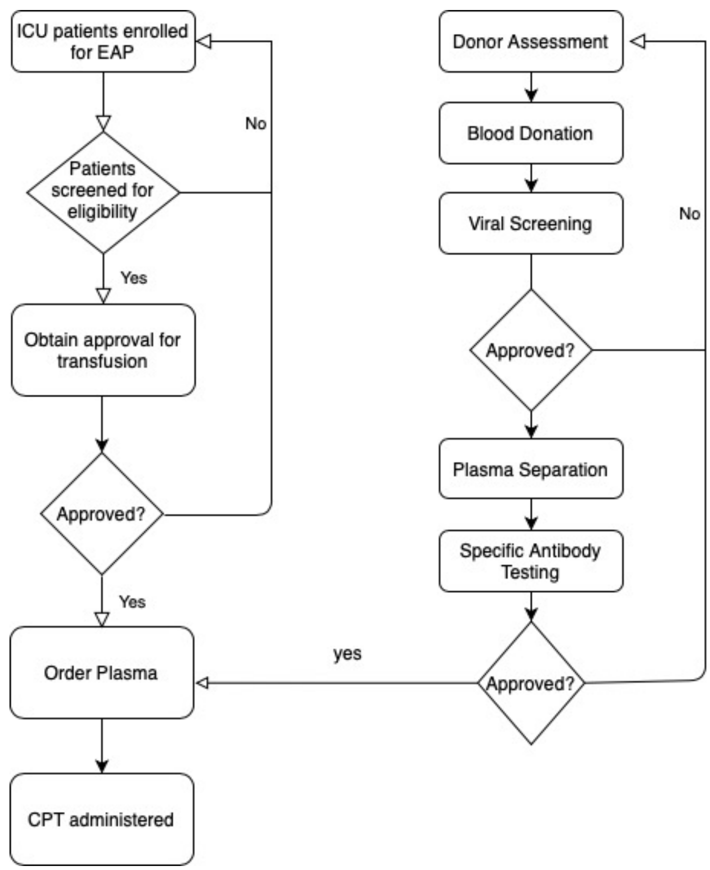
[9] https://www.henryford.com/coronavirus/covid19-symptoms-testing-treatment/covid-plasma
[10] https://www.mayoclinic.org/tests-procedures/convalescent-plasma-therapy/about/pac-20486440

often may depend on the amount and type of infused antibody (Sahu et. al., 2020). All these aspects require a broader perspective of considering the CPT as a service innovation.

Figure 2.1 Convalescent Plasma Therapy Administration Process



2.2.1.2. Information Exchange Coalition: The Case of the Mi-COVID19 Initiative

For fighting the COVID-19 pandemic, health systems required access to external information structures to gain insights into best practices in treating virulent patients across geographic, economic and demographic boundaries. Towards this end, on 2nd April 2020, Michigan Hospital Medicine and Safety Consortium launched Mi-COVID19 registry (HMS, 2020) in collaboration with Blue Cross Blue Shield of Michigan that involved more than 40 hospitals from different health systems across the state of Michigan. According to HMS (2020) the purpose of the registry was to identify factors leading to critical COVID-19 occurrences and outcome; to identify patient characteristics, care practices and treatment regimens associated with improved outcomes; to understand long-term complications for hospitalized patients; to identify variability in care processes in order to identify processes associated with better outcomes; and to provide HCPs with operational models and frameworks to facilitate improved care across Michigan hospitals.

Mi-COVID19 required participating hospitals to upload anonymized patient level data. The participating health systems get an exclusive right to access the patient data across state so that they can analyze the data and identify patient characteristics as well as treatment regimens associated with improved outcomes. Additionally, the exchange held webinars to share findings and inferences by analyzing the shared data. These health systems were then able to use the knowledge to treat patients better and faster[11]. Our study empirically examines if participation in this information exchange coalition helped health systems manage their intensive care capacity. Additionally, our study investigates whether HIE participants were able to gain benefits from administering the service innovation.

2.2.2. Hypotheses Development

2.2.2.1. Effect of service innovation on ICU bed utilization

Miles (1995) argues that service innovation generates competitive advantage for organizations. In the health care context, service innovation may manifest in the form of new ways of offering patient care, which have been shown to decrease the length of stay of the patients (Tong et. al., 2016). In the acute care context, Tong et. al. (2016) suggests that decrease in the length of stay frees up bed capacity and reduces ICU bed utilization. During a pandemic, this reduction in

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[11] https://www.uofmhealth.org/news/archive/202004/michigan-medicine-teams-blue-cross-blue-shield-michigan-and

ICU bed utilization helps health systems to become more responsive to the high demand. Service innovation, however, requires associated operational and logistical planning activities to administer new therapy effectively. Burgis et. al. (2011) notes that whether patient experience and outcomes of a treatment will materialize depends on the amount of planning, preparation, and coordination within the health system delivering the treatment. Tong et. al. (2016) presents the case of a medical innovation tPA (tissue plasminogen activator), which significantly reduces the average acute care treatment time of cerebral infraction. tPA is a weight-based dosing regimen which requires standard infusion rate. The procedure is prone to administrative error unless it is supported by systematic operational and logistical plan (Tong et al., 2016). Chung (2016) asserts the need to consider tacit and codified knowledge flow when implementing service innovation. In the absence of a well-coordinated operational plan, tPA administration may be fatal and may increase the need for intensive patient care post tPA administration and increase the intensive care bed utilization.

The CPT represented a new way of treating COVID-19 patients during the pandemic, which was similar to tPA in terms of the associated administrative and operational coordination challenges. Due to the novelty of the COVID-19 virus, use of the service innovation was associated with a significant level of uncertainty related to donor selection, patient eligibility, and consideration of related side effects (Sahu et al., 2020). To address these issues, the service innovation required significant planning and judgement on the part of administrators and clinicians. The physicians need to decide on the amount and type of infused antibody, which determines the length of immunity of the treatment lasting from weeks to months (Sahu et. al., 2020). These decisions may impact the effect of the service innovation on the antibody levels (Chen et. al., 2020). Recent studies show that, if administrative processes are executed correctly, the innovation has potential to suppress the viremia and enhance the recovery rate of the patients suffering from COVID-19 (Chen et. al., 2020; Duan et. al., 2020; Ye et. al., 2020). This should result in the occupancy of ICU beds for a shorter duration, thereby making more ICU beds available for patients. Hence, we hypothesize that adoption of the service innovation (CPT) is associated with lower ICU bed utilization as measured by the ratio of the number of COVID-19 patients in the ICU to the number of ICU beds.

Hypothesis 1: *Service innovation introduced during a pandemic is negatively associated with ICU bed utilization.*

2.2.2.2. Effect of participation in information exchange coalition on ICU bed utilization

Voluntary participation in health information exchange provides health systems the requisite knowledge that can help in strengthening the processes aimed at providing high quality patient care in an efficient manner (Li et. al., 2020). OIPT posits that as organizations operate under uncertainties they require to access and to process more information (Galbraith, 1973; Sharma et. al., 2019). As an example, Burgis et. al. (2011) provides evidence of the impact of the National Surgical Quality Improvement Program (NSQIP) that was implemented by the American College of Surgeons (ACS) to collect data to track surgical quality and its impact on patient outcomes undergoing major surgical procedures. The enrollee hospitals submitted their data on a continuous basis and the program provided benchmark reports about hospital’s risk profiles and outcomes as compared to other hospitals and national averages. Hospitals used this information to re-engineer their workflows, improved internal education of staff members and developed clinical performance improvement initiatives. The participating hospitals reported over 7% to 13% reduction in surgical site infections and a decreased length of stay.

To address the pandemic of COVID-19, health systems participating in Mi-COVID19 shared patient level data and outcomes of various process undertaken to manage the rising COVID-19 cases. Such privileged access of information enabled participating health systems to be aware of the best practices for treating COVID-19, which as per OIPT should enable the provision of better quality and faster care to patients admitted in the ICU (Fontaine et. al., 2010; Everson, 2017). The registry provided critical knowledge asset to participating health systems that was not available for non-participating health systems. Participating health systems were able to access the common knowledge repository, which facilitated the activities performed by their HCPs and improved their ability to address demand placed by the pandemic. We hypothesize that the knowledge exchange and learning facilitated by the information exchange coalition such as the Mi-COVID19 initiative would translate into better and faster patient care, which should enable health systems to reduce ICU bed utilization due to COVID-19 hospitalizations.

> ***Hypothesis 2:*** *Participation of a health system in information exchange coalition during a pandemic is negatively associated with ICU bed utilization.*

2.2.2.3. Effect of geographic proximity among hospitals in a health system on ICU bed utilization

Reliable and evidence-based clinical knowledge is necessary to treat patients effectively and quickly. Employees working in organizations rely on codified and shared information to establish organizational routines (Howells, 2002). Consistent adoption of these routines among hospitals in a health system goes a long way in ensuring that everyone is following prescribed guidelines of care and administrative processes. In this regard, geographic proximity of organizational units can help in sharing these routines and organizational practices (Howells, 2002) since proximity enables interactions among people at different sites and reduces search costs and acquisition barriers that are created by geographical distance (Howells, 2002; Knoben and

Oerlemans, 2006). Interactions among HCPs may manifest in the form of physical interaction or via internet enabled communications. Though internet-enabled communication enables physically dispersed group members to work together, Cramton (2001) attributes interpersonal communication problems like uneven distribution of information, relative differences in the speed of access to information, differences in the salience of information and misinterpretation of silence in communication in internet enabled communications to the lack of geographic proximity. Hence, based on prior research and in accord with the OIPT, we contend that the flow of information between hospitals within a health system would be smoother when hospitals in the health system are located closer to each other, which in turn may improve the speed and quality of care.

Along with an even distribution of information and organizational routines, in the health care context, proximity also enables health systems to move patients and HCPs depending on the need at different sites. During pandemic, this flexibility becomes critically important for health systems to manage their capacity. In the event of increasing demand due to a pandemic, hospital systems can effectively balance capacity utilization by moving patients from overcrowded hospitals to hospitals with lower bed utilization. There have been instances where a hospital moved patients to another hospital, preferably within the same health system, when ICU capacity is constrained[12]. Hospital systems have also moved HCPs between hospitals based on patient demand so as to effectively utilize its dispersed resources[13]. Such transfers are more feasible and less expensive when affiliated hospitals in a health system are in close proximity, which can help manage ICU bed utilization levels better. Hence, we hypothesize that greater average distance among affiliated hospitals in a health system will be associated with higher ICU bed utilizattion.

[12] https://www.stignacenews.com/articles/covid-19-cases-up-by-four-in-mackinac-county-this-week/

[13] https://www.detroitnews.com/story/business/2020/04/05/help-coronavirus-patients-lose-job-beaumont-tells-workers/2948002001/

Hypothesis 3a: *Shorter average distance among hospitals in a health system is associated with lower ICU bed utilization during a pandemic.*

Transfer of patients and movement of HCPs between hospitals within a health system are not devoid of ill consequences. Mueller et. al. (2019) provides empirical evidence that inter-hospital transfer of acute care patients can result in longer length of stay and consume more resources than the non-transferred group of patients. Hernandez-Boussard et.al. (2017) reports that inter-hospital transfer of patients, on average, result in about 9 days longer length of stay. To explain such findings, Germack et. al. (2020) reports that during patient transfers often there are conflict of interest between the sending and receiving groups which can interrupt the flow of communication. A seamless communication is important for an effective transfer of patients in the new care setting. Mueller et. al. (2019) argues that inter-hospital transfers, and care transitions in general, add certain risks of discontinuity of care (e.g., gaps in information transfers) and increase the chances of infection during the transfers. This added risk of patient transfers may result in higher patients to beds ratio as transferred intensive care unit patients may need longer care.

Similar inefficiencies can also manifest when health systems transfer HCPs among affiliated hospitals. Typically, the outgoing HCP has to handover responsibilities to the incoming one for proper continuation of care. Rabøl et. al. (2011) reports that instances of communication error in relation to handovers was the most frequent type of communication error between care professionals. The study notes that hospitals often did not have procedures for communication during the transfer of responsibilities. Given that the likelihood of transfers of patients and HCPs among affiliated hospitals is expected to be more frequent in health systems that have lower average distance among affiliated hospitals, one could expect such systems to have higher inefficiencies related to communication and handoffs. This points to a counter argument linking geographic proximity to ICU patients to beds ratio. In light of competing theoretical arguments, we offer the following alternative hypothesis linking:

Hypothesis 3b: *Shorter average distance among hospitals in a health system is associated with higher ICU bed utilization during a pandemic.*

2.2.2.4. The moderating effect of information exchange coalition

The foremost concern regarding service innovations involving new treatment procedures is to have sufficient level of published evidence, which suggests that the treatment will have the intended effect on patient outcome (Tucker et. al., 2007). Baker (2001) states that medical training emphasizes using practices supported by strong research evidence. However, the strength of such evidence ranges from meta-analyses of randomized clinical trials at the highest and strongest form of evidence to anecdote or opinion which is the lowest form of evidence. Tucker et. al. (2007) states that non-experimental and qualitative studies exist in between these extremes. The Mi-COVID19 initiative aimed to collect patient level and treatment data from the participating hospitals (HMS 2020) and provided a participating health system information about activities carried out by other health systems who were part of the information exchange coalition. In essence, it is an example of non-experimental descriptive and qualitative sharing of information as can be noted by considering the goals of the initiative. Participating health systems learn about best practices (Horbar et. al., 2001) that are being adopted by health systems to administer the service innovation. According to the OIPT, such "organic" information sharing approaches are required to successfully execute uncertain tasks within innovative service offerings (Tatikonda and Rosenthal, 2000). This is consistent with the evidence from NSQIP program in which access to information on surgical quality and efficiency appropriated from the program helped participating health systems to develop evidence-based management approach and healthcare practitioners to make necessary changes to the treatment procedure (Burgis et. al. 2011).

We contend that health care professionals of participating health systems in the health information exchange initiative will be able to similarly implement the service innovation effectively by utilizing evidence from others who have implemented the procedure. This should help in improving clinical care provided by health systems that are part of the initiative as compared to those that are not part of it. This, in turn, will help in strengthening the ability of participating health systems to increase the effectiveness of service innovation and help in managing their ICU bed capacity. Hence, we present the following hypothesize:

> ***Hypothesis 4:*** *Participation of a health system in an information exchange coalition during a pandemic will strengthen the negative association between service innovation and ICU bed utilization.*

2.2.2.5. The moderating effect of geographic proximity

Internal information sharing structures (e.g., the use of health information technology) aid in connecting different organizational units and thereby enable smoother information flow (Sharma et. al. 2019). Such structures mitigate cognitive load and improves performance. Geographic proximity among organizational units helps in the exchange of tacit and rich information (Shaw and Gilly, 2000; Knoben and Oerlemans, 2006). At a health system level, when the affiliated hospitals are in close proximity, the constraints and associated costs of moving HCPs among hospitals is lower. Avby et. al. (2019) argues that a culture of mobilizing human resources among organizational units improves outcomes obtained from innovative service offerings due to a seamless flow of tacit knowledge. Due to the novelty of the CPT service innovation for treating COVID-19 patients, physicians had to rely on the tacit knowledge related to the underlying processes for administering the treatment effectively. When hospitals in a health system are closely located, there will be a more even distribution of such tacit knowledge among hospitals in the system and, hence, we hypothesize:

Hypothesis 5a: *During a pandemic, shorter average distance among hospitals in a health system will strengthen the negative association between service innovation and ICU bed utilization.*

An alternative perspective is offered by the literature pertaining to the continuity of care. By means of a systematic literature review, Van Walraven et. al. (2010) highlights the importance of provider continuity on improved quality of care and better resource utilization. When hospitals in a health system are closely located, they can more easily share HCPs and patients, thereby enabling the system to become more responsive in the context of higher demand for intensive care. However, this could potentially compromise clinical relationship between a physician and patient (Van Walraven et. al., 2010), which can adversely affect the continuity of care. For example, a physician treating a patient with the service innovation when transferred to a different hospital may not be able to continue providing the required clinical care and may have to handoff the treatment to another physician. Such handoffs may introduce discontinuity of case, risks of miscommunication and poor transfer of relevant information (Batt et. al., 2019), particularly when the treatment is new, and the corresponding outcomes are uncertain. Such gaps in communication may lead to missed actions and delayed care (Batt et. al., 2019). The new physician may take more time to connect to the patient specific treatment and may need the patient to stay longer in the ICU. Given the higher likelihood of compromised continuity of care in closely located hospitals within health systems, we put forth the alternative hypothesis as follows:

__Hypothesis 5b:__ During a pandemic, shorter average distance among hospitals in a health system will weaken the negative association between service innovation and ICU bed utilization.

2.3. Empirical Strategy

2.3.1. Data

The empirical setting of our study is the delivery of intensive care required for COVID-19 patient hospitalizations in all hospital systems across the state of Michigan. Hence, our unit of analysis is a health system operating in Michigan. To ensure timely reporting of critical resources and needs, in pursuant to Michigan Compiled law (MCL 333.2253), Michigan Department of Health and Human Services (MDHHS) made it mandatory for the health systems in Michigan to report data pertaining to personal protective equipment (PPE) inventory, laboratory testing capacity, number of ventilated patients, number of ventilators, patient census, staffing shortages, and units or areas dedicated to COVID-19 treatment. PPE inventory data and patient census data were reported at the health system level. The data on patient census were updated twice every week on Mondays and Thursdays.

On 1st May 2020 CDC announced its practical guidance for health systems to protect healthcare personnel, patients, and communities from the impact of COVID-19. The guideline has five categories namely Worker Safety and Support, Patient Service Delivery, Data Streams for Situational Awareness, Facility Practices and Communications which further have subcategories (CDC, 2020). We started our data collection effort from 7th May 2020, a week after the announcement. We collected the data on health systems until 12th November 2020 since after that (starting from November 16, 2020) MDHHS stopped reporting the health system level data. Since our study focuses on service innovation, information exchange coalition and structural characteristics (geographic proximity of affiliated hospitals) at the health system level, the data provided by MDHHS after 12th November 2020 does not fulfill our research objectives. Overall, we captured data twice every week for 49 time periods for all the 19 health systems in Michigan. The data included information about ICU bed utilization, the number of COVID-19 patients admitted, and the number of COVID-19 patients admitted to intensive care units.

Definitive Healthcare LLC collaborated with Esri's geospatial cloud to develop a dashboard to report current levels of hospitalizations, hospital capacities and county level demographic data across the nation. We downloaded this contextual data for 6090 hospitals using Esri provided API and filtered out the data for Michigan hospitals. The database contains variables such as the number of licensed staffed beds and the number of ICU beds for each of the 106 hospitals in Michigan that are affiliated to the 19 health systems. It also provides information regarding the demographics of respective counties where each of the hospitals belong. We identified the affiliated hospitals in each health system and calculated the total number of ICU beds in the health system. Further, we calculated average staffed beds per health system and the mean values for the demographic data across the counties where the health system has its presence. To understand the geospatial distribution of hospitals in a healthcare system, in concert with literature (Zepeda et. al., 2016), we consider the average distance among a health system's affiliated hospitals. we collected the address for each of the 106 hospitals, used Google Map API to obtain distance between any possible pairs of hospitals, and calculated the average distance between any two hospitals in a system. Among the health systems considered for this study, four systems have one affiliated hospital in Michigan. As we intend to evaluate the effect of geographical dispersion among affiliated hospitals in a health system, we omitted observations related to those health systems from the dataset. This data is combined with the data on health systems as reported by the MDHHS.

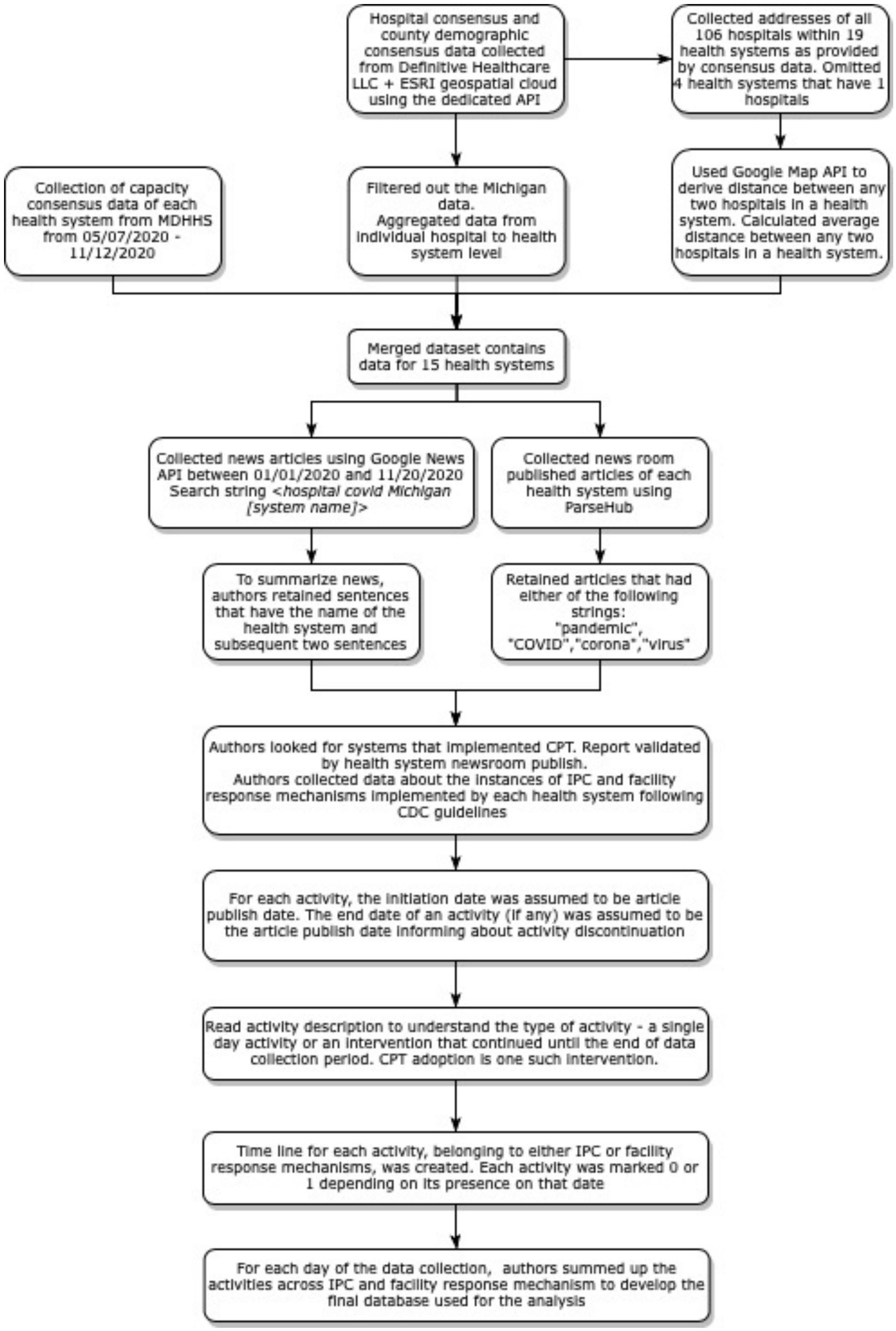
To clearly discern the effect of the service innovation, health information exchange coalition and average distance of hospitals affiliated to a health system on ICU bed utilization due to COVID-19 hospitalizations, we control for several variables that can influence ICU bed utilization. We considered two sources to collect data on various initiatives pursued by health systems. First, we collected news articles from 1st January 2020 until 20th November 2020 for the 15 health systems. Second, we collected data from the newsroom announcements and publications on each health system's website. To provide structure to this data collection effort we considered the set of practices included in the CDC guidelines that were announced on 1st May 2020. We provide details regarding CDC guidelines in the Online Supplement. In this study we particularly considered "infection prevention and control practices" that formed part of the "Worker Safety and Support" category and "facility response mechanisms" that was part of the "Facility Practices" category developed by CDC.

To collect data from news articles, we first used a generic search code "*hospital covid michigan [system name]*" to search any news related to the health system in Google News. We used a Python script and GoogleNews API to download the content of the news. We downloaded more than 7000 news items relating to the health systems considered in this study. ParseHub was used to scrape news from health systems' newsrooms. As a part of this step, we downloaded about 700 additional news items. We filtered the news containing any of the words like "pandemic", "COVID", "corona", "virus". We went through each of the filtered items and collected news of activities by the systems. In the next step we merged these two sets of news to have a combined list of activities by each of the health systems. To extract activities of each of the health systems we first used the Bert Extractive Summarizer (BERT) (Miller, 2019). However, since BERT algorithm utilizes word frequency as the basis for summarizing text, it doesn't capture actions taken by health systems appropriately. Often times, words that are most frequently found in the news article do not correspond with the actions taken by the health systems. Hence, we develop our own algorithm that extracts the sentence in which the name of the health system appears along with two following sentences. Details pertaining to our text summarization strategy and the algorithm are presented in the Appendix A. Using the summarized text, we systematically went through the activity list for each health system to categorize each text into activities specified in the CDC guidelines. The co-authors of this study brainstormed to reach a consensus on the inclusion of a text within a category.

For each activity a timeline of initiation and conclusion (if applicable) were identified from the news items. As we do not know the exact start date of the activities, we consider date of the new article reporting the activity as the date of initiation. If there were multiple instances of same activity, we considered the earliest reporting date as the start date and omitted repetitions. Depending on the activity it may either be a single day activity (e.g., "*Ascension Michigan will host a Community Flu Immunization Fair on Monday afternoon*") or an intervention which started on a date and then potentially continued for some time after that. We observe two types of interventions in our dataset. The first type of intervention are the ones that started on a date and there is an explicit mention in news articles that the activity ended on another date. For example, Ascension Health System, one of the healthcare systems considered in this study, planned to defer the elective procedures from 18th March 2020 to 28th May 2020 as it was reported that the health system had planned to resume elective procedures from 29th May 2020. The system continued with elective surgeries until 15th October 2020 as there were reports that Ascension had decided to stop elective surgeries again from 16th October 2020 due to the second wave of infections and its status did not change until the end of data collection. The second intervention are the ones that started and continued ever after (e.g., *"Ascension Michigan looks forward to safely providing additional non-emergent surgical and medical procedures as appropriate across all of our facilities"*).

Depending on the presence or absence of an activity reference within a news article, we code the activity as 1 or 0, respectively. For a given date, each CDC prescribed activity or approach may have multiple 1s and a summation of these values is considered as the extent to which the health system has undertaken a specific activity on a given date. For example, the Sparrow Health System undertook eight different preparedness checklist related activities on 20th July 2020, one activity related to cohorting of COVID-19 patients, and fifteen different activities related to development and implementation of plans to reduce staffing shortages and assessment of need for alternative care sites. Hence, in total, the health system undertook 24 different facility practices related activities on that date. Additionally, on the same date the health system exercised one activity related to PPE optimization, five different activities related to implementation of COVID-19 source control and two activities in order to track PPE supplies. Hence, in total, the system also enacted 8 infection prevention and control practices. We merged this dataset with our original dataset to get a panel dataset for each of the 15 healthcare systems with hospitalization, geospatial distribution, extent of infection prevention and control practices and facility response mechanisms as specified in the CDC guidelines, and county (where the health system is located) demographics data from 7th May 2020 until 12th November 2020. The flowchart in Figure 2.2 summarizes our data collection process to facilitate replication.

Figure 2.2 Flowchart of data collection process



2.3.2. Intervention Setting

To effectively manage the spread of the virus and a faster recovery of the infected patients, health systems have been introducing new treatments and procedures to manage the pandemic. Most of them have little clinical evidence of effectiveness and experiments are underway. As we stated earlier in the paper, Mayo Clinic developed the CPT for COVID-19 infected people and facilitated the use of the treatment through Expanded Access Program (EAP) after FDA approved EAP on 3rd April 2020 (U.S. Food and Drug Administration, 2020). It started to enroll physicians and patients willing to adopt the therapy. EAP enabled patients with serious or life-threatening COVID-19 to access investigational convalescent plasma outside of clinical trials due to the lack of alternative treatments (Gallagher, 2020). Subsequently, FDA issued Emergency Use Authorization (EUA) on 23rd August 2020 which permitted physicians to use the CPT without being enrolled in Mayo Clinic's EAP Program (Kadlec, 2020). Mayo Clinic stopped the EAP eventually after FDA published EUA. Between 3rd April 2020 and 23rd August 2020, several health systems in Michigan started administering the CPT to enrolled patients with COVID-19 symptoms who were admitted in intensive care units (Joyner et. al., 2020). To understand the date when a health system started using the CPT, we went through the health system's newsroom reports. Whenever a health system reported using the CPT, we considered the date of reporting to be the intervention date. We used the news articles to triangulate and check the validity of the information. We found that four health systems started using the CPT before 7th May 2020, four health systems started using the service innovation after 7th May 2020, and the remaining health systems did not consider the CPT as part of their therapy plan for COVID-19. The introduction of the service innovation in a health system at different time points provides us a unique opportunity to study how the variance in the service innovation adoption impacts intensive care capacity between the adopting and non-adopting health systems.

As noted earlier, on 2nd April 2020, Michigan Hospital Medicine Safety Consortium launched a registry (Mi-COVID19) to disseminate knowledge about practice of different treatments, including the CPT. More that 40 hospitals representing 10 health systems participated in the registry. As all these systems participated in the information exchange coalition by 24th April 2020 (HMS, 2020), we consider the initiative as a unique treatment to study the impact of information sharing initiative on the ICU bed utilization related to COVID-19 hospitalizations. Six of the 10 health systems had over 50% of their affiliated hospitals participating in the registry. For others it was less 50% participation. For our main analysis we assume that if a hospital in the health system participates in such an initiative and acquire some knowledge from the alliance, it will share this knowledge with other hospitals in the same health system. This is a reasonable assumption since most health systems have set up technologies to share information across all hospitals within a system[14]. These IT systems enable physicians to broadcast information to their colleagues within the health system (Vest et. al. 2019). Additionally, organizations such as American Hospital Association have provided guidelines for health systems to communicate with affiliated hospitals information about plans and procedures[15]. In our study we do not focus on the extent of participation. Nevertheless, we check for the robustness of our results by considering the percentage of hospitals in a health system that participated in the registry as an alternative measure.

[14] https://www.uofmhealth.org/provider/care-everywhere
[15] https://www.aha.org/system/files/media/file/2020/07/aha-covid19-pathways-comms-internal-external.pdf

2.3.3. Measures

2.3.3.1. ICU Bed Utilization related to COVID-19 patient hospitalization

In this study we consider ICU bed utilization related to COVID-19 patient hospitalizations ($BedUtilization_{it}$). We note that this variable is not the overall ICU bed utilization. The variable is developed by considering the ratio of the total number of COVID-19 patients admitted to ICU and the total number of ICU beds in the system. The variable, $BedUtilization_{it}$, has high dispersion ranging from a low of 0% to a high of 69% with a mean and standard deviation of 10.4% and 9.7%, respectively. A high proportion of ICU beds utilized by COVID-19 patient hospitalizations results in the availability of a small proportion of ICU beds for other patients. This can also increase the probability of infection in the ICU from patients with the viremia. From a health system's perspective, a lower value of $BedUtilization_{it}$ would help in providing the intensive care needed by all patients, while keeping the hospital infections low.

2.3.3.2. Service Innovation

The service innovation associated with the CPT is a binary variable ($ServiceInnovation_{it}$) that captures whether a system has adopted convalescent plasma therapy at a certain point in time during the COVID-19 pandemic. $ServiceInnovation_{it}$ is equal to 0 if a system *i* did not adopt plasma therapy at time *t* and is set to 1 if a system *i* starts using plasma therapy at time *t*. In our study, we have four health systems that have $ServiceInnovation_{it} = 1$ through all 49 time periods, four health systems that have $ServiceInnovation_{it} = 1$ for some time periods and seven health systems that did not administer the service innovation for all 49 time periods under consideration.

2.3.3.3. Participation in the Information Exchange Coalition

The Mi-COVID19 information exchange coalition is a binary variable ($InfoExchCoalition_i$) that indicates whether a health system has participated in the information echange coalition registry that was developed by HMS. We set this variable to 1 if a health system has participated in the registry and 0 otherwise. We find that 10 out of 15 (66.67%) health systems have participated in the registry.

2.3.3.4. Average Distance between hospitals in a health system

We used *GoogleMap* API to measure the distance (in miles) between any two hospitals in a system. Subsequently, we create a variable $AvgDist_i$ by calculating the average distance between all the hospitals that are part of a health system. On average, hospitals within a health system in Michigan are 104.41 miles apart (S.D = 47.33). We also create a binary variable $BinAvgDist_i$ which is equal to 1 if the average distance between hospitals in a health system is greater than 104.41 miles, and 0 otherwise. This helps in separating out health systems in which hospitals are more closely located from those in which hospitals are further apart. We have 60% of all the health systems (i.e., 9 health systems) with $BinAvgDist_i$=1.

2.3.3.5. Control Variables

As a part of this research investigation, we considered several control variables. We controlled for health system specific time variant infection prevention and control (IPC_{it}) practices and facility response mechanisms ($Facility_{it}$) that we collected from the news articles. These variables account for the extent of systematic effort that a health system had put toward delivering care services to hospitalized patients. These practices and mechanisms may be instrumental in explaining care capacity of the system. The values for IPC_{it} range from 0 to 20 with a mean and standard deviation of 7.38 and 4.78, respectively. The values of Facility_{it} range from 0 to 39 with a mean and standard deviation of 16.48 and 9.55, respectively.

To account for system level fixed effects, we controlled for health system time invariant variables. Specifically, we controlled for $AvgStaffedBeds_i$ (Mean = 163.09; S.D. = 86.52) and

$AffiliatedHospitals_i$ (Mean = 6.8; S.D. = 3.41) to account for average number of staffed beds in hospitals of a system and total number of affiliated hospitals in a system, respectively. The average number of staffed beds ranged from a minimum of 25 to a maximum of 380. The minimum and maximum numbers of affiliated hospitals in a health system are 2 and 14, respectively. For each health system *i* and time-period *t,* we accounted for new COVID-19 cases ($AvgDemand_{it}$) in the county where the health system is located. If hospitals within a health system are spread across multiple counties, we considered the average COVID-19 cases on the date of observation in those counties. The mean and standard deviation of $AvgDemand_{it}$ are 189.54 and 297.52 cases each day, respectively. We accounted for demographic characteristics of counties in which a health system has its presence by controlling for average population of the counties ($AvgPopulation_i$). The mean and standard deviation of $AvgPopulation_i$ are 486,261 and 540,946 respectvely. The variable has highest and lowest values at 1,653,949 and 17,730 people, respectively. Correlations for the variables have been provided in Table 2.1.

Table 2.1 Correlation Table

#	Variables	Mean	S.D.	1	2	3	4	5	6	7	9	10	12
1	$BedUtilization_{it}$	0.10	0.10	1.00									
2	$BinAvgDist_{i}$	0.60	0.49	-0.02	1.00								
3	$InfoExchCoalition_{i}$	0.67	0.47	0.08*	-0.29*	1.00							
4	$ServiceInnovation_{it}$	0.44	0.50	0.05	-0.40*	0.18*	1.00						
5	$AvgDemand_{it}$	189.54	297.52	0.26*	-0.29*	0.16*	0.26*	1.00					
6	IPC_{it}	7.38	4.78	0.07	-0.24*	0.42*	0.29*	0.04	1.00				
7	$Facility_{it}$	16.48	9.55	-0.01	-0.20*	0.54*	0.25*	0.03	0.63*	1.00			
9	$AvgStaffedBeds_{i}$	163.09	86.52	0.26*	-0.43*	0.42*	0.47*	0.56*	0.24*	0.20*	1.00		
10	$AffiiliatedHospitals_{i}$	6.80	3.41	0.14*	0.27*	0.29*	0.34*	0.02	0.50*	0.34*	0.33*	1.00	
12	$AvgPopulation_{i}$	486261	540946	0.30*	-0.43*	0.22*	0.29*	0.67*	-0.04	-0.08*	0.81*	0.00	1.00

2.4. Econometric Approach

We chose our estimation approach to address two potential issues in our data. First, there may always be a possibility of unconditional heteroskedasticity across health systems which needs to be explicitly modeled. Second, differences in care capacity of health systems in a region and their competing objectives can induce correlations in error terms. We use generalized least squares (GLS) panel regression as the estimation methodology since it allows us to model heteroskedasticity and correlation across different health systems in an unrestricted way (Wooldridge, 2010; Gao and Hitt, 2012). Additionally, we include controls for time so that our results are robust to specification errors that could be created by time dependent effects common to all health systems. We performed our estimation using the *xtgls* command in STATA 15.

We ran two different models with GLS: first with inter-system error heteroskedasticity and second with both inter-system error heteroskedasticity and correlation. We consider the first GLS model as our main model based on its better fit with the data (i.e., lower Wald statistic). However, we also run the second GLS model as a robustness check and present those results. We followed Hu and Hoover (2018) methodology to perform power analysis. The result of our tests suggests that our sample provides sufficient power to reject the null findings at standard power threshold of 80% (Hu and Hoover, 2018). Our estimation models consider robust inference clustered around unique health system id to address health system level heteroskedasticity (Wooldridge, 2010).

2.4.1. Identification Strategy: Treatment Effect of Service Innovation on ICU Bed Utilization

We use the difference-in-differences (DiD) approach with propensity score matching. The approach addresses potential endogeneity issues associated with the service innovation adoption by a health system (say, a purposive choice of adopting the service innovation due to the demographics of its location of operation). Angrist and Pischke (2008) provide an exhaustive discussion of social science applications of DiD. Instances of recent application of DiD can also be found in operations management literature (Scott et. al., 2020; Xue et. al., 2019; Dhanorkar and Muthulingam, 2020). To implement the DiD method in our research, we divided the data into treatment group and control group. The treatment group consists of health systems that have opted for the service innovation whereas health systems that have not reported an adoption of the service innovation are part of the control group. There are 8 health systems in the treatment group and 7 health systems in the control group. Four health systems were already using the CPT service innovation all along during the period of analysis and four additional health systems started using the therapy at some time during the data analysis period. Our identification process is enabled by the interventions created by unique variation in the treatment and control groups.

We ascertained that there is no significant difference of trend in the intensive bed utilization across treatment and control groups in the pre-treatment period (Bell et. al., 2018). Table 2.2 presents the summary statistics of illustrative variables used in the analysis. A cursory glance at Table 2.2 indicates that the adoption of the service innovation by health systems may be endogenous to the demand and demographics. For example, the average population of counties where the system in treatment group is present is 660,507 whereas the average population of the counties where the system in control group is present is 348,139. The system may choose to adopt the therapy in response to the fact that higher population may place higher critical care demand on the hospital system.

Table 2.2 Illustrative Health System Level Summary Statistics

Variables	Treatment Group	Control Group	Total
$BedUtilization_{it}$	0.109	0.09	0.104
	(0.079)	(0.11)	(0.097)
$AvgDemand_{it}$	275.98	121.01	189.54
	(375.9)	(190.47)	(297.52)
IPC_{it}	8.95	6.12	7.37
	(2.95)	(5.53)	(4.78)
$Facility_{it}$	19.15	14.37	16.48
	(8.97)	(9.47)	(9.55)
$AvgStaffedBeds_i$	208.83	126.83	163.09
	(93.69)	(59.14)	(86.52)
$AffiliatedHospitals_i$	8.09	5.78	6.8
	(3.54)	(2.92)	(3.41)
$AvgPopulation_i$	660507.1	348139.8	486261.4
	(604629.7)	(438515.5)	(540946.4)

2.4.2. Identification Strategy: Treatment Effect of Geographical Proximity on ICU Bed Utilization

Imbens and Wooldridge (2009) note that two key assumptions must be met in order to find unbiased estimate of the treatment effect. The first assumption is that, beyond the covariates that we considered, there should be no other unobserved characteristics of the health systems that are associated with $BedUtilization_{it}$ and $BinAvgDist_i$ (unconfoundedness) (Rosenbaum and Rubin, 1983). Though such unconfoundedness assumption is untestable, we can perform some tests to assess the plausibility of the assumption. It relies on the presence of two or more control groups (Rosenbaum, 1987). The method suggests that we find a 'pseudo' treatment that further divides the control group into 'pseudo' treatment and control groups. Given the fact that control group observations should have zero effect on $BedUtilization_{it}$, if we find that the 'pseudo' treatment does not reject the null hypothesis of zero impact on $BedUtilization_{it}$, it makes the unfoundedness assumption more plausible. In our study, we find a 'pseudo' treatment in the control group ($BinAvgDist_i$ = 0) depending on the average population of the county where a health system is located. We considered 'pseudo' treatment and control groups that consist of observations above and below average population of about 625,686 residents. We estimate the average 'pseudo' treatment effect after controlling for $AvgDemand_{it}$ and time invariant fixed effects. The chi-square statistic (χ^2 = 445.09; p <0.001) suggests that the model fit is good. We find that the treatment effect (β = -0.04, p>0.05) is insignificant. Hence, as we cannot reject the hypothesis that 'pseudo' treatment effect has zero effect on $BedUtilization_{it}$ at 5% level of significance, it seems plausible that unconfoundedness assumption holds.

The second assumption relates to the overlap restriction. In an ideal experimental setup, we would have randomly assigned the health systems to the control and treatment groups. In that way, we would have made sure that correlation between the treatment and covariates do not exist. However, such random assignment is not possible as health systems may choose to opt the service innovation based on contextual parameters. To estimate average treatment effect, Rosenbaum and Rubin (1983) states that the estimation methodology must have all possible values of covariates with both treated and control units. However, due to systematic differences in the values of covariates in treatment and control groups, this overlap assumption is often violated. Propensity score adjustment is an effective way to account for the imbalances in values of characteristics for treatment and control groups (Rosenbaum and Rubin, 1983; Imbens and Woolridge, 2009). We discuss about the assumption and our weighting process in the next section.

2.4.3. Quasi-Experimental Design: Propensity Scores Weighting

Propensity score is the probability that an observation unit receives treatment conditional on the observed covariates. If our analysis considers the subpopulation of the observations with same propensity score, the overlap assumption is satisfied which eliminates the bias in the estimation of average treatment effect. The propensity scores can be used as sampling weights in such a way that it reweights the treatment and control observations so that overlap restriction is satisfied (Imbens and Woolridge, 2009; Hirano and Imbens, 2001; Bell et. al., 2018; Rosenbaum and Rubin, 1983b). Following the suggestions of Imbens and Woolridge (2009), we use inverse propensity weights (IPW) as our weights. We define, $\omega(W, x) = \frac{W}{\widehat{\varepsilon(x)}} + \frac{1-W}{1-\widehat{\varepsilon(x)}}$, where W = 1 indicates a treated health system and $\widehat{\varepsilon(x)}$ is the estimated probability of being treated. To compute $\widehat{\varepsilon(x)}$ we used IPC_{it}, $Facility_{it}$, $AvgStaffedBeds_i$, $AffiliatedHospitals_i$, $AvgPopulation_i$. We use a binary logit model to estimate the required probability of a system's participation in the treatment group. After obtaining these weights, we estimate both DiD and treatment effects models by including these weights in the estimation.

Next, we verify whether the weights appropriately balance the treatment and control groups. We adopt the strategy suggested by Guo and Fraser (2014) to simply compare estimates from a set of weighted and unweighted regressions. In these regressions we consider one of the covariates ($AvgPopulation_i$) as the dependent variable and treatment indicator (e.g., systems that adopted the service innovation) as the independent variable. When we use linear regression estimation method with IPC_{it}, $Facility_{it}$, $AvgStaffedBeds_i$ and $AffiliatedHospitals_i$ as control variables, the estimate of treatment in the unweighted regression is statistically significant (b = -0.104; p<0.05). This indicates that health systems belonging to denser population region are more likely to adopt the service innovation, an endogeneity that needs to be accounted for. We find that the estimate of treatment in the weighted regression is statistically non-significant ($b = -1.82$; $p > 0.1$). Hence, weighted regressions eliminate all these significant differences between two groups and provides evidence that propensity score method appropriately balances the data. We considered a different covariate ($AvgStaffedBeds_i$) as dependent variable and ran both weighted and unweighted regression. We found similar results which further support that propensity score method helps in balancing the data.

2.4.4. Identification Strategy: Treatment Effect of Information Exchange Coalition on ICU Bed Utilization

2.4.4.1. Estimation of Direct Effect

Whether a health system will participate in a health information exchange may depend on multiple time-invariant and time-varying factors that we may not have exclusively captured. This could potentially violate the unconfoundedness assumption (Rosenbaum and Rubin, 1983; Imbens, 2004) and may bias the treatment effect. For example, we do not have a standard econometric treatment to capture patient level variances of each health system which may confound the relationship between the choice to participate in a health information exchange coalition and intensive care bed utilization. To account for the endogeneity of the HIE participation, we run an instrumental variable (IV) analysis where we use the number of academic articles that a health system has published from 1900 until Nov 12, 2020. We collected data from the SCOPUS database where we searched by each health system's name. The average and standard deviation of the variable are 5493.73 and 10795.98 articles, respectively. To address the wide dispersion in the values of this variable, we considered the natural logarithm transformation of the variable after adding 1 to all the observations so as to avoid dropping of data for systems with 0 publications. We considered two stage least square regression where our first-stage equation is given by,

$$InfoExchCoalition_i = \mu_{it} + b_1 \ln(publish_i) + b_2 AvgDemand_{it} + b_3 IPC_{it} + b_4 AffiliatedHospitals_i + b_5 AvgStaffedBeds_i + b_6 AvgPopulation_i + b_7 Facility_{it} + T_t + \epsilon_{it} \quad (1)$$

The variable, *$publish_i$*, measures the number of academic articles published by health system *I* during the time-period and T_t represents the time trend. We could not control for system level indicator variable since the set of variables are collinear with *$InfoExchCoalition_i$* and fully explain the variance in the variable, thereby making *$publish_i$* redundant. However, we considered *$AffiliatedHospitals_i$* and *$StaffedBeds_i$* to control for system level fixed effects. As the standard 2SLS estimator requires a linear first stage regression, we use linear probability model despite the binary endogenous variable (Bavafa et. al., 2018). Next, we use the predicted value, $\widehat{InfoExchCoalition_i}$, from Equation 1 in Equation 4 as a substitute for *$InfoExchCoalition_i$*. We present the results in columns 1 and 2 of Table 2.4.

A valid instrument should satisfy relevance and exclusion restrictions (Wooldridge, 2010). Generally, publishing academic research papers requires active collaboration among multiple authors. Hence, physicians in a health system that published higher number of academic articles may realize the value of collaboration and are potentially engaged in active information sharing. Often, these collaborations help them to come up with solutions to novel problems. To a group of physicians, treating COVID-19 patients with unproven treatments and unknown processes is nothing short of solving novel problems, which requires information sharing with other physicians in different health system to locate best practices that the latter group might be using. Hence, health systems' propensity to publish may explain the likelihood of them participating in a information exchange coalition registry. The assumption is validated as $b_1 = 0.05$ ($p < 0.001$) is significant and

F-statistic associated with first stage regression (equation 1) is greater than 10 ($F = 38.92$, $p < 0.001$) (Stock and Yogo, 2005).

Exclusion restriction assumption cannot be directly tested, but we can conduct auxiliary analyses that rule out some plausible ways in which the assumption could be violated (Bavafa, 2018). One possibility is that systems with higher propensity of publishing academic research may enforce stricter hospital preparedness which may influence bed utilization. We considered the extent to which a health system used preparedness checklist, a sub-activity within the facility practices guidelines provided by CDC (activity 9a of Table A1 in the Appendix). We had collected this information from the news articles as discussed earlier. We found no significant relationship between this variable and bed utilization. Another possibility is that systems with higher academic output may understand guidance-based discharge better and may practice policies that lower patient readmission chances, which reduces bed utilization. We considered the data from news articles that was used to operationalize the extent to which a health system follows CDC guidelines for patient service delivery by providing guidance to COVID-19 patients discharged to home or long-term care facility (activity 5 of Table A1 in the Appendix). This patient service delivery activity is also not significantly associated with bed utilization.

2.4.4.2. Estimation of the Moderation Effect

We understand that $InfoExchCoalition_i$ may introduce endogeneity in estimation of its moderation effect on the relationship between $ServiceInnovation_{it}$ and $BedUtilization_{it}$ via its first order term and cross product with $ServiceInnovation_{it}$. Hence, we use $\ln(publish_i)$ and $\ln(publish_i)*ServiceInnovation_{it}$ as instrumental variables for $InfoExchCoalition_i$ and $InfoExchCoalition_i*ServiceInnovation_{it}$ respectively. To address the endogeneity, we considered two stage least square regression where our first-stage equations are given by equations 2 and 3,

$$InfoExchCoalition_i = b_0 + b_1 \ln(publish_i) + b_2 \ln(publish_i) * ServiceInnovation_{it} + b_3 ServiceInnovation_{it} + b_4 BinAvgDist_i + b_5 ServiceInnovation_{it} * BinAvgDist_i + b_6 AvgDemand_{it} + T_t + \epsilon_{it} \qquad (2)$$

$$InfoExchCoalition_i * ServiceInnovation_{it} = b_0 + b_1 \ln(publish_i) + b_2 \ln(publish_i) * ServiceInnovation_{it} + b_3 ServiceInnovation_{it} + b_4 BinAvgDist_i + b_5 ServiceInnovation_{it} * BinAvgDist_i + b_6 AvgDemand_{it} + T_t + \epsilon_{it} \qquad (3)$$

$AvgDemand_{it}$ represents the propensity score weighted new COVID-19 cases in the county, where the health system i is located, at t time and T_t represents the time trend. Next, we use the predicted values, $\widehat{InfoExchCoalition_i}$, from Equation 2 and $\widehat{InfoExchCoalition_i} * Plasma_{it}$ from Equation 3 in Equation 8 as a substitute for $InfoExchCoalition_i$ and $InfoExchCoalition_i*ServiceInnovation_{it}$ respectively. We present the results in Table 2.6. The F-statistics associated with first stage regressions (equations 1 and 2) are ($F = 240.85$, $p < 0.001$) and ($F = 142.96$, $p < 0.001$), respectively. As these statistics are greater than 10, the relevance of the instrument assumptions are validated (Stock and Yogo, 2005).

2.5. Results

2.5.1. Impact of Service Innovation on ICU Bed Utilization

To ensure normality, we took the natural logarithm transformation of $BedUtilization_{it}$. We added 1 to the variable to ensure that values of 0 bed utilization do not drop out. Similarly, natural logarithm transformation of $AvgDemand_{it}$ was taken after adding 1 to the variable. The following regression equation captures the effect of the introduction of service innovation on the intensive care bed utilization:

$$\ln(BedUtilization_{it}) = \alpha_0 + \alpha_1 ServiceInnovation_{it} + \alpha_2 \ln\,(AvgDemand_{it}) + T_t + \epsilon_{it}, \quad (4)$$

where $BedUtilization_{it}$ captures intensive care bed utilization in system *i* at time *t* and $ServiceInnovation_{it}$ = 1 indicates the system *i* has opted the service innovation at time *t*, and 0 otherwise. Health systems have opted the service innovation at different points in time, hence $ServiceInnovation_{it}$ captures the variation not only across different health systems but also within a health system across different time. $AvgDemand_{it}$ denotes the number of new virus infected patients in the vicinity of health system *i* at time *t*. We control for the total number of new infections as it partially explains variation in ICU bed utilization due to virulent patient hospitalization. T_t is a time dummy for each time period, which captures any trend in overall bed utilization over time. The coefficient of $ServiceInnovation_{it}$, α_1, captures the change in $BedUtilization_{it}$ relative to the baseline ICU bed utilization for a given system and the seasonality patterns. If α_1 is negative and significant, then adoption of the service innovation indeed reduces the intensive care bed utilization of the health system.

Table 2.3 shows the result without (column 1) and with (column 2) propensity score adjustment, where the latter is our preferred specification. The effect of the service innovation adoption is negative and significant (α_1 = -0.025, p<0.001) which suggest that the new therapy helps to reduce $BedUtilization_{it}$ by 0.025. Hence, the result provides support for hypothesis 1. As the dependent variable is ICU bed utilization, the result is economically meaningful. The adoption of the service innovation helps the health system to reduce intensive care bed utilization due to COVID-19 patient hospitalizations by 2.5%. In Table 2.3 we have also provided additional robustness checks. Column 3 depicts result of the model after controlling for system level fixed effects. In column 4, we provide the results for unrestricted correlations across systems. Both the robustness results support the main result.

Table 2.3 Impact of Service Innovation on ICU Bed Utilization

Variables	(1) ln(BedUtilization)	(2) ln(BedUtilization)	(3) ln(BedUtilization)	(4) ln(BedUtilization)
ServiceInnovation$_{it}$	-0.011** (0.0035)	-.025*** (0.006)	-.079** (0.023)	-.016** (0.004)
ln(AvgDemand$_{it}$)	.022*** (0.001)	.027*** (0.001)	.046*** (0.004)	.024*** (0.001)
Time Controls	Day-Week	Day-Week	Day-Week	Day-Week
System Fixed Effects	No	No	Yes	No
Prop. Score Weighting	No	Yes	Yes	Yes
Observations	735	735	735	735
Wald chi-square	1282.79	1089.36	1470.19	372881.88
Number of systems	15	15	15	15

The standard error has been reported in the parenthesis.
+. p < 0.1 * p < 0.05 **. p < 0.005 ***. p < 0.001

2.5.2. Impact of participation in the Information Exchange Coalition on ICU Bed Utilization

The following regression equation captures the effect of participation in the information exchange coalition on the intensive care bed utilization relating to COVID-19 patient hospitalization:

$$\ln(BedUtilization_{it}) = \mu_{it} + b_1 \widehat{InfoExchCoalition_i} + b_2 \ln(AvgDemand_{it}) + b_3 IPC_{it} + b_4 AffiliatedHospitals_i + b_5 AvgStaffedBeds_i + b_6 \ln(AvgPopulation_i) + b_7 Facility_{it} + T_t + \epsilon_{it}, \quad (5)$$

where $\widehat{InfoExchCoalition_i}$ is the predicted value of *InfoExchCoalition*$_i$ from equation 1. We controlled for trend in time. We used *FacilityResponse*$_{it}$, *AffiliatedHospitals*$_i$ and *StaffedBeds*$_i$ to control for system level effects.

Column 1 in Table 2.4 depicts the first stage equation of the 2SLS. We find that the number of research article published by health systems explains their likelihood of participating in an information exchange coalition like Mi-COVID19. Column 2 shows the result for second stage model represented in equation 3. The effect of participation in the information exchange coalition is negative and significant (b_1 = -0.065, p<0.001). Hence, hypothesis 2 is supported. The result is economically meaningful as the result suggests that by participating in the information exchange coalition initiative the health systems were able to decrease intensive care bed utilization related to COVID-19 patient admission by 6.49%.

For robustness check, we provide Column 3 and Column 4 with the result with propensity score matching and with unrestricted correlations across systems (panels(corr)) respectively. We find the results supporting hypothesis 2 are robust to alternative specifications. We also conducted a robustness check by considering the extent of participation by hospitals in a health system. We define a variable, *PercentParticipation*$_i$, as the percentage of hospitals in a health system that has participated in the Mi-COVID19 initiative. The mean and standard deviation of the variable is 0.279 and 0.364. We normalized the variable so that it follows the normal distribution. Similar to our variable, *InfoExchCoalition*$_i$, we consider *PercentParticipation*$_i$ to be an endogenous variable and consider *publish*$_i$ as a suitable instrumental variable. To estimate the direct effect, we perform the 2SLS regression. The 1st stage regression is performed using model 1. We have provided the results of the first stage regression in Table 2.4 column 5. We find that *publish*$_i$ is highly significant (b_1= 0.03, p < 0.001) and the F-statistic is greater than 10 (F = 79.62, p<0.001), which satisfies the relevance assumption (Stock and Yogo 2005). We provide the results from the second stage in Table 2.4, column 6. We find that the results accord with our original findings. In fact, the direct effects of $InfoExchCoalition_i$ (b_1 = -0.07, $p<0.001$) and $PercentParticipation_i$ (b_1 = -0.1, $p<0.001$) on ICU bed utilization, are very close in magnitude, ascertaining our central argument of information sharing within the health system by a health system participating in the information echange coalition initiative.

Table 2.4 Impact of Participation in Information Exchange Coalition on ICU Bed Utilization

Variables	(1) InfoExchCoalition$_i$	(2) ln(BedUtilization)	(3) ln(BedUtilization)	(4) ln(BedUtilization)	(5) PercentParticipation	(6) ln(BedUtilization)
ln(publish$_i$)	0.051*** (0.0049)				0.031*** (0.002)	-
$\widehat{InfoExchCoalition_i}$	-	-0.065*** (0.019)	-.013* (0.006))	-0.033^{+} (0.019)	-	
$\widehat{PercentParticipation_i}$	-	-	-	-	-	-0.1*** (0.03)
IPC$_{it}$	0.006^{+} (.003)	0.0005 (0.0005)	-	0.0008* (0.0003)	-0.001* (.002)	0.000004 (0.0005)
ln(AvgDemand$_{it}$) (weighted in case of propensity score matching)	-0.117*** (0.027)	0.034*** (0.005)	0.029*** (0.00004)	0.029*** (0.003)	-0.005 (0.01)	0.042*** (0.004)
AvgStaffedBeds$_i$	0.0004 (0.0003)	0.0001^{+} (0.00005)	-	0.00005 (0.00003)	0.003*** (0.0001)	0.0004*** (0.0001)
AffiliatedHospitals$_i$	-0.011^{+} (0.006)	0.0012* (0.0005)	-	0.0012* (0.0006)	-0.027*** (0.002)	-0.001 (0.0009)
ln(AvgPopulation$_i$)	0.154*** (0.034)	-0.017** (0.007)	-	-0.012* (0.004)	-0.045*** (0.0104)	-0.032*** (0.006)
Facility$_i$	0.021*** (0.002)	-0.0011* (0.0005)	-	0.0004 (0.0005)	0.001 (0.001)	-0.0001 (0.0003)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Prop. Score Weighting	No	No	Yes	No	No	No
Observations	735	735	735	735	735	735
R-squared	0.48	-	-		0.75	-

Table 2.4 (cont'd)

Wald chi-square	-	1290.42	497989.33	128225.67	-	1290.42
F-value	38.92	-	-		79.62	-
Number of systems	15	15	15	15	15	15

The standard error has been reported in the parenthesis.
+. $p < 0.1$ * $p < 0.05$ **. $p < 0.005$ ***. $p < 0.001$

2.5.3.Impact of Geographic Proximity on ICU Bed Utilization

The following regression equation captures the effect of average distance between affiliated hospitals in a system on the system's intensive care bed utilization due to COVID-19 patient hospitalizations:

$$\ln(BedUtilization_{it}) = \alpha_0 + \alpha_1 BinAvgDist_i + \alpha_2 \ln(AvgDemand_{it}) + T_t + \epsilon_{it}, \quad (6)$$

where $BedUtilization_{it}$ captures intensive care bed utilization in system i at time t. $AvgDemand_{it}$ denotes the number of new virus infected patients in the vicinity of health system i at time t. T_t is a time dummy for each time period which captures any trend in overall bed utilization over time. The coefficient on $BinAvgDist_i$, α_1, captures the change in $BedUtilization_{it}$ relative to baseline ICU bed utilization. If α_1 is positive and significant, then a health system with sparser distribution of affiliated hospitals indeed sees an increase in the intensive care bed utilization due to COVID-19 patient hospitalizations.

Table 2.5 shows the result without (column 1) and with (column 2) propensity score adjustment. The results presented in column (2) is our preferred specification. The effect of average distance is positive and significant (α_1 = 0.0253, $p<0.001$), which suggests that an increase in the geographical distance between affiliated hospitals in a system increases the intensive care bed utilization. Hence, the result provides support for hypothesis 3. The result is economically meaningful as a health system that is part of the treatment group experiences an increase in intensive care bed utilization due to COVID-19 patient hospitalization by 2.53%.

For robustness check, we provide Column 3 and 4 that reflects results with propensity score matching and considering unrestricted correlations across systems (panels(corr)) and the system fixed effects, respectively. We find that hypothesis 3 still holds. In the results we provided in Column 5 of Table 2.5, we specified $AvgDist_i$ as a continuous variable. We used equation 7 to capture the effect of continuous specification of $AvgDist_i$ on bed utilization. The variable has been normalized before including in the equation.

$$\ln(BedUtilization_{it}) = \mu_{it} + b_1 AvgDist_i + b_2 \ln(AvgDemand_{it}) + b_3 IPC_{it} + b_4 AffiliatedHospitals_i + b_5 AvgStaffedBeds_i + b_6 \ln(AvgPopulation_i) + b_7 Facility_{it} + T_t + \epsilon_{it} \qquad (7)$$

In column 5 we present the results of the estimation. We find that the robustness checks support the main result. Until now, we consider the average distance between any two hospitals in the health system network as the operational measure of the geo-spatial distribution of a health system. Such a measure is often biased by the geographic dispersion of the health system affiliated hospitals. In the next robustness check, we alternatively operationalize geographic proximity as the median distance between all possible pairs of hospitals in a health system so we can control for any outliers. We note that the average of the medians of the 15 health systems is 63.34 mi. We created a variable $BinMedDist_i$ that takes the value of 1 when the median distance of all the health system hospital pairs is greater than (or equal to) 63.34 mi and a value of 0 otherwise. In the results that we present in Table 2.5 column 6 we accounted for propensity score adjustment and heteroskedasticity in standard errors across panels. The effect of average distance is positive and significant ($\alpha_1 = 0.02$, $p<0.05$) which accords well with our results. Further, in Table 2.5 column 7 we present results after controlling for the system fixed effects. The results are consistent with our original findings.

Table 2.5 Impact of Geographic Proximity on ICU Bed Utilization

Variables	(1) ln(BedUtilization$_{it}$)	(2) ln(BedUtilization$_{it}$)	(3) lnBedUtilization$_{it}$)	(4) ln(BedUtilization$_{it}$)	(5) ln(BedUtilization$_{it}$) (distance as continuous)	(6) ln(BedUtilization$_{it}$)	(7) ln(BedUtilization$_{it}$)
$BinAvgDist_i$	0.0225*** (0.0038)	0.0253*** (0.0043)	0.02*** (0.003)	0.0719*** (0.0103)	0.0089* (0.0038)	-	-
$BinMedDist_i$	-	-	-	-	-	0.02* (0.008)	0.039* (0.018)
$ln(AvgDemand_{it})$	0.0248*** (0.0014)	0.0253*** (0.0012)	0.021*** (0.001)	0.0321*** (0.0015)	0.0409*** (0.0042)	0.042*** (0.002)	0.058*** (0.0029)
Time Controls	Day-Week	Day-Week	Day-Week	Day-Week	Day-Week	Day-Week	Day-Week
System Fixed Effects	No	No	No	Yes	No	No	Yes
Prop. Score Weighting	No	Yes	Yes	Yes	No	Yes	Yes
Observations	735	735	735	735	735	735	735
Wald chi-square	1176.27	1286.73	347460.41	1792.67	1220.05	697.3	1302.94
Number of systems	15	15	15	15	15	15	15

The standard error has been reported in the parenthesis.
+. $p < 0.1$ * $p < 0.05$ **. $p < 0.005$ ***. $p < 0.001$

2.5.4. Moderating effects of Information Exchange Coalition and Geographic Proximity

The following regression equation captures the moderating effects of a health system's inter-hospital average distance and its participation in the information exchange coalition on the relationship between the service innovation adoption and intensive care bed utilization due to COVID-19 patient hospitalization:

$$\ln(BedUtilization_{it}) = \alpha_0 + b_1 ServiceInnovation_{it} + b_2 \widehat{InfoExchCoalition} + b_3 BinAvgDist_i + b_4 \widehat{ServiceInnovation_{it} * InfoExchCoalition_i} + b_5 ServiceInnovation_{it} * BinAvgDist_i + b_6 \ln(AvgDemand_{it}) + T_t + \epsilon_{it}, \quad (8)$$

where $\widehat{InfoExchCoalition_i}$ is the predicted value of *InfoExchCoalition*$_i$ from equation 2 and $\widehat{ServiceInnovation_{it} * InfoExchCoalition_i}$ is the predicted value of $ServiceInnovation_{it} * InfoExchCoalition_i$ from equation 3. We controlled for trend in time and the effects of new COVID-19 infections.

Columns 1 and 2 in Table 2.6 depicts the first stage equations of the 2SLS. We find evidence of the strength of instrumental variable used (F>100; p<0.001), which satisfies Stock and Yogo (2005) test of instrumental variable relevance. Column 3 shows the result for the second stage equation. We find that the coefficient of the interaction term, $ServiceInnovation_{it}*InfoExchCoalition_i$, is negative and significant (b_4 = -0.237, p<0.01). Hence, hypothesis 4 is supported. The result suggests that participation in the information exchange coalition helps in decreasing intensive care bed utilization due to COVID-19 patient hospitalization by 23.7%. Further, we find that the coefficient of interaction term, $ServiceInnovation_{it}*BinAvgDist_i$, is negative and significant (b_5 = -0.089, p<0.005). Hence, hypothesis 5b is supported. The results suggest that a health system may be able to reduce intensive care bed utilization by 8.9% when the affiliated hospitals are sparsely located. In columns 4 and 5 we treat moderation terms separately. We find results are in congruence with the results from earlier model.

Table 2.7 contains results of robustness checks for the moderation terms. In columns 1 and 2 we provide results with propensity score matching, considering unrestricted correlations across systems (panels(corr)), and $AvgDist_i$ as a continuous variable. We find support for hypotheses 4 and 5b. In column 3, we explicitly model the auto correlation in the unobserved error terms within a panel structure across the cross-sectional units since it is plausible that some of the unobserved variables, that we couldn't control, may be correlated across time. We estimated the random effects model with AR(1) correlation between the disturbances using the *xtregar* command. The results lend further support for hypotheses 4 and 5b. We undertook robustness checks by alternatively operationalizing $InfoExchCoalition_i$ as $PercentParticipation_i$. The results considering propensity score matching and controlling for heterogeneity across health systems in the unobserved error terms are presented in columns 4 of Table 2.7. The results lend further support for hypotheses 4 and 5b. Next, we introduce a robustness check by alternatively operationalizing geographic proximity as the median distance between all possible pairs of hospitals in a health system ($BinMedDist_i$) as discussed before. We present the results in Table 2.7 column 5. The results consider propensity score adjustments and control for heterogeneity across health systems in the unobserved error terms. The results lend further support for hypotheses 4 and 5b. In the next robustness check, we introduce alternative operationalization of both the independent variables, $PercentParticipation_i$ and $BinMedDist_i$. We present results from the propensity score adjusted and endogeneity corrected (in $PercentParticipation_i$) estimation model in Table 2.7 column 6. We find the results lend further support for the hypotheses 4 and 5b.

Table 2.6 Moderating Effects

Variables	(1) InfoExchCoalition$_i$	(2) ServiceInnovation$_{it}$ X InfoExchCoalition$_i$	(3) ln(BedUtilization$_{it}$)	(4) ln(BedUtilization$_{it}$)	(5) BedUtilization$_{it}$)
$ln(publish_i)$	0.148*** (0.006)	0.013*** (0.0025)	-	-	-
$ServiceInnovation_{it}$	0.954*** (0.141)	0.71*** (0.1211)	0.206* (0.1002)	0.094* (0.044)	0.011 (0.012)
$ServiceInnovation_{it}$* $ln(publish_i)$	-0.118*** (0.014)	0.016 (0.0121)	-	-	-
$\widehat{InfoExchCoalition_i}$	-	-	0.054** (0.019)	0.024 (0.018)	-
$\widehat{ServiceInnovation_{it}}$ * $InfoExchCoalition_i$	-	-	-0.237* (0.115)	-0.159** (0.058)	-
$BinAvgDist_i$	0.303*** (0.059)	0.047*** (0.011)	0.058*** (0.014)		-0.05*** (0.014)
$ServiceInnovation_{it}$ *$BinAvgDist_i$	-0.532*** (0.083)	-0.284*** (0.056)	-0.089** (0.034)		-0.033* (0.016)
$ln(AvgDemand_{it})$	-0.006 (0.004)	-0.012*** (0.002)	0.025*** (0.002)	0.025*** (0.0015)	0.028*** (0.001)
Time Controls	Day-Week	Day-Week	Day-Week	Day-Week	Day-Week
Prop. Score Weighting	Yes	Yes	Yes	Yes	Yes
Observations	735	735	735	735	735
F-statistic	240.85	142.96	-	-	-
R^2	0.414	0.686	-	-	-
Wald chi-square	-	-	982.68	1046.79	1035.92

Table 2.6 (cont'd)

Number of systems	-	-	15	15	15

The standard error has been reported in the parenthesis.
+. $p < 0.1$ * $p < 0.05$ **. $p < 0.005$ ***. $p < 0.001$

Table 2.7 Robustness Checks for Moderating Effects

Variables	(1) ln(BedUtilization$_{it}$)	(2) ln(BedUtilization$_{it}$) (AvgDist$_i$ as continuous)	(3) ln(BedUtilization$_{it}$)	(4) ln(BedUtilization$_{it}$)	(5) ln(BedUtilization$_{it}$)	(6) ln(BedUtilization$_{it}$)
$ServiceInnovation_{it}$	0.464*** (0.04)	0.411* (0.176)	0.628*** (0.147)	0.063* (0.028)	0.354*** (0.096)	0.113*** (0.032)
$\widehat{InfoExchangeCoalition_i}$	0.109*** (0.014)	0.076* (0.03)	0.232*** (0.064)	-	0.176*** (0.043)	-
$\widehat{PercentParticipation_i}$	-	-	-	0.099* (0.042)	-	0.265** (0.08)
$\widehat{ServiceInnovation_{it}} * MiCOVIDInfoExchCoalition$	-0.771*** (0.065)	-0.524* (0.215)	-1.063*** (0.238)	-	-0.396*** (0.102)	-
$\widehat{ServiceInnovation_{it}} * PercentParticipation_i$	-	-	-	-0.171** (0.063)	-	-0.356*** (0.088)
$BinAvgDist_i$	0.043*** (0.007)	0.049** (0.015)	0.101* (0.047)	0.045*** (0.013)	-	-
$BinMedDist_i$	-	-	-	-	0.136*** (0.029)	0.068*** (0.016)
$ServiceInnovation_{it} * BinAvgDist_i$	-0.167*** (0.017)	-0.191** (0.074)	-0.251** (0.083)	-0.061* (0.025)	-	-
$ServiceInnovation_{it} * BinMedDist_i$	-	-	-	-	-0.228*** (0.054)	-0.113*** (0.026)
$ln(AvgDemand_{it})$	0.014*** (0.001)	0.019*** (0.004)	0.005^{+} (0.003)	0.025*** (0.002)	0.018*** (0.003)	0.019*** (0.003)
Time Controls	Day-Week	Day-Week	Day-Week	Day-Week	Day-Week	Day-Week
Prop. Score Weighting	Yes	Yes	Yes	Yes	Yes	Yes
Observations	735	735	735	735	735	735
Wald chi-square	197211.62	1024.78	58.42	982.68	1101.25	1101.25
Number of systems	15	15	15	15	15	15

The standard error has been reported in the parenthesis.
+. $p < 0.1$ * $p < 0.05$ **. $p < 0.005$ ***. $p < 0.001$

2.5.5.Additional robustness checks

It is possible that there may be within health system heterogeneity that may explain the variance in the dependent variable. Hence, we conduct additional robustness check to account for potential within health system differences. We collected data on the number of staffed beds in each of the hospital in a health system. Varying number of beds in the affiliated hospitals of a health system can introduce within health system heterogeneity. Additionally, the number of COVID-19 cases handled by different affiliated hospitals can also introduce heterogeneity. To account for these within health system heterogeneity, we control for the standard deviation of these variables. We refer to these variables as $StdStaffedBeds_i$, and $StdDemand_{it}$, respectively. We normalized $StdDemand_{it}$ by taking a natural log transformation of the variable.

The results of our analysis are presented in Table 2.8. In column 1 we present the result from the propensity score weighted difference-in-difference analysis. The effect of the service innovation adoption is negative and significant (α_1 = -0.017, p<0.05) which is in accord with our main result. Column 2 presents the direct effect of endogeneity corrected $InfoExchCoalition_i$ variable that captures the community health information exchange. The effect of $InfoExchCoalition_i$ is negative and significant (b_1 = -0.065, p<0.001), which is similar to our main results. In column 3 we present the propensity score weighted treatment effect of $BinAvgDist_i$. The effect of average distance is positive and significant (α_1 = 0.0253, p<0.001) in concert with our main results. In column 4 we provide the results from propensity score weighted difference-in-difference analysis of the service innovation adoption (i.e., the variable $ServiceInnovation_{it}$) that involves both the interaction terms. Please note that we consider $InfoExchCoalition_i$ and $InfoExchCoalition_i*ServiceInnovation_{it}$ as endogenous variables and undertake endogeneity correction by using instrumental variables similar to the main results presented in the paper. As before the instruments are strong and relevant. We present the results from the two stage panel-data linear model by using feasible generalized least squares (xtgls) regression in column 4. We find that the coefficient of the interaction term, $ServiceInnovation_{it}$ * $InfoExchCoalition_{i}$, is negative and significant ($b_4 = -0.237$, $p<0.01$). Further, we find that the coefficient of the interaction term, $ServiceInnovation_{it}$*$BinAvgDist_{i}$, is negative and significant ($b_5 = -0.107$, $p<0.05$). These results are consistent with our main results.

Table 2.8 Controlling for within health system heterogeneity in the models

Variables	(1) ln(BedUtilization)	(2) ln(BedUtilization) (IV corrected)	(3) ln(BedUtilization)	(4) ln(BedUtilization) (With moderators; IV corrected)
$ServiceInnovation_{it}$	-0.017* (0.007)	-	-	0.209** (0.068)
$BinAvgDist_i$	-	-	0.025*** (0.005)	0.052*** (0.014)
$InfoExchCoalition_i$	-	-0.052** (0.018)	-	0.029 (0.031)
$InfoExchCoalition_i$ $X ServiceInnovation_{it}$	-	-	-	-0.237** (0.075)
$ServiceInnovation_{it}$ $X BinAvgDist_i$	-	-	-	-0.107* (0.049)
$ln(AvgDemand_{it})$ *(weighted in case of propensity score matching)*	0.022*** (0.003)	0.033*** (0.007)	0.027*** (0.004)	0.021*** (0.005)
IPC_{it}	-	0.0006 (0.0006)	-	-
$Facility_{it}$	-	0.001** (0.0004)	-	-
$AvgStaffedBeds_i$	-	0.0001* (0.00005)	-	-
$AffiiliatedHospitals_i$	-	0.002^{+} (0.001)	-	-
$ln(AvgPopulation_i)$	-	-0.019** (0.007))	-	-
$StdStaffedBeds_i$	-0.0001^{+} (0.00003)	-0.0001 (0.00006)	--0.0001*** (0.00003)	0.0001 (0.0001)
$ln(StdDemand_i)$	0.006* (0.003)	0.003 (0.003)	-0.0010 (0.0035)	0.002 (0.0035)
Time Fixed Effects	Yes	Yes	Yes	Yes
Prop. Score Weighting	Yes	No	Yes	Yes
Observations	735	735	735	735
Wald chi-square	1087	1403.41	1292.13	1056.22
p-value	0.00	0.000	0.00	0.00
Number of systems	15	15	15	15

The standard error has been reported in the parenthesis.
+. $p < 0.1$ * $p < 0.05$ **. $p < 0.005$ ***. $p < 0.001$

2.6. Discussion

2.6.1. Theoretical Contribution and Implications

The results of our study contribute to three distinct streams of literatures. First, we inform the service innovation literature (Fang et al., 2008; Neely, 2008; Kastalli and Looy, 2013; Tong et. al., 2016; Witell et. al., 2016; Berry, 2019), particularly to the stream of research that considers service innovation in health care context involving novel procedures (Sahu et. al., 2020; Tong et. al., 2016; Tucker et. al., 2007). In the context of the ongoing pandemic, our research uses propensity score weighting approach to create a quasi-experimental setup that takes into account multiple endogeneity issues and provides an unbiased estimation of the effect of service innovation on ICU bed capacity utilization. Different health systems adopted the CPT service innovation at different times, which enables us to study the variance of the impact of the service innovation on intensive care bed utilization related to virulent patient hospitalization. The results of the study suggest that health systems that adopted the service innovation during the uncertain times presented by the pandemic were able to lower the ICU bed utilization due to COVID-19 hospitalization.

Second, we contribute to the understanding of the impact of community-based HIE (Fontaine et. al., 2010; Everson, 2017) on intensive care bed utilization directly as well as its moderating role on the relationship between service innovation and intensive care bed utilization. The results of the study show that by participating in an information exchange coalition, health systems were able to reduce the ICU bed utilization due to virulent patient admission. Additionally, we found that the effect of adoption of the service innovation in reducing bed utilization is stronger when a health system, that adopted the service innovation, also participated in Mi-COVID19 registry.

Third, add to the geographic proximity literature (Howells, 2002; Letaifa and Rabeau, 2013; Knoben and Oerlemans, 2006) and show that while, in general, closer proximity of affiliated hospitals within a health system reduces intensive care bed utilization, this effect is reversed when a health system also introduces service innovation. We find that health systems with less distance among associated hospitals observed an increase in ICU bed capacity utilization due to the service innovation. These are novel findings and provide additional understanding of how geographic proximity of affiliated hospitals of a health system can have both positive and negative impact on outcome.

By integrating service innovation, information sharing coalition, and geographic proximity within an overarching theoretical framework provided by OIPT, we critically examine the roles played by external and internal information sharing structures in strengthening the outcome of innovation efforts. Consideration of these distinct information sharing structures help in extending the underlying predictions of OIPT. A coalition of peer organizations provide the external information sharing structure that can help with managing uncertain times. Environmental uncertainty, such as a pandemic, impacts all organizations and having access to external information sharing structures enables access to a wide range of information that an organization can process to distill the requisite insights for handling the situation. Innovative service offerings aimed at addressing environmental uncertainty are characterized by complexities pertaining to overall planning as well as process management. Information sharing coalitions provide the required structure for learning spillovers (Thornton and Thompson, 2001)

Although dense network structure and the associated distribution of information is valuable for accomplishing routine tasks, the complexity and uncertainty brought about by a new service offering add constraints to the ease and quality of information sharing. Clinical handoffs when administering health service innovation require smooth transfer of patient information and knowledge, along with a transfer of authority and responsibility between two clinical care team (Batt et. al., 2019). These smooth transfers are often difficult, especially when the uncertainty of external environment combines with the complexity and uncertainty associated with offering a new service. In such situations, information can get lost during handoffs, thereby impacting the information processing capability of the organizations.

The results of our study are generalizable to contexts beyond health care and inform theory about managing tasks with uncertain steps or tasks performed in uncertain environment. Such situations can result in various settings. As an example, in humanitarian relief operations disaster response could entail new service delivery mechanisms that would depend on the quality of information shared among the participants in a cluster (Altay and Pal 2014; McGuire and Silvia 2010; Koliba et al. 2011). Similarly, studies focusing on manufacturing plants (Wiengarten and Longoni 2018), retail organizations (Ramanathan, 2012; Li and Zhang, 2008), and projects (Grewal et al. 2006) that are embedded in a network can also leverage lateral communication to manage innovation efforts by sharing relevant information.

2.6.2. Managerial and Policy Implications

Our study offers important insights to health system administrators. The results show that by adopting the service innovation, a health system can reduce COVID-19 related intensive care bed utilization by about 2.57% (Table 2.3, Column 2). This effect is of great significance to a health system. For instance, one of the largest health systems in Michigan that was part of our dataset and didn't adopt the CPT during the time-frame of our data collection, has made available 169 beds for intensive care delivery. On 12th Nov 2020, the bed utilization due to COVID-19 patient hospitalization in the system was 46.15%, which translates to 78 COVID-19 patients admitted to ICU. If the system had adopted the service innovation, then on the same day the system would have registered 2 less intensive care beds along with required critical care staffing which the system could have made available for critical care delivery that is not aimed at COVID-19 patients. However, health care managers should be aware that the decision to implement such novel services often comes with multiple administrative challenges, and the outcome of a therapy often depends on the decision making ability of HCPs.

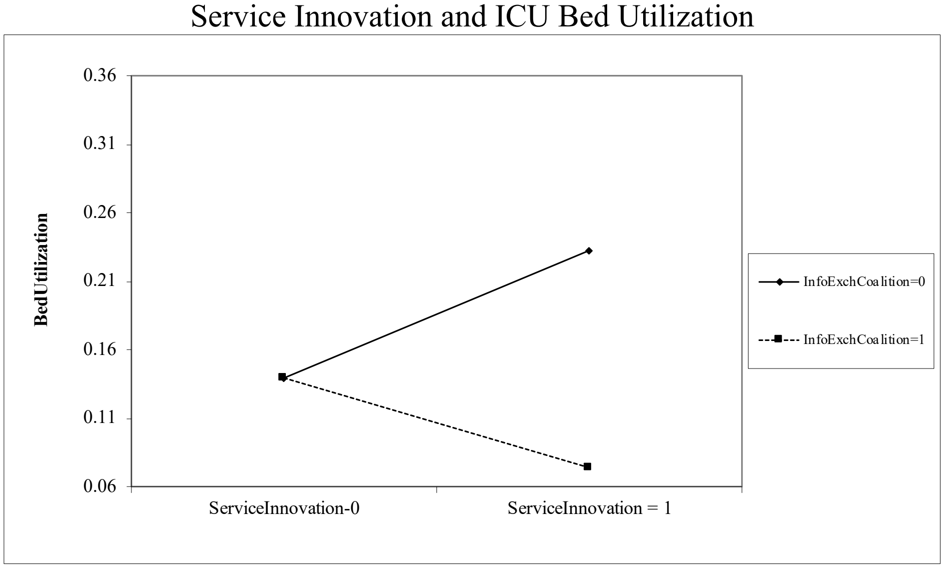
Our study considered the role played by a health system's participation in health information exchange initiative and informs practitioners how to leverage such initiatives. We show that participation of health systems in the HIE initiative is associated with 6.49% lower ICU bed utilization as compared to those who did not participate (Table 2.4, Column 2). This information is of great relevance to another big health care system within our dataset that never participated in the information echange coalition initiative. For example, on 2nd Nov 2020 this health system reported COVID-19 patient hospitalization related ICU bed utilization at 19.92%. Given that the health system has a total of 271 beds, the total number of COVID-19 patients admitted to ICU on that day was 54 patients. Participation in the information echange coalition would have enabled the health system to free up at least 3 beds allocated to treating COVID patients.

Practitioners should realize that participation of health system in HIE initiatives, like Mi-COVID19, provides the system an opportunity to look beyond its boundary and learn from other health systems. An information exchange coalition provides a structure for acquiring external information that a health system can leverage. Such information may enable health systems to develop more robust procedures to offer innovative services. Our results show that the effect of adopting service innovation associated with the CPT on decreasing ICU bed utilization is stronger when a system has participated in the information exchange coalition (Table 2.6, Column 3). A health system that has adopted the service innovation at some point in time and has participated in the health information exchange coalition initiative would be able to reduce bed utilization by 23.71%, ceteris paribus, as compared to a health system that has not participated in the initiative.

If the health system in our dataset with 271 beds had adopted the service innovation on 19th April 2020, participation in the information exchange coalition by this health system would have freed up at least 12 more ICU beds.

The positive moderating effect of the participation in the health information exchange coalition on the relationship is evident in the interaction plot in Figure 2.3. The figure shows that if a health system does not participate in such initiatives over time, it may lose the advantage of using service innovation. Our findings suggest that to reap the benefits of a service innovation, health systems should develop mechanisms to connect with multiple outside entities and learn how they can continue to improve their processes. For example, health system managers may want to build relationships with blood banks across the country to ensure steady supply of plasma necessary for the therapy. The health systems may also want to touch base with patients, who were once admitted to the system due to COVID-19 complications but are now virus-free, to solicitate plasma donation. Our study motivates health systems to incentivize active participation or HCPs in information sharing coalitions to learn best practices so as to treat virulent patients better and faster

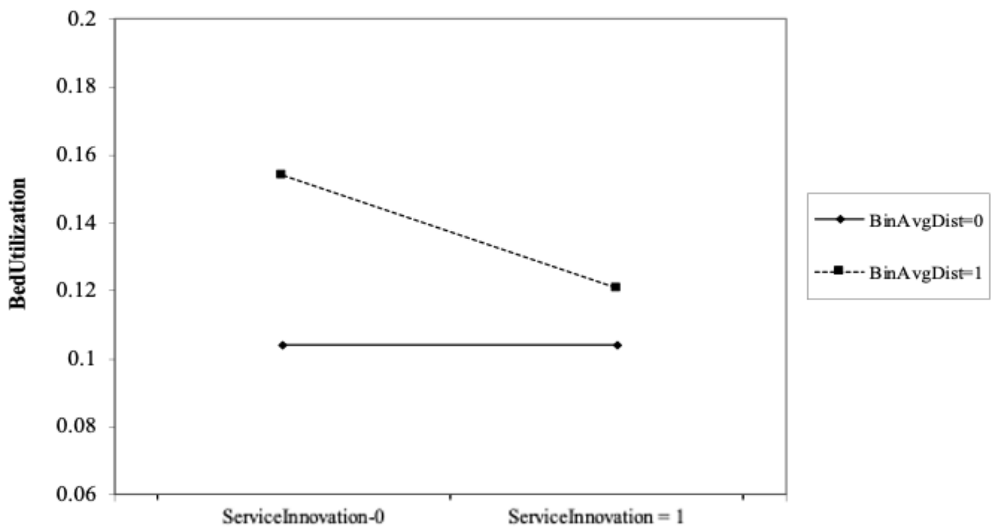
Figure 2.3 Moderation Effect of Information Exchange Coalition on the relationship between Service Innovation and ICU Bed Utilization



Our study informs healthcare administrators about the ways to leverage the geographical distribution of the affiliated hospitals. Results suggest that health systems in which affliliated hospitals are more closely located, on average, have 2.53% lower COVID-19 patient hospitalization related ICU bed utilization (Table 2.5, Column 2). To understand how the bed utilization increases due to per mile increase in average distance between affiliated hospitals in a system, we consider column 5 of Table 2.5 that reports the average distance between affiliated hospitals of a health system as a continuous variable. We find that if the average distance increases by one mile, it increases bed utilization by 0.89%, ceteris paribus. Health systems with closely located affiliated hospitals may share HCPs among these hospitals, which creates an opportunity for even distribution of knowledge across the system. They can also transfer patients, which enables a hospital to create homogeneity in capacity utilization across the system. As such the entire system can come together to offer better and faster treatment against the infection and reduce the intensive care bed utilization in the process.

However, we also show that when health systems with close proximity of affiliated hospitals implement the CPT service innovation, the effectiveness of the procedure decreases by 8.9% (Table 2.6, Column 3). The interaction plot in Figure 2.4 depicts the negative moderating effect of the geographic proximity. This implies that when a system decides on administering service innovation, it should enhance provider continuity of care to avoid miscommunication and other issues related to handoffs. The likelihood of patient and HCP transfers are higher when affiliated hospitals are closely located, and this can impede the continuity of care that is particularly needed when new services are introduced (Van Walraven et. al., 2010).

Figure 2.4 Moderation Effect of Geographic Proximity on the relationship between Service Innovation and ICU Bed Utilization



The interesting fact that Figure 2.4 depicts is that, overall, a health system is better off having affiliated hospitals closeby. However, such advantage wanes when the hospital decides to introduce additional complexity in the form of new service innovation. It is plausible that when a health system decides to adopt a new therapy, it sets guidelines and associated processes that the affiliated hospitals need to follow when administering the treatment. Our study suggests that the marginal increase in risks due to incorrect handoffs of responsibility and information about patients undergoing a new therapy tend to outweigh the gains of even distribution of clinical and administrative information across the system. The findings motivate health systems to invest in and leverage internal IT systems like electronic health record to update patient records in a comprehensive manner, especially when they adopt and administer a service innovation.

Our study also provides some policy implications. First, the results of this study motivate policymakers to develop statewide policy of pooling information when a service innovation is introduced during uncertain times such as a pandemic. For instance, information about plasma inventory at the blood banks and apheresis centers across the states could help health systems to reap benefit from the CPT service innovation. One of main challenges of administering the CPT is to ensure steady supply of liquid plasma. During the timeframe of this research, the country witnessed severe scarcity of plasma. To ensure steady supply of plasma, health systems have been collecting plasma from COVID-19 patients who have been treated for the disease. Hospitals and blood banks managed their own inventories, and this decentralized setup potentially increases the likelihood of mismatch of demand and supply. Setting up an information registry that keeps track of inventory levels of plasma across facilities in a state would help in mitigating this issue. Such a registry can enable health systems experiencing high COVID-19 patient admissions to procure plasma from hospitals that may have excess plasma inventory. Policymakers should proactively establish such information exchange initiatives and encourage competing health systems to share information. Additionally, policymakers should consider forming an analytics team whose task is to uncover best practices that participating health systems have been pursuing to effectively manage their care capacity.

2.6.3. Limitations and Directions for Future Research

This study has few limitations that provide opportunities for future research. First, our study focuses on health systems in the state of Michigan, which limits us from capturing locational heterogeneity. Future research should study the relationships across multiple states or even countries. A second limitation is that we had to rely on news articles to inform us about different operational variables that we had controlled for. We provide transparency regarding our data collection approach and ensured that the data was carefully collated and analyzed so that we do not miss any important operational aspects. We were unable to capture specific instances of patient and HCP transfers within and outside of health systems. Understanding of such instances would have allowed us to shed further light on our research objectives. Given the paucity of such data, future research could undertake in-depth case-studies to understand the activities that health systems have undertaken and how these activities impacted their intensive care capacity. Although the effects of service innovation, information exchange and geographic proximity on capacity are not limited to healthcare, the third limitation of our study stems from the fact that the data considered in our study focuses on critical health care services. Future research should investigate how these relationships hold in a different industry context. Fourth, our research objectives aimed at clearly discerning the *differential* role of external (the information exchange coalition) and internal (geographic proximity) information sharing structures on increasing the effectiveness of service innovation. We do not investigate the joint effect of these information sharing structures due to the lack of a clear theoretical foundation. Theory development and empirical investigation of the joint effect present promising avenues for future research.

In conclusion, this study undertakes an integrated investigation of factors influencing intensive care bed capacity in health systems. Since new service innovations, such as the CPT. come with a set of challenges that can be attributed to a lack of evidence of benefits, scarce organizational knowledge and multiple operational and logistical considerations, our study presents directions to strengthen the effect of service innovations. Our findings advance theory and practice of managing capacity in situations when organizations are faced by disruptions that are characterized by long-term uncertain demand and where there is a lack of capabilities and resources to address the demand.

3. Chapter 3: Growing the Vaccine Distribution Network During a Pandemic: Implications for Increasing Access

3.1. Introduction

"Let's be clear, we are at war with the virus (SARS-CoV-2). And if you are at war with the virus, we need to deal with our weapons with rules of a war economy, and we are not yet there. And this is true for vaccines....." ~ António Guterres, UN Secretary-General[16].

Indeed, vaccines are one of the important interventions to manage a pandemic like the one caused by SARS-CoV-2 (henceforth, COVID-19) (Duijzer et. al., 2018). After the COVID-19 pandemic struck, medical researchers rapidly developed vaccines to control the pandemic. On 11th December 2020 the Food and Drug Administration (FDA) granted emergency use authorization (EUA) to BNT162b2, the vaccine developed by Pfizer, Inc. and BioNTech[17]. Eventually, two more vaccine candidates, aka mRNA-1273 by Moderna, Inc and JNJ-78436735 by Janssen Pharmaceuticals Companies of Johnson & Johnson (JnJ), were granted EUA by FDA. The vaccination campaign involving federal, state, and local governments entities and private providers began in the U.S. on December 14, 2020. Depending on vaccine manufacturing capacity, the federal government procured and allocated vaccines throughout the country by states and territories (Bushwick, 2021). Each of these jurisdictions, in turn, decided how to distribute vaccines to each vaccine provider by considering existing infrastructure and several provider specific parameters such as the vaccine inventory status at a facility. Vaccine providers estimate

[16] https://www.un.org/sg/en/content/sg/statement/2021-05-21/secretary-generals-statement-the-global-health-summit-delivered
[17] https://www.ajmc.com/view/fda-agrees-to-eua-for-covid-19-vaccine-from-pfizer-biontech

the demand and place orders to planning authorities in the state or territory on an ongoing basis. These authorities compile and submit orders to a federal vaccine management system from where this information is passed on to the vaccine manufacturers (i.e., Pfizer, Moderna, JnJ) or the distributor (i.e., McKesson). These organizations proceed to fulfill orders to each of the providers so that they can inoculate people in the region. The information about vaccinations administered by these providers is then updated in the CDC vaccine tracking system (Bushwick, 2021).

As supplies gradually caught up with the demand, policymakers started to make vaccines more accessible. On March 11, 2021, the federal government instructed states to make vaccines available to all adults 18 years and older by May 1, 2021[18]. To increase the availability of vaccines and to make it more convenient for people to get inoculated, many states introduced two major infrastructural changes. First, state governments increased their vaccine provider network. For example, on March 2021 Blue Shield of California announced that the state's enhanced COVID-19 provider network would continue to expand as the state policymakers plan to double the number of vaccine providers in the coming weeks[19]. This raises the question of how the introduction of new vaccine providers in a region impact the vaccination rates of incumbent providers in that region. This is an important consideration since it provides information on the effectiveness of the expansion plan for administering vaccines. On one hand, if addition of new vaccine providers reduces vaccines administered by incumbent facilities, there is a substitution effect as also evidenced in the retail context (Pancras et. al., 2012). For example, Arcidiacono et. al. (2019) has shown that with the introduction of a Walmart supermarket within one mile of an incumbent supermarket, the market experienced a 16% drop in revenue due to the substitution effect. From a

[18] https://www.ajmc.com/view/a-timeline-of-covid-19-vaccine-developments-in-2021
[19] https://www.prnewswire.com/news-releases/californias-enhanced-covid-19-vaccine-provider-network-managed-by-blue-shield-of-california-expands-enrolled-providers-reach-and-capacity-301251317.html

policy perspective this reduces the efficacy of newly added facilities in increasing the overall vaccination levels in a region. On the other hand, it is also possible that the addition of new facilities can enhance the capacity of the incumbent facilities (Landon et. al., 2018) to meet the increasing vaccine demand as these facilities can collaborate to understand demand (Rahal and Bouffard, 2020) or pool their resources (Murphy, 2021). Given the diversity of vaccine providers that range from those with higher capacity (e.g., hospitals) to those with lower capacity (e.g., pharmacies), it is also important to understand if these vaccine providers differ in terms of the relative impact on their vaccine administration levels with the introduction of new facilities in the region. Our research examines this issue and contributes to the literature of infrastructure scaling in health care (Mills et. al., 2018; Aanestad et. al., 2014) with a particular focus on pandemic (Gutierrez and Rubli, 2021). Further understanding of this issue can help policymakers to effectively allocate vaccines to providers to avoid wastages. It can also help vaccine providers to estimate demand better and to allocate resources more effectively towards the inoculation campaign.

In addition to existing infrastructure provided by hospitals, local health departments, community clinics, medical practices, and pharmacies, several states have also opened vaccine 'super sites' (vaccine hubs) with a goal to vaccinate thousands of people each day. These vaccine hubs substantially increase vaccination capacity of a region, but also raise the importance of carefully considering the location of these hubs when introducing new facilities in a region. The geo spatial distribution of vaccine hubs, with their extremely high vaccination capacity and dedicated infrastructure support, may impact the inoculation rates of smaller providers as it may share its infrastructure with the smaller providers to generate positive externality in the vaccine administration ecosystem. As a part of this research, we investigate how the number of vaccines administered by a facility is impacted by its proximity to a vaccine hub. Addressing this issue can offer insights into how to geo-spatially structure vaccination sites by considering the distance from vaccine hubs.

To inform our research we carefully compiled a panel data from the Texas vaccination campaign for 1627 vaccine providing facilities. To examine the impact of the introduction of new facilities on vaccine administration levels of incumbent facilities, we performed a difference-in-difference analysis by considering the introduction of new providers in a zip code as an exogenous intervention introduced by policymakers. To understand the effect of geo-spatial distance between a vaccine hub and a vaccine provider, we performed an instrumental variable analysis by considering the geo-spatial distance as an endogenous variable. Our analysis indicates that with the introduction of one new provider in the zip code of the incumbent vaccine provider, the vaccination rate of the incumbent provider increases by about 7.5%. Further, vaccine providers that offer greater accessibility due to their relative proximity to the general population in a region, such as the pharmacies and medical clinics, benefit the most from the introduction of new providers in their zip code of operation.

Our findings contribute to two distinct streams of literatures. First, we demonstrate that in the context of pandemic-induced uncertainty, a burgeoning ecosystem of vaccine providers does not have a substitution effect on the incumbent providers and does not negatively impact their vaccine administration abilities. Hence, our study shows that the mechanism in the healthcare context is distinct from that in the retailing context. We speculate that, unlike the retailing context where competition among retailers result in a substitutive effect on store sales, in the context of public health during a pandemic vaccine providers collaborate with each other and enhance their service capability to address the demand. This collaborative mechanism results in a complementing effect, thereby increasing the vaccine administration rates of providers. In this regard, our research contributes to prior operations management (OM) research that deals with streamlining the downstream vaccine supply chains for better vaccine accessibility (Arifoğlu and Tang, 2021; Dai et. al., 2016; Araz et. al., 2012; Westerink-Duijzer et. al., 2020; Duijzer et. al., 2018; Stamm et. al., 2017). Second, the finding regarding relatively higher benefits accrued by the pharmacies and medical clinics contributes to the literature on health care access (Ostermann and Vincent, 2019; Vahidnia et. al., 2009; Singh et. al., 2015).

The rest of the paper is organized as follows. In section 2 we review the literature and develop our hypotheses. We present our research design in section 3 that details the data collection efforts, intervention setting, variables considered for this study, and the econometric approach including the identification strategy and description of the quasi-experimental design using propensity score matching. The results and robustness checks are presented in section 4 and in section 5 we discuss the implications of our study, limitations, and directions for future research.

3.2. Literature Review and Hypothesis Development

3.2.1. Literature Review

Existing OM literature on vaccine supply chain has primarily dealt with issues of *vaccine shortages* (e.g., Arifoğlu and Tang, 2021; Martin et. al., 2020) and *vaccine yield uncertainty* challenges (e.g., Deo and Corbett, 2009; Jansen and Özaltın, 2016). Studies focusing on *vaccine allocation and last mile distribution* issues within this stream of research is relatively sparse (e.g., Westerink-Duijzer et. al., 2020; Stamm et. al., 2017). Stamm et. al. (2017) report that there are significant geographical differences in vaccine accessibility across U.S. states. Araz et. al. (2012) suggests that demographic and spatial structures of communities should be factored in vaccination policies. Duijzer et. al. (2018) studies effective allocation of vaccines in the context of a pandemic and limited vaccine stockpile. Our study extends this stream of research by…

A stream of research that accords with our study relates to infrastructure scale-up. A significant portion of this literature base has investigated factors that determine the location of new facilities (He et. al., 2021; Holmes, 2008; Jia, 2008; Ellickson et. al., 2010; Luo and Sun, 2016; Liu et. al., 2021). Some studies (e.g., Yu and Bayram 2021) have investigated how organizations plan scaling up of infrastructure. A set of studies have also examined the effects of infrastructure scale-up on organization performance. In the retail context, Arcidiacono et. al. (2019) demonstrates that introduction of a supermarket within a mile of an incumbent supermarket results in a 16% drop in revenue of the later. Ellickson et. al. (2010) shows the existence of differential competitive pressures depending on the type of discount retailer introduced in the area of operation of the incumbent retailers. In the healthcare context, Atasoy et. al. (2018) report that a positive spillover of demand from a hospital that has adopted electronic health record system to the neighboring hospitals that get introduced to the same health information exchange networks. Due to the ease of information flow and patient exchanges, the cost of care of these hospitals are lower. These studies investigate the impact of infrastructure scale-up in an environment of competition. Studies focusing on infrastructure scale-up have primarily considered competitive environment. We extend this literature base by considering the non-competing environment of vaccine administration by various facilities during a pandemic.

Unlike for-profit retailers, vaccine providers forfeit economic gains in pursuit of promoting social welfare by administering vaccines to the population. In the presence of uncertainties of vaccine supply and demand, these providers often collaborate with each other autonomously to better manage the vaccine administration process and to make more vaccines available to the community. For example, vaccine providers in Chapel Hill, North Carolina have been reported to share ultra-cold freezer space with each other to store doses of vaccines to vaccinate North Carolina population (Murphy, 2021). These collaborative practices create an ecosystem with positive externalities. Westerink-Duijzer et. al. (2020) analytically investigates the conditions in which autonomous cooperation among vaccine providers is possible. The study alludes to the formation of a sustainable vaccine provider ecosystem and reports cooperative arrangements between providers in the presence of supply and demand mismatch (e.g., by means of re-distribution of vaccines). Our study further develops on this concept to understand how introduction of new vaccine providers boost the ecosystem in its goal of distributing more vaccines.

Additionally, it is important to examine how positive externalities in a burgeoning vaccine provider ecosystem is shared among the providers depending on vaccine providers' characteristics. In our study we examine two specific characteristics, namely the accessibility of the provider to the population and its distance from the vaccine hub. Accessibility of facilities has been a topic of research in extant literature. Leng et. al. (2013) develops a game-theoretic framework to determine the optimal pricing strategy that enables retailers share spaces under space-exchange strategy to increase accessibility of their products. To define spatial accessibility in health care context, Guagliardo (2004) suggests that the concept of spatial accessibility encompasses both the number of service providers in an area and travel impedance between patient location and service points. Travel impedance relates to the distance a patient must travel to reach a provider. We adopt the concept of travel impedance to define spatial accessibility of a vaccine provider. Groenewegen et. al. (2021) studies accessibility of primary care in 31 countries and identifies significant differences in accessibility across different countries and across general practices of varied characteristics.

Studies have examined the variance in the accessibility of endocrinologists in the US (Lu et. al., 2015; Lu et. al. 2012) and how accessibility affects the probability of utilization of different health care services (Fortney et. al. 1995; Fortney et. al. 1999). However, to the best of our understanding, no study has investigated how spatial accessibility of a health care provider impacts the benefit that the provider derives from scaling up of vaccine provider ecosystem. This is an important area of investigation that is particularly relevant during a pandemic when policy makers take decisions to scale the infrastructure of vaccine distribution and create a vaccine provider ecosystem. Our study examines how a provider's ability to administer vaccines in a region is influenced by the provider's accessibility as the vaccine ecosystem evolves with the introduction of new providers in the region.

In addition to the issue of access, geographic proximity of a facility to another relatively larger facility is also an important consideration for establishing a service delivery network. The retail literature has examined the impact of the proximity of a smaller organization with lower service capability to a larger competitor. In the seminal article, Reilly (1931) discusses the importance of distance to provide a framework that guides the distribution of consumers between two competing retailers. Converse (1949) refined the framework by accounting for the service capacity of the competing providers and suggests that consumers' likelihood of visiting a provider is proportional to the service capacity of the provider. More recent literatures (Kabra et. al., 2020; Lim et. al., 2021) provides evidence that the distance between service providers with various capacity and consumers affects consumers' choice. These studies suggest that the proximity of a smaller service provider to a larger provider can reduce its ability to service more consumers and lower its service rate. Ellickson et. al. (2020) shows that supermarkets (e.g., Walmart) draw demand away from the smaller grocery stores (e.g., Albertson's) as compared to a big club retailer (e.g., Costco). Arcidiacono et. al. (2019) demonstrate that with increasing distance between two supermarket retailers the substitution effect quickly decreases. Much of this research stream focuses on a competitive context where the providers vie for the same set of consumers. However, very few research studies have investigated how smaller provider may be affected by its proximity to larger providers in a non-competing environment (e.g., vaccine distribution, food redistribution effort) where providers might actively collaborate with each other. Mousa and Freeland-Graves (2017) provides evidence that a major food bank had collaborated with churches and government agencies to distribute food to food insecure population. Efficient food redistribution is enabled by the proximity of the agencies to the food bank. Facchini et. al. (2018) offers similar example to demonstrate that bigger charities enable smaller local charities to extend the social welfare through active resource redistribution. In the context of vaccine distribution, our study extends this stream of research by investigating whether the proximity of a larger provider to a smaller one enables the latter to appropriate positive externalities of a burgeoning vaccine provider ecosystem and help the smaller provider inoculate more people.

3.3. Hypotheses Development

3.3.1. Introduction of Newer Vaccine Providers and Incumbent Providers' Vaccination Rate

The extant literature reports that vaccine providers increase total health benefits in a region by collaborating with each other (Westerink-Duijzer et. al., 2020; McQuillan et al., 2009). Vaccine providers generally collaborate in three major ways: by redistributing vaccines (CDC, 2021; Westerink-Duijzer et. al., 2020; Chen, 2017; Rahal and Bouffard, 2020), by sharing infrastructural resources (Murphy, 2021) and by sharing information (Rahal and Bouffard, 2020). These collaborative practices influence supply by making providers more efficient in managing their vaccine supplies. These collaborations form the basis of a networked vaccine provider ecosystem in a region that create positive externalities. For example, when hospitals collaborate by sharing labor and assets, it creates positive externalities in the form of information spillovers across hospitals and enables smoother information flow (Atasoy et. al. 2018). As new providers are added, these collaborative ecosystems tend to grow stronger (Coleman, 1988; Landon, 2017). The burgeoning ecosystem contributes to the pool of resources that existing providers can leverage to manage their vaccination efforts effectively. Consequently, we expect that an increase in the number of providers in an area and the consequent higher levels of vaccinations increase the average demand of vaccines that each provider in the area experiences. Accordingly, we hypothesize:

H1: As newer providers are introduced in an area, the vaccine administration rate of incumbent facilities increases.

3.3.2. Moderation effect of Vaccine Provider's Accessibility

The goal of every health care provider is to provide quality service that is cheap and accessible to people. However, health care providers differ in terms of the complexity of the services that they provide. For example, hospitals are higher up in the service complexity spectrum as they deal with wide range of ailments. On the other hand, medical practices deliver primary care services to provide continuous and comprehensive care to patients[20] and pharmacies primarily have the objective of making medicines, drugs, and vaccines widely available to people. The objective of providing high quality and complex services competes with the objective of greater access to the population in an area due to inherent tradeoffs. As the complexity of health care

[20] https://ccchclinic.com/importance-benefits-primary-health-care/

services increase, there are increased risk of failures (Sharma et. al., 2019) and organizations tend to improve their processes by learning from the evidence that emerges from handling high volumes of cases (Finks et. al., 2011; Siemens et. al., 2020). To provide wide range of services, health care organizations such as hospitals resort to geo-spatial centralization that helps in pulling their resources together (Siemens et. al., 2020). Such centralization of services, however, increases the distance that patients have to travel to get health care services, thereby decreasing the level of accessibility (Ostermann and Vincent, 2019). Hence, we argue that complex health care service providers (e.g., hospitals) are more centralized, resource rich but less accessible as compared to health care service providers that are on the lower end of the service complexity spectrum such as pharmacies and medical practices.

As an illustration, in the online supplement, we show that in one of the representative zip codes in the state of Texas (78550), pharmacies and medical practices are more evenly distributed within the region as compared to hospitals. We assert that, within the vaccination context, more accessible providers such as pharmacies and medical clinics would benefit more by the addition of new facilities in the region due to relative resource augmentation. As argued before, more accessible providers such as pharmacies and medical clinics typically have lower resource endowments at their disposal, which may lead to inefficient administration of vaccines. This can result in wastages of vaccines as has been noted in the popular press that reports that pharmacies such as Walgreens and CVS contributed toward 70% of the vaccine wastages in the country due to broken syringes and inappropriate cold storage of vaccines[21]. However, as the number of providers in a region increases, these smaller providers can share resources of larger providers in the burgeoning ecosystem of vaccine providers. For example, Murphy (2021) note that pharmacies

[21] https://www.npr.org/2021/05/09/995264941/cvs-walgreens-are-americas-epicenters-for-covid-19-vaccine-waste

and medical clinics in North Carolina accessed the ultra-cold freezer facilities made available by the University of North Carolina Health Care System (a large vaccine provider in the area) to vaccinate the local population. On the other hand, larger providers already have the required infrastructure to manage their vaccine administration efforts.

Thus, we expect that the relative resource augmentation that these smaller and more accessible providers obtain from the positive externalities of an evolving ecosystem of vaccine providers is higher as compared to the value that more resourceful providers can derive. Smaller but more accessible providers can access the pooled resources to increase their vaccine administration capabilities. This enhanced capability may be needed to fulfil the increased demand that more accessible vaccine providers may experience as people may try to reach out to a venue that offers minimum travel impedance. Hence, we hypothesize that the level of accessibility of a provider will positively moderate the relationship between the increase in the number of providers in a region and an incumbent provider's vaccination rate.

H2: The relationship between the increase in number of vaccine providers in a region and vaccine administration rate of an incumbent provider is moderated by the incumbent's level of accessibility.

3.3.3. Moderation Effect of a Vaccine Provider's Proximity to the Nearest Vaccine Hub

Vaccine hubs are endowed with a robust infrastructure that enhances their capacity to vaccinate more people. Their purpose of establishment is to streamline their operations toward vaccinating more people in the community. Their abundant resource pool attracts smaller providers to connect to them in order to augment the limited inoculation infrastructure of these providers. The basis of this relationship is the need to access inoculation materials and related infrastructure.

The vaccine hub may leverage such relationship to assume the role of a relationship broker in the vaccine provider ecosystem. In this role, vaccine hubs can access information about these smaller providers and facilitate knowledge recombination by bridging the existing gaps (aka., structural holes) between these providers depending on their specific requirements (Burt, 1992; Burt, 2017; Lan et. al., 2020).

Though the burgeoning vaccine provider ecosystem provides opportunities to the incumbent providers to collaborate with the newer providers and take advantage of their resources and infrastructure (as argued in H1), the ecosystem itself starts getting complex as more providers are introduced. Consequently, the marginal effort to maintain additional connections by a small provider increase. As such, if a vaccine hub in its proximity, the provider may only want to coordinate with the hub and exploit their enhanced status in the ecosystem as broker. Such preferential bridging of structural hole with another suitable provider by the hub, reduces the managerial effort by the provider considerably and it can focus on the inoculation efforts. Hence, a provider's proximity to a vaccine hub enables it to manage its managerial resources better while maintaining connection to stronger resource pool in the burgeoning ecosystem when required, which may translate to higher inoculation capacity and subsequent inoculation rate.

H3: The relationship between the introduction of new vaccine providers in an area and an incumbent provider's vaccine administration rate strengthens with the incumbent provider's proximity to the nearest vaccine hub.

3.4. Research Design

3.4.1. Data

The Center for Disease Control and Prevention (CDC) requires each state in the U.S. to report their vaccine administration data and the states, in turn, collect vaccine administration data from each of the vaccine providers. As shown in Figure S1 (online supplement), the country experienced steep vaccine uptake between February 28th and April 8th, 2021, which has been driven by the rapid scale-up of the vaccine administration infrastructure. We observe that Texas follows similar vaccine distribution curve with identical growth in vaccination rate between February 27th and April 10th, 2021, as shown in Figure S2 (online supplement). We identify this growth is attributed to the vaccine infrastructure ramp-up in the state. We intend to focus on this initial stage of infrastructure ramp-up to investigate the research questions. Hence, in our study we consider data from the state of Texas where the vaccination plan drafted by Texas Department of State Health Services (DSHS) requires each of the vaccine providers to report the number of vaccines they received, their vaccine inventory status, and any wastages that may have happened (DSHS, 2020). We started the data collection effort from February 26, 2021 and continued until 29th March 2021 since after that date the DSHS stopped reporting total shipment of vaccines that a provider had received, a measure that is critical toward the estimation of daily vaccine administration by each provider. The DSHS portal reports two different datasets. The first dataset provides information about the number of vaccines allocated, number of vaccines administered, and the total number of people vaccinated in a county (at least one dose as well as fully vaccinated). The dataset also reports county demographics namely population above 16, population above 65, population of health care workers, population of long-term care residents, population between 16 and 64 with any medical condition, and population of education and childcare personnel for each of the 254

Texas counties. Daily cumulative data pertaining to the variables, except the demographic variables, were reported the next day after 4pm Central Time. We collated daily data indexed by date into our first database. To calculate the number of daily doses of vaccine distributed by a county on a given day, we subtracted the cumulative measures of the number of vaccines distributed on the previous date from those reported on the given day.

The second dataset captures vaccine provider level data i.e., the name of the vaccine providers, the type of the provider (e.g., pharmacy, hospital, etc.), the address of the provider, the zip code and the county of operation, the date of last update provided, the total number of vaccines shipped to the provider, and the inventory status of the three vaccines (Pfizer, Moderna and JnJ). The data reports the cumulative total number of vaccines that a provider had received on a given day. Since a random subset of vaccine providers received shipments each day and updated their records on the DSHS portal, we collected the data daily to keep track of these shipments. We collated these daily data to create our second database. This results in an unbalanced panel data since most of the providers had not received shipments of vaccines on each day in the time period considered for the study.

We considered the address of each provider as the provider identifier since the names of some of the providers were not consistent across the periods of data collection. For the providers with missing addresses in the database, we searched online to get the information. We estimated the shipment that a provider had received on a given date by the difference of the cumulative total of vaccine received on that date and the cumulative total of the vaccine that the provider had reported on the previous date of updating the portal. The initial observations of all the providers in the database was dropped in the process. We use county-date as our level of analysis and merged the two databases. The data contains information about the type ($Type_i$) of a provider i namely vaccine hubs, hospitals, local health departments, community clinics, medical practices, pharmacies, and ‘others’. Since our study aims to examine how different types of providers are influenced by the addition of new providers in their vicinity, we dropped observations where the provider type was reported as ‘*others*’. We used ESRI geospatial cloud API to download additional county level demographics data of the state of Texas. Additionally, we used *uszipcode* module in Python to download several zip code specific variables.

We calculated the number of vaccines administered by a vaccine provider, *i*, on a given date, *t*, ($\text{VacAdministered}_{it}$) as per the following equation.

$$VacAdministered_{it} = CountyVacAdministered_{it} * Ratio_{it} \quad (1)$$

where, $CountyVacAdministered_{it}$ is the number of vaccines that the county in which *i* operates has administered at time *t* and $Ratio_{it}$ is the ratio of total number of vaccine doses that provider *i* has received during a specified time interval. As the providers report their data at different time points, it is important to observe the shipments of each provider relative to that of other providers across a time interval to estimate $Ratio_{it}$. Since different counties experience different demand for vaccines, it is possible that some providers may have to hold on to their vaccine stockpile longer than providers in counties that experience higher vaccine demand. We assumed that a provider had to replenish their vaccine inventory in, at least, 21 days which forms the basis of considering the time interval to calculate $Ratio_{it}$ as per the following equation.

$$Ratio_{it} = \frac{\sum_{T=1}^{21} VaccineReceived_{i(t-T+1)}}{\sum_{T=1}^{21}\sum_{I=1}^{N} VaccineReceived_{I(t-T+1)}}$$

where $VaccineReceived_{it}$ is the total number of vaccines that the provider i has received at time t.

We used *GoogleMap* API in Python to download the coordinates of each provider corresponding to its address. For each provider we calculated the Haversine distance (Robusto, 1957; Brinck et. al., 2017) between the provider and the nearest vaccine hub (with respect to the provider) listed in the database (*NearestHub*$_{it}$). McKesson was responsible for the distribution of Moderna and JnJ vaccines and ancillary kits for all the vaccines[22]. Pfizer vaccines were distributed by FedEx and UPS. McKesson also used FedEx and UPS as its logistics partners. Hence, we collected the address for all (six) McKesson warehouses and all (three) FedEx hubs, and the UPS hub in Texas. We calculated the average distance of each provider from all the McKesson warehouses (*AvgDistMcKesson*$_i$) and the distances between each provider and the nearest FedEx hub (*NearestFedEx*$_i$) and UPS hub (*DistUPS*$_i$) (with respect to the provider).

During the period of our data collection, state policymakers started adding more providers to strengthen the vaccine provider ecosystem. For example, CVS added 74 new vaccination locations across Texas during this time period[23]. For every vaccine provider *i* in a zip code at time *t*, we calculated the total number of unique providers in a zip code area (*ZIPUniqueProviders*$_{it}$) by finding the number of providers within the zip code where *i* operates in the last 21 days. There may be four different scenarios associated with *ZIPUniqueProviders*$_{it}$. First, during the time interval considered in the study, a provider *i* may have witnessed no changes in *ZIPUniqueProviders*$_{it}$. We categorize these providers as *Cat0*. Second, a provider may have witnessed only increase in *ZIPUniqueProviders*$_{it}$ over time. We categorize these providers as *Cat1*. Third, a provider may have witnessed only decrease in *ZIPUniqueProviders*$_{it}$. We categorize these providers as *Cat2*. Lastly, there may be a group of providers that may see both an increase and a decrease in *ZIPUniqueProviders*$_{it}$. We categorize these providers as *Cat3*.

For every provider *i* at time *t*, we define *Jump*$_{it}$ = *ZIPUniqueProviders*$_{it}$ - *ZIPUniqueProviders*$_{it'}$, where *t'* represents the time when we started collecting data on provider *i*. Hence, for a provider *i* in Cat0, Cat1, Cat2, or Cat3 in the time interval *t*, *Jump*$_{it}$ is respectively

[22] https://www.mckesson.com/About-McKesson/COVID-19/Vaccine-Support/
[23] https://www.kxan.com/texas-coronavirus-vaccine/cvs-adding-74-more-covid-19-vaccine-sites-in-texas/

zero, an increasing function, a decreasing function or an increasing and decreasing function. It is important to note that the time when the jump occurs may vary across the providers which offers the required variance to econometrically estimate the effects. As we are estimating the effect of $NearestHub_{it}$ for a random provider i, we dropped the observations that relate to vaccine hubs. We dropped observations that had no values for county and zip code specific variables. The resulting unbalanced panel dataset contains 1639 unique providers spanning 12,950 observations. There are 4424, 5911, 595 and 2020 observations corresponding to Cat0, Cat1, Cat2 and Cat3, respectively.

3.4.2. Model Identification

3.4.2.1. Difference-in-Difference Approach

With the availability of more vaccines, state policymakers started adding new vaccine providers to different zip code areas to increase access to these vaccines. These additions are akin to exogenous vaccine supply shocks to incumbent providers. Hence, the interventions of introduction of new providers in the zip code of incumbent providers at different time points provides us a unique opportunity to study how the variance in additional provider introduction impacts the vaccination rate of incumbent vaccine providers. We use the difference-in-difference (DiD) approach with propensity score matching to estimate the effect size. The approach addresses potential endogeneity issues associated with policy makers' decision to introduce additional vaccine providers in a zip code (for example, a purposive choice of introducing additional providers in a zip code may be due to the demographics of the location) (Angrist and Pischke, 2008). Instances of recent application of DiD can be found in operations management literature (Scott et. al., 2020; Xue et. al., 2019). In the vaccine manufacturing context, Adbi et. al. (2019) studies the H1N1 pandemic response of domestic vaccine manufacturer as compared to that of multi-national vaccine manufacturer by considering a natural quasi-experimental set up. To implement the DiD method in our research, we divided the data into the treatment group and the control group. The treatment group consists of vaccine providers in Cat1. Providers in Cat0, that experienced no provider addition in the zip code area, are part of the control group. The identification process was enabled by the intervention created by distinct variations (monotonic increasing versus zero) in the treatment and control groups. We do not use providers in Cat2 and Cat3 as the treatment group due to fewer observations and, hence, lower statistical power. However, we use providers in those categories as alternative operationalization of treatment group in the robustness checks.

3.4.2.2. Quasi-Experimental Design: Propensity Scores Weighting

Propensity score is the probability that an observation unit receives treatment conditional on the observed covariates. If our analysis considers the subpopulation of the observations with same propensity score, the overlap assumption is satisfied since it eliminates the bias in the estimation of average treatment effect. The propensity scores can be used as sampling weights in such a way that it reweights the treatment and control observations so that the overlap restriction is satisfied (Imbens and Woolridge, 2009; Hirano and Imbens, 2001; Bell et. al., 2018; Rosenbaum and Rubin, 1983). Following Imbens and Woolridge (2009), we use inverse propensity weights (IPW). We define, $\omega(W, x) = \frac{W}{\widehat{\varepsilon(x)}} + \frac{1-W}{1- \widehat{\varepsilon(x)}}$, where W = 1 indicates the vaccine providers in the treatment group and $\widehat{\varepsilon(x)}$ is the estimated probability of being in the treatment group. To compute $\widehat{\varepsilon(x)}$ we used the zip code population ($ZipPopulation_i$), percentage of the type of provider i with respect to the total providers in its zip code at time t ($PercentTypeProvider_{it}$), $AvgDistMcKesson_i$, $NearestFedEx_i$, zip code population with full employment ($ZipPopulationFulEmp_i$), zip code population that were enrolled in public school ($ZipPopulationPublic_i$), and population density

(2010 Census report) (*ZipPopulationDensity*$_i$). We use a probit model to estimate the required probability of a vaccine provider being in the treatment group. After obtaining these weights, we estimate the DiD model by including these weights in the estimation.

3.4.3. Estimation of the Direct Effects

Our estimation approach addresses two potential issues in our data. First, there may always be the possibility of unconditional heteroskedasticity across the providers which needs to be explicitly modeled. We use panel ordinary least square regression (OLS) with heteroskedasticity robust inference clustered around unique vaccine provider id to address heteroskedasticity across the providers (Wooldridge, 2010). Second, there may be an average trend in the data that guides vaccination rate of a provider toward a certain direction. For example, it is possible that, over time, more vaccines become available which may enable each provider to vaccinate more people. Hence, we introduced time fixed effects to control for the time trend in the data. We performed our estimation using *xtreg* command in STATA 15. To satisfy the normality assumption, we transformed some of the variables by using natural log transformation. In case the lowest value of a variable is 0, we added 1 to the variable before normalization. We followed multiple steps before running the regression to estimate the hypothesized effects. First, we ran a probit model to obtain propensity score weights which is modeled as per the following equation,

$$W_i = \alpha_0 + \alpha_1 ZipPopulation_i + \alpha_2 PercentTypeProvider_{it} + \alpha_3 AvgDistMcKesson_i + \alpha_4 NearestFedEx_i + \alpha_5 ZipPopulationFulEmp_i + \alpha_6 ZipPopulationPublic_i + \alpha_7 CountyPopulationDensity_i + \epsilon_i \quad (2)$$

Next, we used $\omega(W, x)$ to derive the weighted variables to be used to estimate the direct effects by means of the following equation:

$$VacAdministered_{it} = \mu_{it} + \beta_1 Jump_{it} + \beta_2 \text{ZIPUniqueProviders}_{it'} + \beta_3 PopulationAbv65_i + \beta_4 Income_i + \beta_5 HomeValue_i + \beta_6 EducAttain_i + \beta_7 VaccineShipped_{it} + \beta_8 DailyCOVID_{it} + \beta_9 Rural_i + \beta_{10} Storm_i + \beta_{11} Political_i + T_t + \epsilon_{it} \quad (3)$$

where $VacAdministered_{it}$ is the dependent variable and $Jump_{it}$ *is the independent variable* as discussed before. We controlled for the zip code fixed effects using the following zip code specific demographics data: binary variable whether the zip code belongs to a rural area ($Rural_i$), population above 65 years ($PopulationAbv65_i$), median income of the zip code population ($Income_i$), median home value ($HomeValue_i$), population above 25 years that have attained college education ($EducAttain_i$). It is likely that there may be heterogeneity in vaccination rate across different providers due to the variation in total shipment received by a provider. Hence, we controlled for the total vaccine shipment that provider *i* received at time *t* ($VaccineShipped_{it}$). We realize that the winter storm in the month of February 2021 may have impeded vaccination efforts of providers located in some of the counties. We considered a binary variable, $Storm_i$, to control for this effect. Additionally, we controlled for the daily COVID-19 new infection count ($DailyCOVID_{it}$) in all the counties that the providers in our dataset belong to as well as the dominant political affiliations within the zip codes ($Political_i$).

3.4.4. Estimation of the Moderation Effects: Two Stage Least Square (2SLS) Approach

The reason that a vaccine provider will choose to locate near a vaccine hub may depend on multiple time-invariant and/or time-varying factors that we may not have exclusively captured. Hence, there may be omitted variable bias that may confound our understanding of the moderating effect of $NearestHub_{it}$. To account for the endogeneity in $NearestHub_{it}$, we run an instrumental variable (IV) analysis where we use the radius of the ZIP code area ($ZipRadius_i$) in which provider i operates as the instrumental variable of the endogenous variable. The mean and standard deviation of $ZipRadius_i$ are 10.38 miles and 8.21 miles, respectively. We considered 2SLS estimation method where in the first stage we estimate the variance in $NearestHub_{it}$ as explained by $ZipRadius_i$ using equation 5. Introduction of a moderation term involving the endogenous variable ($\mathrm{NearestHub_{it}XJump_{it}}$) necessitated another instrumental variable ($\mathrm{ZipRadius_iXJump_{it}}$) to be considered in the analysis. The first stage of the endogenous variable is estimated using equation 6. In the second stage, we use the estimated variance, $\widehat{NearestHub}_{it}$ and $\mathrm{Nearest}\widehat{\mathrm{Hub}_{it}}XJump_{it}$, in the main model (equation 7) to estimate the unbiased effects of $NearestHub_{it}$ and $NearestHub_{it}XJump_{it}$. A valid instrument should satisfy the relevance and exclusion restriction conditions (Wooldridge, 2010). In a smaller zip code, the population may be clustered in an area and to serve them vaccine providers may tend to co-locate. Hence, on average, distance between any two vaccine providers will be smaller than that in a bigger zip code area where population may be more spread out. As vaccine hub is a specific type of provider, we expect a strong positive relationship between $NearestHub_{it}$ and $ZipRadius_i$. Our assumptions are validated as the instrumental variables are highly significant with respect to the endogenous variables $NearestHub_{it}$ ($\beta = 0.03$, $p < 0.001$) and $NearestHub_{it}XJump_{it}$ ($\beta = 0.04$, $p < 0.001$) and the F-statistic associated with the first stage regressions are greater than 10 ($F=234.19$ & $F=192.54$; $p<0.001$), which satisfies the Stock and Yogo (2005) test.

As exclusion restriction cannot be established econometrically, we provide logical reasoning and auxiliary analyses. The vaccination rate may depend on the following factors - supply of vaccines, efficiency of vaccine delivery, and demand. As per CDC and DSHS guidelines, supply of vaccines is a function of vaccine provider infrastructure, inventory capacity and highest number of flu vaccines administered during peak flu season, which again relates to the demand of vaccines in the area. We do not see the first two criteria are related to the radius of the zip area. Efficiency of vaccine management is a provider centric criterion, which should not depend on how big the zip code area is. However, demand may depend on the size of the zip code area due to potential disproportional distribution of vaccine providers. To establish the fact that distribution of the vaccine providers in a zip code area is not a function of zip code radius we regressed $ZIPUniqueProviders_{it}$ on $ZipRadius_i$ after controlling for relevant zip and county specific variables. We find that the coefficient is not significant (ß = 0.01; p > 0.1). Hence, we establish, ex-ante, that $ZipRadius_i$ do not impact demand that a vaccine provider may witness and thereby its rate of inoculation. Thus, we establish that exclusion restriction holds. We use the predicted values of $NearestHub_{it}$ *and* $NearestHub_{it}XJump_{it}$ from equations 4 and 5, respectively.

$$\begin{aligned}\text{NearestHub}_{it} = {} & \mu_{it} + b_1 Jump_{it} + b_2 Jump_{it}XZipRadius_i + b_3 Type_i + \\ & b_4 Jump_{it}XType_i + b_5 \text{ZIPUniqueProviders}_{it'} + b_6 PopulationAbv65_i + \\ & b_7 Income_i + b_8 HomeValue_i + b_9 EducAttain_i + b_{10} VaccineShipped_{it} + \\ & b_{11} DailyCOVID_{it} + b_{12} Rural_i + b_{13} Storm_i + b_{14} Political_i + b_{15} ZipRadius_i + \\ & T_t + \epsilon_{it} \qquad (4)\end{aligned}$$

$$\begin{aligned}\text{NearestHub}_{it}XJump_{it} = {} & \mu_{it} + b_1 Jump_{it} + b_2 Jump_{it}XZipRadius_i + b_3 Type_i + \\ & b_4 Jump_{it}XType_i + b_5 \text{ZIPUniqueProviders}_{it'} + b_6 PopulationAbv65_i + \\ & b_7 Income_i + b_8 HomeValue_i + b_9 EducAttain_i + b_{10} VaccineShipped_{it} + \\ & b_{11} DailyCOVID_{it} + b_{12} Rural_i + b_{13} Storm_i + b_{14} Political_i + b_{15} ZipRadius_i + \\ & T_t + \epsilon_{it} \qquad (5)\end{aligned}$$

From these equations, we estimated the predicted variable $\widehat{NearestHub}_{it}$ and $\widehat{\text{NearestHub}}_{it} XJump_{it}$ and used them in second stage regression to estimate the moderation effect. *Type*$_i$, another independent variable, is a categorical variable, and we consider *hospital* as the reference category to which the vaccination rate of providers *i* in other categories is compared. Our second stage equation is as follows:

$$VacAdministered_{it} = \mu_{it} + b_1 \widehat{NearestHub}_{it} + b_2 Jump_{it} + b_3 \widehat{\text{NearestHub}}_{it} XJump_{it} + b_{41} Type_i.LocalHealthDepartment + b_{42} Type_i.CommunityClinic + b_{43} Type_i.MedicalPractice + b_{44} Type_i.Pharmacy + b_{51} Jump_{it} XType_i.LocalHealthDepartment + b_{52} Jump_{it} XType_i.CommunityClinic + b_{53} Jump_{it} XType_i.MedicalPractice + b_{54} Jump_{it} XType_i.Pharmacy + b_6 \text{ZIPUniqueProviders}_{it'} + b_7 PopulationAbv65_i + b_8 Income_i + b_9 HomeValue_i + b_{10} EducAttain_i + b_{11} VaccineShipped_{it} + b_{12} DailyCOVID_{it} + b_{13} Rural_i + b_{14} Storm_i + b_{15} Political_i + T_t + \epsilon_{it} \quad (6)$$

3.5. Results

The summary statistics of the variables used in this study is presented in Table 3.1. We observe that *VacAdministered*$_{it}$ has a significant dispersion in data with mean at 68.89 vaccines administered each day and standard deviation of 258.17 vaccines which alludes to the presence of different types of vaccine providers with different inoculation capacities. *Jump*$_{it}$ has a mean of almost 1 which seems to suggest that, on average, any vaccine provider has seen a new vaccine provider being introduced in its zip code of operation during the period of data collection. We note that *NearestHub*$_{it}$ has a significant dispersion in data with a mean of 18.96 mi and a standard deviation of 19.51 mi. We find that each zip code in Texas has, on average, about three vaccine providers ($ZipUniqueProvider_i$ has a mean value at 2.62). However, we observe significant variation in $ZipUniqueProvider_i$ (S.D. = 2.52) which suggests that some zip codes may have fewer or even no vaccine provider. We observe high correlation between $NearestHub_{it}$ and $Rural_i$ (γ = 0.68) which suggests that, on average, vaccine hubs are situated farther from rural areas in Texas.

3.5.1. Estimation of Direct Effects

In equation 3 if $\beta_1$is significant and positive, the vaccination rate by a provider increases as newer providers are included in the ecosystem. The estimation results of equation 3 with propensity score adjustments are provided in Table 3.2(column 1). We find that the effect of $Jump_{it}$ is positive and significant (β_2 = 0.0725, p <0.05) which suggests that burgeoning vaccine provider ecosystem increases the vaccination rate of an incumbent provider. This lends support for hypothesis 1. The result is economically meaningful as it suggests that with each additional provider in the ecosystem, $VaccineAdministered_{it}$ increases, on average, by approximately 7.25%.

Table 3.1 Summary Statistics and Correlation Table

#	Variables	Mean	S.D	1	2	3	4	5	6	7	8	9	10	11	12
1	*VaccineAdministered*	68.89	258.17	-											
2	*NearestHub*	18.96	19.15	-0.1*	-										
3	*Jump*	0.99	1.5	0.02*	-0.2*	-									
4	*ZIPUniqueProviders*	2.62	2.52	0.1*	-0.3*	0.24*	-								
5	*VaccineShipped*	151.3	1093.01	0.49*	-0.1*	-0.01	0.05*	-							
6	*PopulationAbv65*	2835.4	1856.98	-0.01	-0.3*	0.28*	0.45*	0.01	-						
7	*Income*	50798.	21767.4	0.001	-0.2*	0.2*	0.12*	-0.01	0.06*	-					
8	*HomeValue*	128552	82698.8	0.15*	-0.3*	0.18*	0.23*	0.06*	0.09*	0.7*	-				
9	*EducAttain*	3220.7	3316.64	-0.02	-0.2*	0.12*	0.22*	0.01	0.61*	-0.3*	-0.24	-			
10	*DailyCOVID*	139.35	273.66	0.12*	-0.3*	0.01	0.08*	0.06*	0.11*	0.16*	0.26*	0.2*	-		
11	*Rural*	0.36	0.48	-0.1*	0.7*	-0.2*	-0.3*	-0.1*	-0.3*	-0.3*	-0.4*	-0.3*	-0.4*	-	
12	*Storm*	0.75	0.42	0.06*	-0.5*	0.12*	0.14*	0.03*	0.21*	0.3*	0.3*	0.1*	0.3*	-0.5*	-
13	*Political*	0.15	0.36	0.001	-0.1*	0.004	0.08*	0.01	0.16*	-0.2*	-0.1*	0.3*	0.01	-0.2*	0.1

3.5.2. Estimation of Moderation Effects

The moderation effects of the independent variables have been estimated in equation 6. If b_3 is significant and negative, $NearestHub_{it}$ negatively moderates the relationship between $Jump_{it}$ and $VaccineAdministered_{it}$. As $Type_i$ is a categorical variable, moderation effect of each category needs to be measured with respect to a baseline category, the hospital. The coefficients b_{51}, b_{52}, b_{53} and b_{54} measure the moderation effect of local health departments, community clinics, medical practices, and pharmacies, respectively, on the relationship between $Jump_{it}$ and $VaccineAdministered_{it}$ as compared to the hospital. Hence, for example, if b_{54} is significant and positive, then the effect of $Jump_{it}$ on $VaccineAdministered_{it}$ is higher when the provider is a pharmacy as compared to the case when the provider is a hospital. Our results provide support for H2.

The estimation results of equation 6 with propensity score adjustments are provided in Table 3.2 (column 4). We find that the moderation effect of $NearestHub_{it}$ on the relationship between $Jump_{it}$ and $VaccineAdministered_{it}$ is not significant (b_3 = -0.08; $p > 0.05$). Hence, we do not find support for hypothesis 3. Next, we find that the moderation effects of more accessible, but less resourceful vaccine providers, on the relationship between $Jump_{it}$ and $VaccineAdministered_{it}$, on average, are higher than that of less accessible but more resourceful providers (e.g., hospitals) (b_{54} = 0.29, $p < 0.05$; b_{53} = 0.21, $p < 0.05$; b_{52}= 0.17, $p < 0.05$). We find no significant differences in the moderation effect of local health departments as compared to that of a hospital (b_{51}= 0.09, $p > 0.1$). Hence, the results support hypothesis 3. Figures 3.1, 3.2 and 3.3 illustrate these relationships. In Figure 3.1, we can see that when Type = Pharmacy, the relationship between $Jump_{it}$ and $VaccineAdministered_{it}$ is strongest. However, the relationship is weaker in Figures 3.2 and 3.3 when Type = Medical Practice and Type = Community Clinic respectively.

However, in all these figures we can see that the relationship between $Jump_{it}$ and $VaccineAdministered_{it}$ is stronger than when Type = Hospital.

Table 3.2 Effect of Introduction of New Providers in Incumbent Provider Zip Code on Vaccination Rate

Variables	(1) VaccineAdministered	(2) NearestHub	(3) NearestHubXJump	(4) VaccineAdministered
$\widehat{NearestHub}$	-	-	-	0.754^{+} (0.39)
Jump	0.0725** (0.025)	-0.003 (0.011)	-0.061*** (0.012)	-0.073 (0.058)
Type.Local Health Department	-	0.27* (0.136)	-0.118 (0.087)	0.958* (0.478)
Type.Community Clinic	-	-0.126 (0.09)	-0.053 (0.043)	-1.123** (0.327)
Type.Medical Practice	-	-0.155^{+} (0.085)	-0.016 (0.045)	-1.067** (0.339)
Type.Pharmacy	-	-0.046 (0.075)	-0.023 (0.039)	-1.185*** (0.303)
ZipRadius	-	0.026*** (0.007)	-0.005*** (0.0012)	-
$\widehat{NearestHubXJump}$	-	-	-	-0.074 (0.067)
JumpXZIpRadius	-	-0.005*** (0.001)	0.044*** (0.001)	-
JumpXType.Local Health Department	-	0.001 (0.024)	-0.049^{+} (0.029)	0.092 (0.109)
JumpXType.Communit y Clinic	-	0.014 (0.0177)	-0.096*** (0.021)	0.173* (0.075)
JumpXType.Medical Practice	-	0.025 (0.017)	-0.095*** (0.019)	0.209* (0.077)
JumpXType.Pharmacy	-	0.011 (0.015)	-0.07*** (0.017)	0.295*** (0.072)
ZIPUniqueProviders	-0.361** (0.116)	-0.138*** (0.03)	-0.002 (0.01)	-0.273* (0.113)
PopulationAbv65	-0.262 (0.233)	0.051 (0.054)	-0.002 (0.032)	-0.192 (0.244)

Table 3.2 (cont'd)

Income	-0.791* (0.366)	1.053*** (0.117)	0.002 (0.053)	-1.696** (0.591)
HomeValue	1.071* (0.393)	-0.907*** (0.101)	-0.009 (0.062)	1.799*** (0.552)
EducAttain	0.188 (0.124)	-0.154*** (0.034)	0.019 (0.015)	0.244^+ (0.137)
VaccineShipped	0.063*** (0.01)	-0.004 (0.003)	-0.0004 (0.001)	0.067*** (0.009)
DailyCOVID	-0.04** (0.013)	-0.0004 (0.004)	0.006*** (0.002)	-0.027* (0.013)
Rural	0.325^+ (0.189)	1.145*** (0.095)	0.581*** (0.045)	-0.739 (0.645)
Storm	-0.106 (0.177)	0.02 (0.096)	0.053 (0.034)	0.051 (0.193)
Political	-0.344 (0.214)	0.334*** (0.065)	-0.067^+ (0.036)	-0.534* (0.231)
Time Controls	Day	Day	Day	Day
Observations	10,232	10,232	10,232	10,232
Number of Providers	1336	1336	1336	1336
Wald chi-square	2019.75	3415	2747	2093.18
R^2 (within)	0.42	-	-	0.4132
R^2 (between)	0.656	-	-	0.6203
R^2 (Overall)	0.594	-	-	0.6018

The standard error has been reported in the parenthesis.
+. $p < 0.1$ * $p < 0.05$ **. $p < 0.005$ ***. $p < 0.001$

Figure 3.1 Moderation effect of Type = Pharmacies on the relationship between Jump and VaccineAdministered

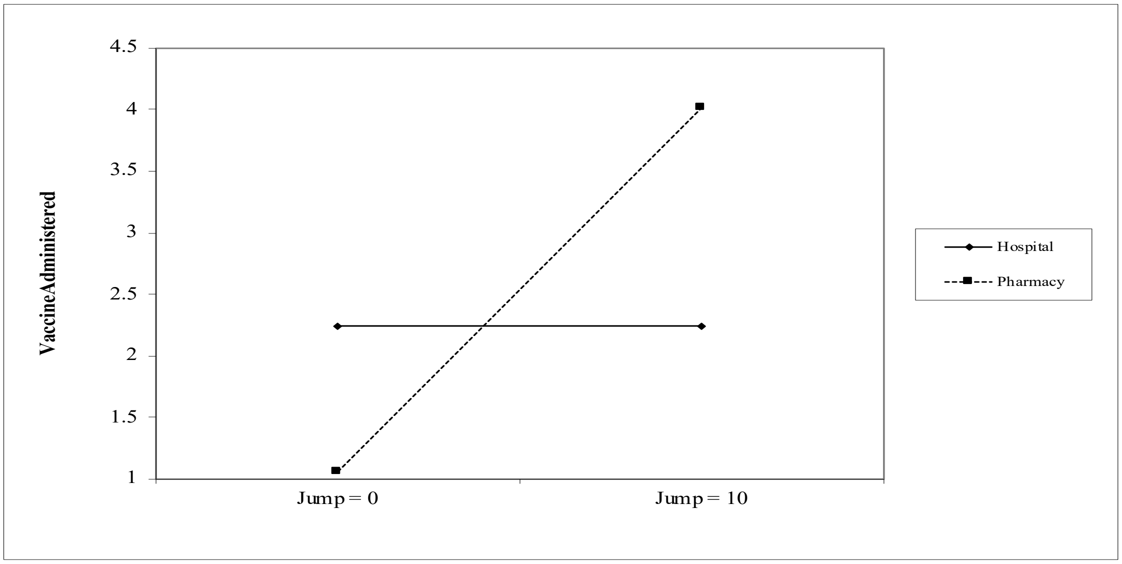


Figure 3.2 Moderation effect of Type = Medical Practice on the relationship between Jump and VaccineAdministered

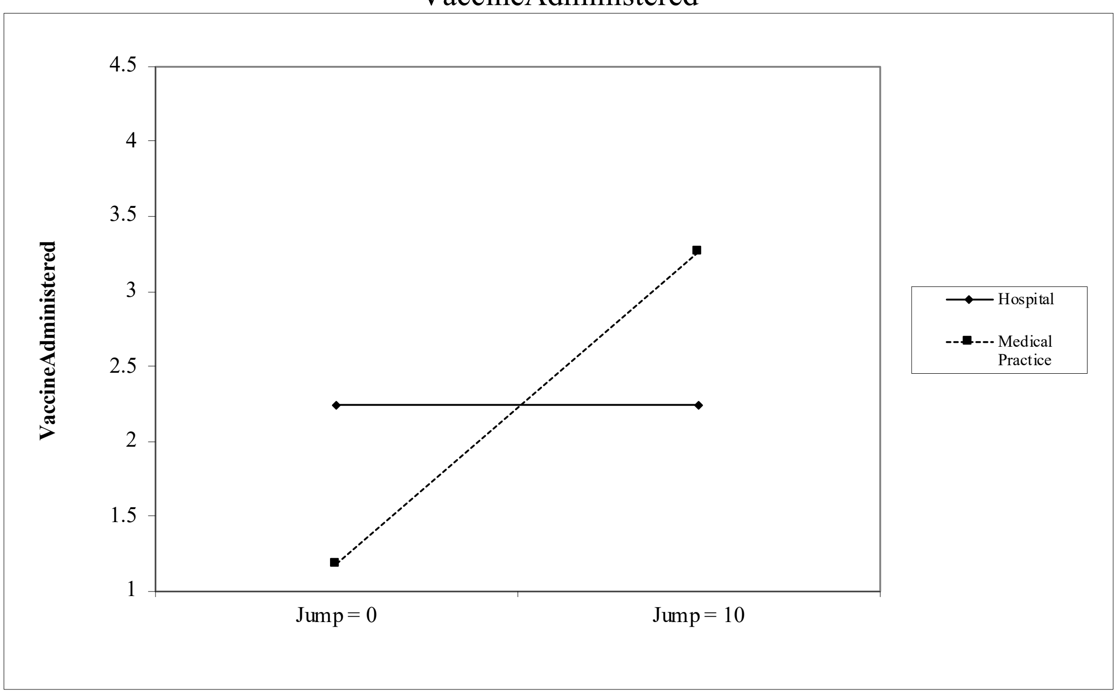
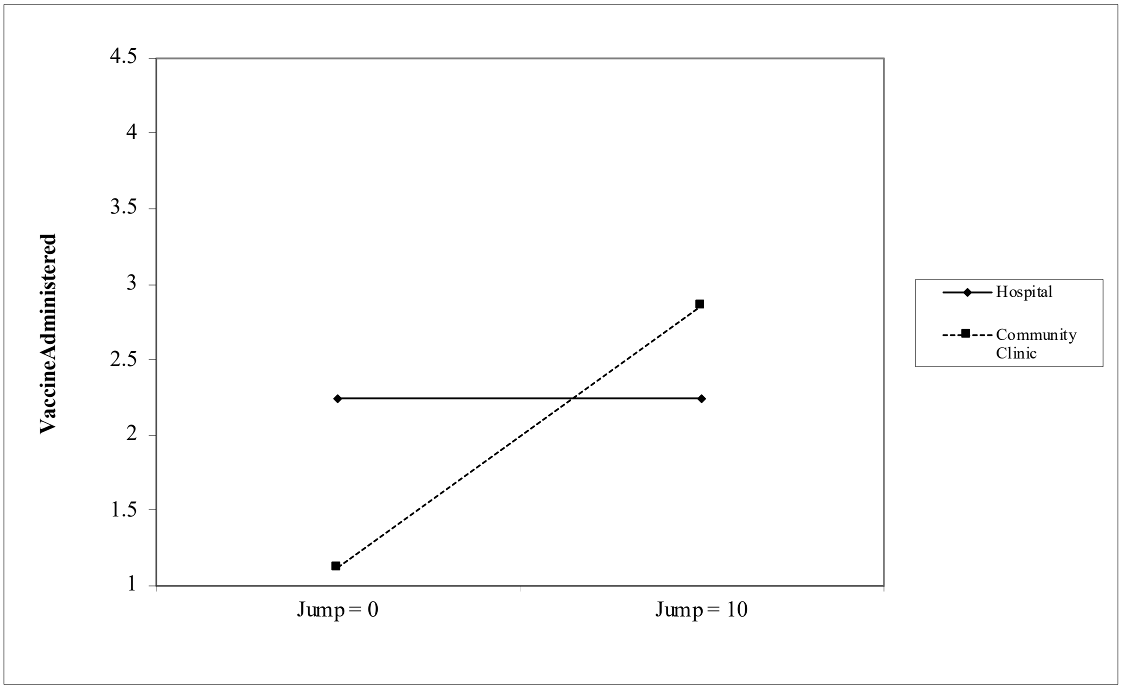


Figure 3.3 Moderation effect of Type = Community Clinics on the relationship between Jump and VaccineAdministered



3.5.3. Robustness

We conducted several additional analyses to ascertain the robustness of our findings. We present four robustness tests in this section and three additional robustness checks in the online supplement.

3.5.3.1. Robustness 1: Setting up a New Treatment Group

In the main analysis, we set up our pseudo-experiment by considering Cat0 as the control group and Cat1 as the treatment group. To test the robustness of the results, we now define the treatment group in different way. The treatment group now encompasses providers that belong to Cat1, Cat2 and Cat3. The new treatment group, now, offers higher variance in the $Jump_{it}$ value as it includes the providers that experience increase and/or decrease in the total number of providers in the zip area of operation. The observations in both the groups have been propensity score weighted. Endogeneity in $NearestHub_{it}$ variable has been considered as earlier and instrumental variable corrected model has been estimated. The main effect results are reported in Table 3.3

column 1 and moderation effect results have been reported in column 2. The λ^2 statistics are significant for both models at 2156.74 and 2154 respectively. There are 1627 unique providers spanning about 12,839 observations. We find that the results agree with the main results.

3.5.3.2. Robustness 2: Considering synthetic matching of zip codes across Treatment and Control Groups

In our main analysis we had used propensity score matching to remove the systematic differences between the providers in the control versus providers in the treatment group. We considered certain provider specific (e.g., $AvgDistMcKesson_i$), zip code specific (e.g., $ZipPopulation_i$) and county specific (e.g., $CountyPopulationDensity_i$) variables to match two sets of providers synthetically. However, there may be confounding effects due to missing variables in our dataset. Hence, in this analysis we consider providers in both the control and treatment groups that belong to same zip codes. The providers in control group belong to Cat0 and the providers in treatment group belong to Cat1. We understand that the provider set in the pre-test belonging to a zip code and the provider set in the post-test in the same zip code are disjoint sets, however, in all the analyses we control for the time trend in our model that captures any differences in time trend across these disjoint sets to give us an unbiased analysis. Endogeneity in $NearestHub_{it}$ variable have been addressed as earlier and an instrumental variable corrected model has been estimated. The main effect results are reported in Table 3.3 column 3 and moderation effect results are reported in column 4 of the same table. The λ^2 statistics are significant for both models at 1550.64 and 1583.42 respectively. We find 894 unique providers spanning 6907 observations. We find that the results are similar to the main results with one minor differences. In column 8, we find that moderation effect of community clinics on effect between $Jump_{it}$ and $VaccineAdministered_{it}$ is not significant (b_{52} = 0.084; p > 0.1).

3.5.3.3. Robustness 3: Alternative Operationalization of Jump

In all the previous analyses, we set up $Jump_{it}$ in such a way that for the providers in the treatment group, the variable can assume any integer value once it flips from 0 as policymakers start adding new providers in the zip code. In that case, we can capture more variance in $Jump_{it}$ that is necessary to explain the variance in the dependent variable. Now, we cast $Jump_{it}$ in a more traditional quasi-experiment format; we call the new variable $binJump_{it}$. At certain point in time when new providers are added, $binJump_{it}$ switches from 0 to 1 and assumes constant value then onward regardless of the number of providers being added. The point in time when the switch from 0 to 1 happens marks the intervention point that may vary across different providers thus providing us enough variance in $binJump_{it}$ to conduct our analysis. We considered providers in Cat1 in the treatment group and that in Cat0 in the control group. The observations in both the groups have been propensity score weighted. Endogeneity in $NearestHub_{it}$ variable has been considered and instrumental variable corrected model has been estimated. The main effect results are reported in Table 3.3 column 5 and moderation effect results are reported in column 6 of the same table. The λ^2 statistics are significant for both models at 2035.64 and 2145.24 respectively. We find 1336 unique providers spanning 10,232 observations. We find that the results are similar to the main results with one minor differences. In column 2, we find that moderation effect of community clinics on effect between $Jump_{it}$ and $VaccineAdministered_{it}$ is not significant (b_{52} = 0.389; p > 0.1).

3.5.3.4. Robustness 4: Alternative Estimation Methodology

In the previous analyses, we used panel OLS to estimate the effects of the independent variables as the estimated dependent variable ($VaccineAdministered_{it}$) is continuous. It may be argued that number of vaccines administered should assume integer values. To this end, we rounded $VaccineAdministered_{it}$ to the nearest integer values and used panel negative binomial regression (*xtnbreg* in STATA 15.1) to estimate the effects of the independent variables on the newly constructed count dependent variable. We used xtnbreg to account for corner solutions in count $VaccineAdministered_{it}$ at 0. The providers in control group belong to Cat0 and the providers in treatment group belong to Cat1. In this analysis we matched providers in the same zip codes in both the treatment and the control groups. We understand that the provider set in the pre-test belonging to a zip code and the provider set in the post-test in the same zip code are disjoint sets, however, in all the analyses we control for the time trend in our model that captures any differences in time trend across these disjoint sets to give us an unbiased analysis. Endogeneity in $NearestHub_{it}$ variable has been addressed as earlier and an instrumental variable corrected model has been estimated. The main effect results are reported in Table 3.3 column 7 and moderation effect results are reported in column 8 of the same table. The λ^2 statistics are significant for both models at 2032.75 and 2180.36 respectively. We find 894 unique providers spanning 6907 observations. We find that the results agree with the main results.

Table 3.3 Robustness Checks

Variables	(1) DV	(2) DV	(3) DV	(4) DV	(5) DV	(6) DV	(7) DV	(8) DV
NearestHub	-	1.263* (0.466)	-	0.553^{+} (0.285)	-	0.726^{+} (0.386)	-	-0.57*** (0.138)
Jump	0.059* (0.023)	-0.081^{+} (0.042)	0.075*** (0.018)	-0.013 (0.037)	0.257** (0.095)	-0.152 (0.226)	0.026*** (0.031)	-0.048* (0.018)
Type.Local Health Department	-	0.556 (0.564)	-	0.681* (0.256)	-	0.922^{+} (0.507)	-	0.201* (0.091)
Type.Community Clinic	-	-1.183** (0.385)	-	-0.388* (0.157)	-	-1.163** (0.359)	-	-0.118^{+} (0.072)
Type.Medical Practice	-	-1.27*** (0.388)	-	-0.491** (0.155)	-	-1.152** (0.386)	-	-0.038 (0.062)
Type.Pharmacy	-	-1.365*** (0.346)	-	-0.625*** (0.142)	-	-1.27*** (0.333)	-	-0.05 (0.058)
NearestHubXJump	-	0.013 (0.078)	-	0.05 (0.12)	-	-0.214* (0.097)	-	0.0003 (0.029)
JumpXType.Local Health Department	-	0.052 (0.096)	-	0.071 (0.068)	-	0.248 (0.354)	-	-0.009 (0.027)
JumpXType.Community Clinic	-	0.179** (0.063)	-	0.084 (0.059)	-	0.389 (0.321)	-	0.1*** (0.025)
JumpXType.Medical Practice	-	0.18** (0.61)	-	0.094^{+} (0.048)	-	0.586^{+} (0.33)	-	0.057* (0.021)
JumpXType.Pharmacy	-	0.18*** (0.053)	-	0.163*** (0.045)	-	0.751** (0.255)	-	0.114*** (0.021)
ZIPUniqueProviders	-0.47** (0.139)	-0.201 (0.133)	-0.119^{+} (0.071)	-0.032 (0.112)	-0.366** (0.115)	-0.275* (0.11)	0.146** (0.033)	0.091* (0.044)

Table 3.3 (cont'd)

PopulationAbv65	0.134	0.225	-0.044	-0.0001	-0.258	-0.18	0.005	-0.05
	(0.199)	(0.234)	(0.102)	(0.1)	(0.232)	(0.244)	(0.047)	(0.048)
Income	-0.492	-2.055*	-0.609**	-1.037**	-0.788*	-1.678**	-0.3***	0.128
	(0.322)	(0.835)	(0.202)	(0.325)	(0.364)	(0.584)	(0.066)	(0.139)
HomeValue	0.679*	2.002*	0.482**	0.848***	1.068*	1.779**	0.291**	0.031
	(0.284)	(0.723)	(0.176)	(0.231)	(0.391)	(0.547)	(0.068)	(0.102)
EducAttain	-0.042	-0.006	0.066	0.065	0.185	0.237^{+}	-0.029	-0.012
	(0.133)	(0.148)	(0.069)	(0.076)	(0.123)	(0.136)	(0.034)	(0.037)
VaccineShipped	0.059**	0.063***	0.048***	0.046***	0.064***	0.068***	0.04***	0.041***
	(0.016)	(0.011)	(0.005)	(0.005)	(0.009)	(0.009)	(0.003)	(0.004)
DailyCOVID	-0.124	-0.036*	-0.009	-0.01	-0.041**	-0.027*	0.013*	0.012^{+}
	(0.205)	(0.016)	(0.007)	(0.008)	(0.013)	(0.013)	(0.006)	(0.006)
Rural	0.115	-1.902*	0.101	-0.459	0.302	-0.642	-0.28***	0.286+
	(0.184)	(0.762)	(0.098)	(0.339)	(0.189)	(0.624)	(0.047)	(0.165)
Storm	-0.124	0.063	0.215*	0.272**	-0.109	0.024	0.36***	0.318***
	(0.205)	(0.252)	(0.094)	(0.093)	(0.177)	(0.191)	(0.043)	(0.044)
Political	-0.23	-0.453	-0.081	-0.075	-0.352	-0.546*	0.081	0.078
	(0.232)	(0.299)	(0.127)	(0.125)	(0.214)	(0.227)	(0.05)	(0.051)
Time Controls	Day	Day	Day	Day	Day	Day	Day	Day
Observations	12,839	12,839	6907	6907	10,232	10,232	6907	6907
Number of Providers	1627	1627	894	894	1336	1336	894	894
Wald chi-square	2156.74	2154	1550.64	1583.42	2035.64	2145.24	2032.75	2180.36
R^2 *(within)*	0.317	0.312	0.1912	0.1896	0.419	0.412	-	-
R^2 *(between)*	0.734	0.625	0.0675	0.1343	0.656	0.624	-	-
R^2 *(Overall)*	0.673	0.609	0.1029	0.1662	0.594	0.604	-	-

The standard error has been reported in the parenthesis.
+. $p < 0.1$ * $p < 0.05$ **. $p < 0.005$ ***. $p < 0.001$

3.6. Discussion

Addition of vaccine providers in a region is expensive as it entails higher logistics and inventory costs and higher chances of wastages. However, having few vaccine providers in a region may contribute to low administration of vaccines to the population. Using a unique provider level vaccine administration data and treating addition of providers by the policymakers in Texas as exogenous shocks, we examine how additional providers in a zip code enhances incumbent vaccine providers' vaccine administration rate as newer providers continue to contribute toward a collaborative ecosystem. We find that not all incumbent providers can uniformly appropriate the advantage created by additional vaccine providers. More accessible vaccine providers like pharmacies and medical practices tend to gain the most out of the burgeoning vaccine provider ecosystem. Our results further reveal that the distance between a provider and the nearest hub has no bearing on a provider's ability to appropriate benefits from a burgeoning vaccine provider ecosystem.

3.6.1. Theoretical Contribution

We make several fundamental contributions to the extant literature. First, our findings contribute to the OM literature on downstream vaccine supply chains that has primarily looked at the allocation and administration of vaccines (e.g., Duijzer et. al., 2018; Stamm et. al., 2017; Westerink-Duijzer et. al., 2020) in the context of external uncertainties caused by an ongoing pandemic. Our findings provide novel empirical evidence that addition of new providers in the area increases the inoculation rate of the incumbent provider. In our study we explicate the underlying mechanism through which such increase in vaccination rate is enabled.

Second, our study makes significant contribution to the stream of literature that has investigated the role of service accessibility in the health care context (e.g., Ikkersheim et. al., 2013; Beal et. al., 2020; Siemens et. al., 2020). Our findings inform extant research by showing that higher accessibility of health care providers often comes with a tradeoff of not having enough infrastructure to treat a high volume of patients. However, in the context of uncertainties introduced by a raging pandemic, accessibility of vaccine providers enables them to appropriate maximum leverage from collaborative vaccine ecosystem to inoculate more people. To the best of our knowledge, this is a novel finding that provides empirical evidence of how different providers offering varying levels of health care service accessibility achieve different positive externalities of a burgeoning vaccine provider ecosystem, and how this affects the inoculation rate of a vaccine provider. Our findings contribute to prior studies that have focused on enhancing the acceptability of novel pharmaceutical products when there is a tension between high product demand but higher degrees of information asymmetry about the product (e.g., Lenselink et. al., 2008; Henrich and Natalie, 2009; Sheldenkar et. al., 2019).

Third, our study makes significant contribution to the OM and marketing literatures that have examined the impact of proximity of a smaller organization with lower service capability to a larger organization in a non-competing environment. Most of the studies in competing retail context suggest that the proximity of a smaller service provider to a larger provider can reduce its ability to service more consumers and lower its service rate (Reilly, 1931; Kabra et. al., 2020; Lim et. al., 2021). Our study informs literature that, in a non-competing environment, vaccine providers experience higher vaccination rate as they are situated farther from the nearest mass vaccination site. The results suggest that, on average, the vaccination rate of a provider increases by 0.75% as the provider moves 1% away from the vaccine hub. The finding runs counter to the example Facchini et. al. (2018) offers that depicts bigger charities enable smaller local charities to extend the social welfare through active resource redistribution. A possible explanation may be the increased reliance of the population on a local vaccine hub (if present) which diminishes the importance of a nearby vaccine provider which has much lower vaccine administration capacity as compared to the hub. Our study provides no evidence that a vaccine hub helps an incumbent vaccine provider to extract positive externality from a burgeoning ecosystem.

3.6.2. Implications to Policymakers

The findings from our study have important implications for the public policymakers who are responsible for structuring the last-mile vaccine supply chain in the context of high vaccine information asymmetry to fight a raging pandemic with a goal of effective and efficient vaccine administration. The findings suggest that a burgeoning collaborative vaccine ecosystem helps providers to administer, on average, more vaccines every day. For instance, at a random zip code if policymakers approve one additional vaccine provider, the activity translates to 7.5% increase in vaccine administration rate by the incumbent providers which directly pushes the total national vaccination count toward the goal of total inoculation required for herd-immunity. For example, a generic vaccine provider (e.g., Memorial Hermann – The Woodlands) in Spring, TX (Zip Code: 77380) administers, on average, 255 vaccine doses in a day. Following the introduction of a new provider in Spring, TX the provider is expected to experience, on average, around 19 more people to get vaccination each day which translates to 418 more people to get vaccinated in a month (excluding the holidays). Given the population of Spring, TX is 23,136, decision of policy makers enables a single incumbent provider to vaccinate about 1.8% of the population in a month. Additionally, our findings show that if the incumbent provider is more accessible to general population (e.g., medical practice or pharmacy), it experiences, on average, an additional 29.5% increase in inoculation rate as compared to what a lesser accessible hospital would have experienced, ceteris paribus.

Figures 3.4 and 3.5 explicate how the effect size of one new provider in Pearland, TX (Zip Code: 77584) on the incumbent providers vaccination levels differs based on the type of the provider. Provider vaccination rates have been standardized for easier comparison. Figure 3.4 plots the vaccination rates of a HEB pharmacy outlet across time whereas Figure 3.5 depicts the vaccination rate by HCA Houston Hospital. The arrow denotes the intervention of addition of new provider in Pearland, TX. The figures indicate that the shift in the trend of vaccination by the pharmacy is higher than the trend that we can see for the hospital. This finding has significant relevance for determining policies for structuring the vaccine administration network. Our findings suggest that policy makers should realize the potential of smaller but more accessible providers in their ability to mobilize their resources effectively to generate more social welfare by leveraging the positive externalities of provider ecosystem. Hence, policy makers should support smaller providers so that they can vaccinate more people to help combat the risk of infection from the virus. The Federal Retail Pharmacy Program introduced on 11th February 2021 is a step in this direction. The purpose of the initiative is to augment the state supply of vaccine to the participating pharmacies across the nation so that these pharmacies can have enough supply to vaccinate people. The goal of the program is to tap into the expertise of pharmacies to rapidly vaccinate American public[24]. This does not mean that more resourceful and bigger providers like hospitals are less important. They tend to provide the infrastructural backbone of the ecosystem that smaller providers can leverage to vaccinate more people.

[24] https://www.cdc.gov/vaccines/covid-19/retail-pharmacy-program/index.html

Figure 3.4 Vaccination Growth curve of a pharmacy in Pearland, TX

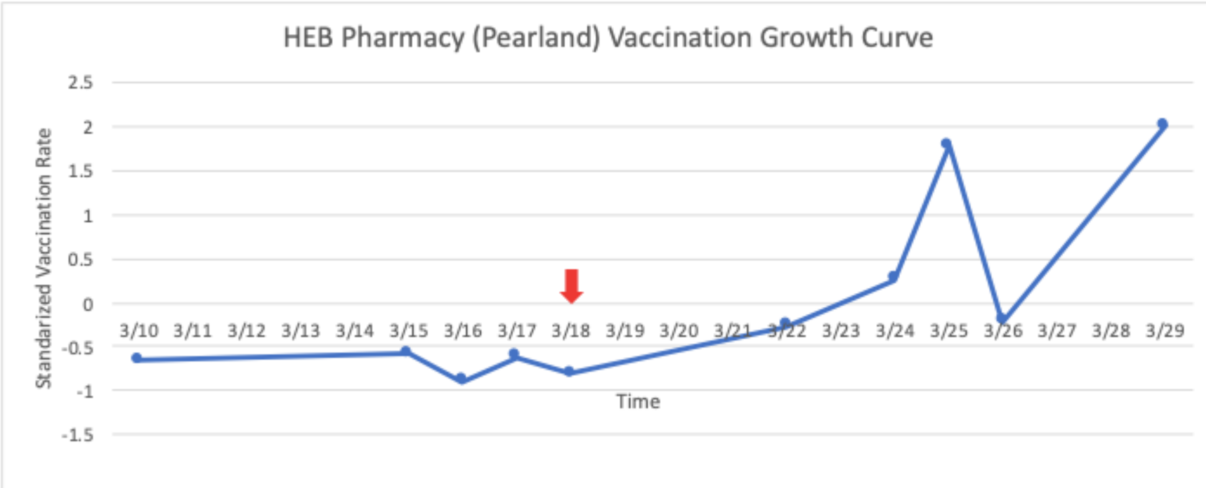
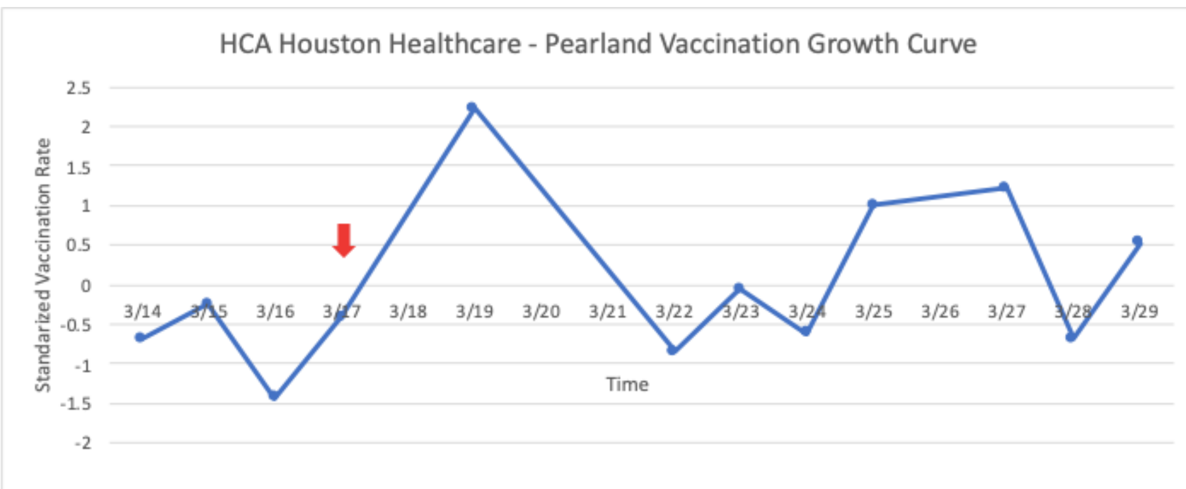


Figure 3.5 Vaccination Growth curve of a hospital in Pearland, TX



Our findings show that with a 10% increase in the distance between a generic vaccine provider and the nearest vaccine hub, the vaccination rate of the smaller provider increases by 7.54%. Hypothetically, if a vaccine provider in Dallas, TX, that is 10 mi away from the nearest vaccine hub, vaccinate 100 people every day, another provider in, suppose, Pearland, TX, that is 11 mi away from a vaccine hub should be able to vaccinate around 108 people in a day. Hence, in a month, the provider in Pearland should be able to get 176 more people inoculated, which is approximately 0.76% of Pearland population. The findings highlight the importance of considering geo-spatial distribution of providers in an area in the decision-making process of selecting a location for the vaccine hub. Ideally, regional policymakers should select a site for vaccine hubs that is farther away from a local provider ecosystem. Our findings indicate that policymakers should consider establishing vaccine hubs in locations that are relatively underserved by vaccine providers.

3.6.3. Limitations and Future Research

There are a few limitations of this study that provide directions for future research. First, we calculated daily vaccine administration by assuming that the variable is a function of a county's cumulative vaccine effort, vaccine allocation to the provider, provider infrastructure, and its ability to predict demand. However, due to the paucity of data, the estimation process does not account for inventory management practices and associated shrinkages. Future research should consider operationalizing this variable after accounting for inventory management practices. Second, our study focuses on vaccine providers in the state of Texas, which limits us from capturing heterogeneity across states as well as across other countries of the world. Future research should study the relationships across multiple states or even countries and thereby extend the boundary conditions of this research. Third, we used the argument that more vaccine providers enhance the positive externalities of the ecosystem as we assume that vaccine providers tend to collaborate with each other. We supported the assumption by providing instances of such collaboration across the U.S. However, our data does not capture any interaction between these providers explicitly. Future research should empirically investigate to what extent addition of providers impact the collaboration pattern of the existing network to understand the rise of positive externalities in the burgeoning provider ecosystem.

4. Chapter 4: Managing Trade-off between PPE Inventory and Patient Care Services: Do Isolation Wards Really Help?

4.1. Introduction

When the COVID-19 pandemic hit the country, personal protective equipment (PPE) quickly became critical asset for the hospitals as they struggled to maintain inventory to meet the required demand of providing care to the population. Eventually, as the supply of the PPE relatively stabilized, hospitals were loading up PPE in preparation of future peaks in hospitalization. Bigger hospitals and health systems pivoted to managing PPE inventory in a central warehouse with many days of inventory at hand. Due to the shorter shelf life of the PPE and the fact that these are not required in procedures that does not involve treating infectious patients, healthcare supply chain professionals fear that they might have to write off such inventory when the hospitalization rates due to the pandemic subsides. According to the vice president of supply chain at Henry Ford Hospital in Michigan:

> *"....in five years healthcare would likely be at pre-covid levels. Typically, what will happen in lifecycle of healthcare is we will have a pandemic and we would invest in emergency preparedness and bulk up inventories and shove everything in the corner and then in 5 years everything disintegrates when we pull it out ...academia could provide guidance how do we prevent the next supply chain shock wave (sic, bulking up of PPE inventory)"*

The opportunity cost of such events is detrimental for smaller independent hospitals. These hospitals cannot exercise enough power on the PPE suppliers to fulfill their demand as bigger hospitals pile on the PPE[25]. Consequently, these smaller hospitals are unable to protect their

[25] https://www.modernhealthcare.com/supply-chain/hospitals-say-theyre-better-prepared-ppe-spring-supply-chain-uncertain

healthcare workers and the quality of care, eventually, deteriorates for these smaller hospitals. Often, these hospitals provide healthcare services that are accessible to the population unlike the bigger health systems which are more likely to cater to the urban population. Hence, such pandemic response practices by bigger hospitals may negatively impact public health.

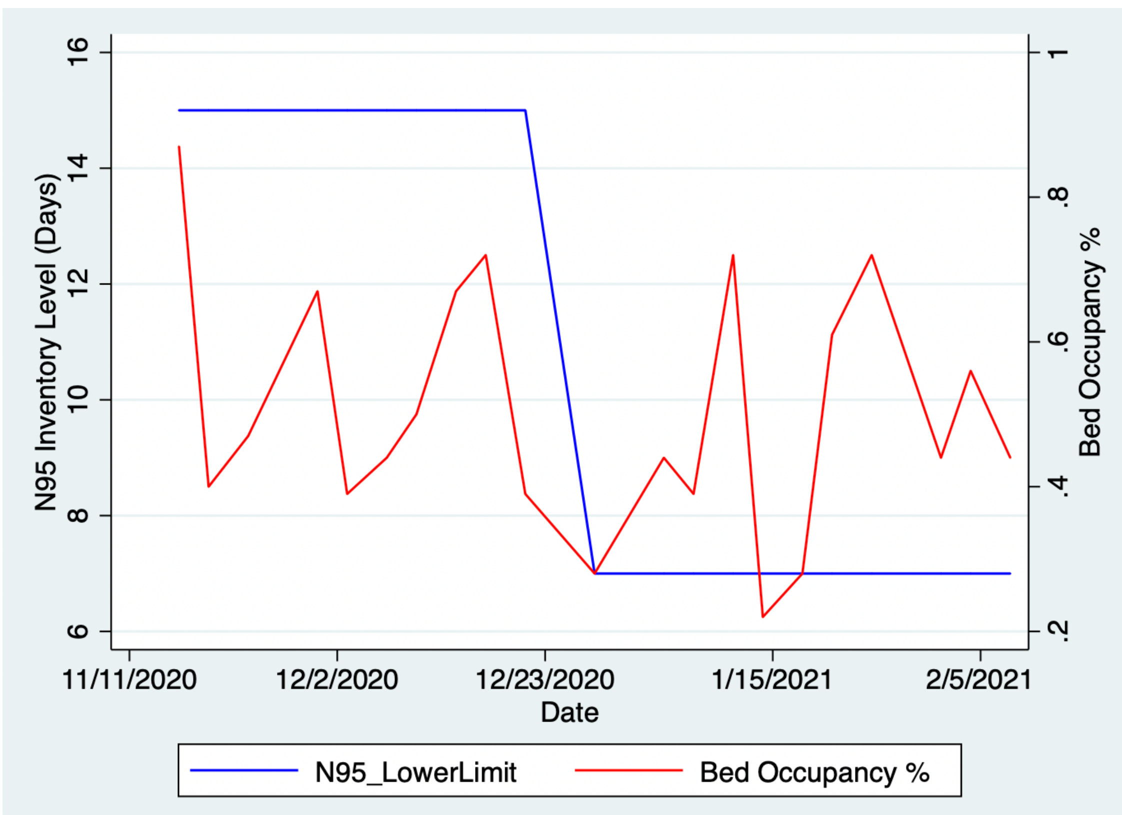
During a pandemic, higher bed occupancy levels are often characterized by high PPE demand uncertainties placed on the hospitals. The situation is particularly worse when the COVID-19 hospitalization cases peaked. For example, Figure 4.1 depicts the relationship in one of the big Mid-western hospitals. We find that as the hospital experienced higher bed occupancy levels it maintained higher PPE (N95 in the figure) inventory (in days). However, the inventory level tends to trend down as the hospital experienced lower bed occupancy levels. As the hospitals witnessed higher bed occupancy levels procurement managers led the organization to store higher inventory to buffer against potential equipment shortage in case of potential shortage (Zepeda et. al. 2016; Fisher and Raman 1996). However, during the pandemic hospitals witnessed PPE supply shortage (Furman et. al. 2021). Hence, the hospitals may not load up on PPE inventory as much as they would want, and the relationship may not hold true. In fact, recent healthcare literature (Saha and Ray 2019) has demonstrated that hospitals that experience higher bed occupancy tend to have fewer equipment in their reserve during pandemic.

Multiple practitioner outlets provide contradictory reports about the state of PPE inventories in hospitals as COVID-19 infection rates peaked. For example, Greene (2020) reported that multiple hospitals were able to build up their PPE inventories for about 90 days, whereas Jacobs (2020) has reported that during high bed occupancy rates in December 2020 healthcare workers faced daunting shortage of PPE. Our first research question seeks to answer this ambiguity:

RQ1: During a pandemic, do hospitals in a health system tend to build up more PPE inventory as their bed utilization rates go up?

We collected the data on 101 hospitals as reported by Michigan Health and Human Services (MDHHS) and conducted an empirical investigation to answer the research question. We performed endogeneity corrected regression analysis after controlling for multiple hospital level control variables to demonstrate that for a group of hospitals the PPE inventory level indeed increases as the bed utilization rates of those hospitals went up. However, our analysis also demonstrates that for few hospitals (read, smaller hospitals) in our dataset the burgeoning bed occupancy decreases the PPE inventory levels.

Figure 4.1 N95 Inventory Level and Bed Occupancy



The empirical result indicates an unsustainable healthcare practice of managing critical PPE inventory during a pandemic. If the healthcare practitioners respond to increasing care demand by bulking up the PPE inventory it may create twofold stress on the healthcare system. First, such practice may appreciate the price of the PPEs which may make treating patients costlier. Second, smaller hospitals may not be able to procure the required PPE inventory to protect their healthcare workers. Consequently, these hospitals, which often are more accessible to the marginalized communities, may fail to provide required service to the community. This may result in uneven distribution of healthcare services within the community. Fortunately, hospitals started adopting different practices to reduce the consumption of PPEs, while maintaining high quality care services.

Using the insights gained from the investigation of the data, in the next phase of the study we conduct case studies wherein we interview supply managers and clinical practitioners from five of the biggest hospitals in Michigan to understand the policies that the hospitals have adopted which enabled them to maintain such high inventory levels despite higher care demand during the pandemic. The interviews revealed that hospitals adopted two distinct strategies to manage PPE inventory. First, the hospital administrators were able to locate alternative sources to procure the PPEs. Second, they were able to control the demand for PPE, primarily, by rearranging their internal assets. The interviews reveals that one of the ways in which the hospitals rearranged their assets is by creating an isolation ward to treat COVID-19 patients. This allows hospitals to de-pool existing free beds and resources to create isolation ward to accommodate only COVID-19 patients. These wards typically have dedicated beds and set of HCWs to treat COVID-19 patients. Access to these wards was controlled to prevent viral transmission among the patients in the isolation and general wards. Depending on the demand and occupancy of the COVID-19 patients in the hospital the administration may decide to allocate proportional resources to these wards.

Existing research on capacity/resource de-pooling offers contrasting view of the way capacity de-pooling can help managers to manage capacity and offer quality services. For example, in the humanitarian domain capacity de-pooling has led to inconsistent service offering that has increased the deprivation costs of the efforts undertaken (Eftekhar et. al. 2018; Natarajan and Swaminathan 2014). On the other hand, capacity de-pooling has been demonstrated to increase service speed during high demand scenarios (Hu and Benjaafar 2009). Our next research objective of this study is to seek further insights to understand the conflicting findings in the literature. Specifically, this study aims to understand the tradeoff between the way hospitals manage PPE inventory and the quality of patient care services that the hospitals aim to achieve. To accomplish this research objective, we develop an agent-based simulation, grounded in practice by the feedback we received from clinicians, to model the care-giving operations of a generic hospital during the pandemic. We model the nosocomial transmission using the SEIR model (Mwalili et. al. 2020; Wan et. al. 2020; Pham et. al. 2021). Such a model helps us capture the evolution of quality and speed of patient care, and nosocomial propagation of the virus depending on the type of policies implemented by the hospital. We then use this model to compare between the scenario in which a hospital has established an isolation ward and the base scenario where a hospital has no isolation ward. We have four distinct metrics which forms the basis of the comparison – PPE inventory levels, number of patient rejections, and nosocomial transmission among patients and healthcare workers. The analysis of the simulation data provides some evidence of tradeoffs between the inventory management goals and quality of patient care services.

The rest of this essay is structured as follows. In section 4.2 we present the literature review of the effect of facility utilization on inventory management and resource de-pooling to provide an understanding of the state of the current literature about the topics of interest and find gaps in literature to position our study. In section 4.3 we explore, empirically, the effect of bed occupancy rates of hospitals on their PPE inventory levels. In section 4.4 we conduct case studies to explore the ways in which supply chain and clinical practitioners managed PPE inventory during pandemic and focus on the policy of establishing isolation wards in the hospitals. In section 4.5 we define agent-based simulation to explore the tradeoff among managing PPE inventory, patient care and care capacity involved in the creation of isolation wards in the hospital. In section 4.6 we discuss the theoretical and managerial implications of the study and conclude by identifying some limitations of the study and consequent future research avenues.

4.2. Literature Review

4.2.1. Facility Utilization and Inventory Management

Utilization of facilities is a major factor influencing inventory management decisions in organizations (Lee et. al., 1997). During a pandemic, higher bed occupancy levels are often characterized by high PPE demand uncertainties placed on the hospitals. The situation is particularly worse when the COVID-19 hospitalization cases peak. Extant research in healthcare OM (Zepeda et. al. 2016; Fisher and Raman 1996) argues that the medical equipment inventory level and associated costs increases with increasing bed utilization during the time of uncertain demand. The studies suggest that procurement managers tend to lead the organizations to store higher inventory to buffer against potential equipment shortage. Sheehan et. al. (2020) provides a framework using which healthcare professionals can manage the relationship. The study shows that usage of lean methodology in healthcare operations may help mitigate the effect of bed occupancy on the need to keep higher inventory levels. However, these studies assume that there is no supply constraint when procuring the items which may not be valid during the times when the pandemic was raging though the country. Research informing PPE inventory status report of severe PPE supply shortage during the surging COVID-19 hospitalization peaks (Furman et. al. 2021; Pingol 2021; Cohen and Rodgers 2020; etc.). Hence, clearly the procurement managers may not be as free to amass PPE inventory. Using a Markov decision process model, Saha and Ray (2019) report that when high bed occupancy rates are characterized by high hospitalization demand rates, the inventory level tends to go down. Conditions of depleting inventory levels due to high hospital resource utilization has been reported by Bauchner et. al. (2020).

Multiple practitioner outlets also provide contradictory reports about the state of PPE inventories in hospitals as COVID-19 infection rates peak. For example, Greene (2020) reported that multiple hospitals were able to build up their PPE inventories for about 90 days, whereas Jacobs (2020) has reported that during high bed occupancy rates in December 2020 healthcare workers faced daunting shortage of PPE. Hence, the understanding of the relationship between bed occupancy and PPE inventory level is ambiguous and we need further research on the topic. The most interesting aspect to investigate is the relationship between bed occupancy and inventory level in the context of an environmental uncertainty, a study that has no precedence.

4.2.2. Resource De-pooling

Extant service OM literature has examined capacity/resource de-pooling. The research informs that generally as organizations de-pools capacity the resource utilization rates drop. Contrary to the belief, in the context of restaurant operations that are often characterized by under-a-rush hour regime with many customers arriving at the beginning of the rush hour period, Hu and Benjaafar (2009) has shown that partitioning servers to serve specific customer groups enables the restaurant to provide faster service to the patrons, which improves the service quality of the restaurant. On the other hand, extant research in the humanitarian context argues that uncertainty in the partition in the budget increases the expected deprivation costs of the humanitarian effort where in more beneficiaries suffer due to insufficient humanitarian service delivery (Fard et. al. 2019; Eftekhar et. al. 2018; Natarajan and Swaminathan 2014). In the healthcare context, Day et. al. (2012) has suggested the benefit of de-pooling surgeon OR slot. The study suggests that de-pooling of OR slots enable the surgeons to predict their schedules, and better manage clinic, office hours, and other aspects of their professional life. The study then extends the idea of a risk pooling strategy of sharing the surgeon OR slots that offers a predictable and reliable access to the operating room while maintaining high-capacity utilization. Hence, the extant literature provides an ambiguous understanding of the benefits of de-pooling of capacity, which we seek to address through our research.

4.3. Empirical Investigation

4.3.1. Empirical Context and Estimation Model

To investigate the first research question, we collected hospital level data across the state of Michigan as published by Michigan Department of Health and Human Services (MDHHS). To ensure timely reporting of critical resources, in pursuant to Michigan Compiled law (MCL 333.2253), MDHHS made it mandatory for the hospitals in Michigan to report data pertaining to personal protective equipment (PPE) inventory, and patient census. As our analysis is at individual hospital level, we started our data collection since November 16, 2020, as before this date MDHHS published data on individual health system in the state. This date fortunately coincided with the second peak of COVID-19 new infections that the state experienced (the peak reached on December 3, 2020, with the upward and downward inflection points originating on October 15, 2020, and February 8, 2021, respectively). As the bed utilization rate increases with higher infection rate, it is worthwhile to observe the relationship during this period. We collected data until February 8, 2021. Hence, we collected a panel data with 101 unique hospitals that belong to a health system in Michigan spanning over 21 time periods. We have 2121 observations in the dataset. The data on patient census were updated twice every week on Mondays and Thursdays.

The data included information about hospital bed utilization ($BedUtilization_{it}$), and inventory levels (in days) of N95 masks, surgical masks, gloves etc. In our analysis, we accounted for the inventory level of N95 masks to represent the PPE inventory levels that the hospital seeks to maintain. The reasons we chose the N95 masks as representative of the PPEs are twofold. First, N95 masks registers the highest demand of the PPEs that are most often used to control exposures to infectious pathogens transmitted via the airborne route[26]. Second, the N95 masks were consistently in short supply in the country[27]. The inventory level was reported in intervals of days of inventory: 4-6 days (lowest), 7-14 days, 15-30 days and >30 days (highest). We considered the lowest number in each of these intervals to represent the interval. For example, we considered 31 days to represent the interval >30 days. This variable, $Inventory_{it}$, represents an ordered categorical variable.

Definitive healthcare collaborated with Esri's geospatial cloud to develop a dashboard to report current levels of hospitalizations, hospital capacities and county level demographic data across the nation. We downloaded this contextual data for 6090 hospitals using Esri provided API and filtered out the data for Michigan hospitals. The database contains variables like number of licensed staffed beds ($StaffedBeds_i$) for each of the 101 hospitals in Michigan, that are affiliated to the 19 health systems, and the demographics – population of the county ($Population_i$) and median age of the

[26] https://www.maine.gov/dhhs/mecdc/infectious-disease/hai/documents/COVID-19_Personal%20Protective%20Equipment%20Supply-Strategies-N95_9.27.21.pdf
[27] https://www.npr.org/sections/health-shots/2021/01/27/960336778/why-n95-masks-are-still-in-short-supply-in-the-u-s

population of the county ($MedAge_i$) - of respective counties where each of the hospitals belong. We referred to the Rural-Urban Commuting Area Codes database by U.S. Department of Agriculture to understand whether the zip code, related to each of the hospital, is a rural zip code. We created a binary variable, $Rural_i$, that assumes 1 when the zip code is a rural zip code else it assumes 0. We also collected the age of the health systems ($SystemAge_i$) to which each of the hospital in the dataset belong. This data is combined with the data on the hospitals reported by MDHHS. We collected the data about new COVID-19 cases in a county to which a hospital belonged at each time period from the COVID-19 dashboard published by the Johns Hopkins University and Medicine. We assume that the hospitalization demand ($Demand_{it}$) of COVID-19 patients in hospital at a given time is the product of the new COVID-19 cases in a county at the given time and the fraction of total number of staffed beds in the county that the hospital possess.

The association between $Inventory_{it}$ and $BedUtilization_{it}$ could be influenced by several factors. To clearly discern the variance of $Inventory_{it}$ that can be attributed to that of $BedUtilization_{it}$ we controlled for $Demand_{it}$ since hospitals' inventory management decision may differ depending on the COVID-19 patient demand of the county. We control for patient demographics - $Population_i$ and $MedAge_i$ – as counties with higher and older population may experience higher hospitalization demand and, consequently, may carry differing inventory levels. We control for hospital level variables - $StaffedBeds_i$ and $SystemAge_i$ – to account for hospital specific fixed effects that may impact inventory management decisions. We controlled for $Rural_i$ as a hospital in an urban zip code may more easily procure PPE from suppliers located the urbanized regions. We also accounted for time fixed effects (T_t) to control for differing conditions during different period of data collection that may influence the inventory levels. We consider November 16, 2020, as the base time category. We used the following model to estimate the effect of $BedUtilization_{it}$ on $Inventory_{it}$:

$$Inventory_{it} = \beta_0 + \beta_1 BedUtilization_{it} + \beta_2 Demand_{it} + \beta_3 Population_i + \beta_4 MedAge_i + \beta_5 StaffedBeds_i + \beta_6 SystemAge_i + \beta_7 Rural_i + T_t + \varepsilon_{it} \tag{4.1}$$

We use ordered pooled probit to estimate the model as $Inventory_{it}$ is an ordered categorical variable. To control for heterogeneity and correlation across error variance structure we used Huber/White sandwich estimator (Wooldridge 2010).

As none of the hospitals capture and report exclusive set of variables that we can control in our model, there always will be opportunity for omitted variable bias that may confound the relationship between the predictor and dependent variable. Besides, we cannot rule out the possibility of reverse association between inventory level and bed utilization as the hospital may consider more patients as they maintain higher levels of PPE inventory. We adopt instrumental variable approach to correct for the endogeneity in the independent variable $BedUtilization_{it}$. We use lagged values of the endogenous variable ($BedUtilization_{it}$) as the respective instrumental variables. In the absence of exogenous instrument, usage of lagged values of the endogenous variables is common in OM literature (Sharma et. al. 2016; Tan and Netessine 2014; etc.). To determine the threshold lag beyond which we need to consider the instruments, we performed the Arellano-Bond test for autocorrelation. We find that for the estimation model, the AR(1) is significant at 10% level of significance, whereas AR(2) is non-significant at 10% level of significance. Hence, we consider three lags of the endogenous variable starting at lag 2. We find that the over identification criteria are satisfied.

In case of non-linear regression, Wooldridge (2015) suggests that control function approach provides more consistent estimates compared to the traditional "plug-in" two stage regression. In the first step of this approach, we regress the endogenous variables on the instrumental variables following equation 4.2. In the model, X_{it} denotes all the control variables in model 4.1. We find that the instrumental variables are highly significant to the endogenous variable. We also find the F-statistic of the model is greater than 10 which satisfies Stock and Yogo (2005) of relevant instrument.

$$BedUtilization_{it} = \alpha_0 + \alpha_1 BedUtilization_{it-2} + \alpha_2 BedUtilization_{it-3} + \alpha_3 BedUtilization_{it-4} + X_{it} + T_t + \varepsilon_{it} \quad (4.2)$$

Next, we derive the residuals of the regression. These residuals encompass the variance in the predictors that is endogenous to the idiosyncratic error terms. In the second step, we introduce the endogenous predictors along with these residuals in the ordered probit regression as depicted in equation 4.3. Consequently, we control for endogeneity in the predictors and derive unbiased estimation of the coefficients. We use STATA 15.1 for estimation.

$$Inventory_{it} = \beta_0 + \beta_1 BedUtilization_{it} + \boldsymbol{\beta} X_{it} + T_t + \widehat{Resid} + \varepsilon_{it} \quad (4.3)$$

4.3.2. Empirical Analyses and Results

We first examined some of the relevant descriptive statistics of the overall dataset. The mean and standard deviation of the bed utilization of the hospitals in the dataset are 63.44% and 25.89%, respectively. We find that about 45.54% of the hospitals belong to a rural zip code whereas the remaining 44.46% of the hospitals belong to the urban zip code. The mean and standard deviation of the median age of the population in a county are 39.68 and 4.36 years, respectively. We provide the summary statistics and correlation table in Table 4.1. We find that there are 80 distinct hospitals that have maintained N95 inventory>30 days at some point in time consisting of 1645 observations in the dataset. Hence, about 80% of the hospitals in the data subset maintained above 30 days of N95 inventory. The mean and standard deviation of the bed utilization of the hospitals in this data subset are 63.9% and 25.47%, respectively. We find that about 47.17% of the hospitals belong to a rural zip code whereas the remaining 52.83% of the hospitals belong to the urban zip code. Hence, we find that larger portion of the hospitals that had maintained high N95 inventory levels belong to urban zip codes. The mean and standard deviation of the median age of the population in a county are 39.52 and 4.68 years, respectively.

Table 4.1 Summary Statistic and Correlation Table

#	Variables	Mean	S.D.	1	2	3	4	5	6	7
1	BedUtilization	0.63	0.26	1.00						
2	Rural	0.46	0.498	-0.6	1.00					
3	Demand	52.67	64.94	0.31	-0.39	1.00				
4	MedAge	39.68	4.36	-0.36	0.38	-0.26	1.00			
5	Population	496484	615329	0.36	-0.65	0.19	-0.28	1.00		
6	SystemAge	72.38	39.63	0.08	-0.11	-0.05	-0.14	0.08	1.00	
7	StaffedBeds	201.54	212.31	0.42	-0.59	0.53	-0.36	0.44	0.09	1.00

We find that there are 19 distinct hospitals that have maintained N95 inventory 15 - 30 days at some point in time consisting of 339 observations in the dataset. Hence, about 19% of the hospitals in the dataset maintained between 15 and 30 days of N95 inventory. The mean and standard deviation of the bed utilization of the hospitals in the data subset are 62.4% and 27.24%, respectively. We find that about 40.11% of the hospitals belong to a rural zip code whereas the remaining 49.89% of the hospitals belong to the urban zip code. The mean and standard deviation of the median age of the population in a county in this subset of the data are 40.31 and 3.32 years, respectively. We find that there are 10 distinct hospitals that have maintained N95 inventory below 15 days at some point in time consisting of 137 observations in the dataset. Hence, about 9.9% of the hospitals in the data subset maintained less than 15 days of N95 inventory. The mean and standard deviation of the bed utilization of the hospitals in the dataset are 60.42% and 27.35%, respectively. We find that about 39.41% of the hospitals belong to a rural zip code whereas the remaining 60.59% of the hospitals belong to the urban zip code. The mean and standard deviation of the median age of the population in a county are 40.02 and 1.59 years, respectively. Hence, generally, we observe that hospitals that had maintained lower levels of N95 inventory are associated with lower bed utilization rates.

We present the results of endogeneity corrected ordered probit (*oprobit*) model in column 1 of Table 4.2. We considered natural logarithm transformation to control the spread of the variables whenever required. To ensure that variables with values equal to zero do not drop out during the natural logarithm transformation, we added one to the variables before transforming them. We find that $BedUtilization_{it}$ is significant and positively associated with the $Inventory_{it}$. We performed average marginal effects analysis to understand how $BedUtilization_{it}$ impacts hospitals that belong to different inventory categories. We find that for the hospitals that maintain N95 inventory level > 30 days, the inventory level increases ($\beta = 0.156$; $p < 0.05$) with increasing bed utilization. We find that $BedUtilization_{it}$ does not have a significant effect on $Inventory_{it}$ for the hospitals in the groups 7-14 ($\beta = -0.046$; $p > 0.05$) and 15-30 days ($\beta = -0.09$; $p > 0.05$) at 5% level of significance. However, we find that in case of the hospitals in the group 4-6 days of N95 inventory, the $BedUtilization_{it}$ have a significant negative effect on $Inventory_{it}$ ($\beta = -0.019$; $p < 0.05$).

In columns 2 and 3 of Table 4.2 we present the results of pooled oProbit and pooled oLogit respectively. We find that the results and the average margins effects analyses holds fine. Hence, these analyses exhibit that majority of the hospitals in the dataset tend to accumulate and store higher levels of N95 mask inventory when they experience higher bed utilization rates in the hospital. Our analysis shows that these set of hospitals primarily belong to urban areas (52.83%) which may experience higher COVID-19 hospitalization demand.

Table 4.2 Panel Regression Analysis

Variables	(1) *$Inventory_{it}$* *(Endogeneity Corrected)*	(2) *$Inventory_{it}$* *(oProbit Model)*	(2) *$Inventory_{it}$* *(oLogit Model)*
$BedUtilization_{it}$	0.635* (0.321)	0.535* (0.238)	1.013* (0.483)
$Demand_{it}$	-0.103 (0.085)	-0.102 (0.081)	-0.162 (0.148)
$Population_{i}$	0.081* (0.036)	0.107*** (0.03)	0.091 (0.061)
$MedAge_{i}$	-2.15*** (0.341)	-1.83*** (0.314)	-3.779*** (0.583)
$StaffedBeds_{i}$	0.583*** (0.064)	0.558*** (0.056)	0.947*** (0.112)
$SystemAge_{i}$	-0.63*** (0.054)	-0.616*** (0.048)	-1.173*** (0.1)
$Rural_{i}$	1.059*** (0.157)	1.113*** (0.139)	1.758*** (0.284)
Time Controls	Day-Week	Day-Week	Day-Week
Hospital Fixed Effects	Yes	Yes	Yes
Observations	1717	2121	2121
Wald chi-square	278.88	326.85	276.28
Pseudo-R^2	0.1232	0.118	0.1167

The standard error has been reported in the parenthesis.
+. $p < 0.1$ * $p < 0.05$ **. $p < 0.005$ ***. $p < 0.001$

4.3.3. Discussion of Empirical Findings

The empirical analysis indicates an unsustainable inventory management practice by hospitals. As the hospitals continue to bulk up inventory, they may incur higher inventory management costs which may be passed on to the patients as treatment costs. Such practice may increase the PPE costs which may increase the cost of treating patients and may make these PPEs less accessible to the smaller hospitals. Additionally, in case the COVID-19 cases subside, these PPEs may not be used and may have to written off due to limited shelf life, incurring huge opportunity costs that those wasted PPEs could have been utilized by other hospitals in dire need of PPEs. Hence, we need to investigate practical ways which the hospital can use to pivot from such unsustainable practices.

In the remainder of the study, we continue to research about ways that the hospital can adopt to attenuate the demand of PPEs and conserve PPEs. However, to investigate such ways we need to first understand how these hospitals were able to build PPE stockpile in times when other hospitals struggled to procure PPEs. Hence, the empirical results help us define our next research question:

RQ2: How were the hospitals able to maintain such high PPE inventory during pandemic? More importantly, how did the hospitals manage their assets to attenuate the demand of PPE to treat patients?

To answer the research question, we conducted field research where we interviewed both supply chain professionals and clinicians at five of the biggest hospitals in Michigan to gain firsthand insight how these professionals managed the hospital resources successfully to circumvent the adversities of the pandemic as they continued to offer critical care services to the community.

4.4. Case Studies

4.4.1. Data Collection

To investigate into the hospital activities, which enabled them to sustain high inventory levels during the pandemic, we enlisted seven of the biggest hospitals in Michigan by number of beds.

We wanted to interview both the supply chain and the clinical professionals at the hospitals to get an encompassing view of the effectiveness of the policies the hospitals adopted to managing PPE inventory. We sent interview requests to both the supply chain and clinical points of contact in those hospitals. Five supply chain professionals and two clinical professionals from five hospitals, in total, agreed to be interviewed. The seven interviewees enabled us to understand both the supply side and clinical side of the policy implementations at those hospitals. The hospitals considered in the case study have average of 558 beds and standard deviation of 307 beds. The biggest hospital A has 1007 beds. Hospital B has 693 beds. Hospital C has 533 beds, whereas hospital D has 305 beds. Hospital E is the smallest with 252 staffed beds. Four of the supply chain respondents held the position of the vice president of the hospital supply chain and remaining one of them was senior vice president of the hospital supply chain. On average they have more than 15 years of experience in procurement and supply chain management domain. Both the clinicians were principal resident nursing professional with more than 10 years of clinical experience.

We collected the data from May 2022 to July 2022 since by this time hospitals were able to create more consistent routines to respond to the pandemic and were also able to reflect on their management practices during the peak time of the pandemic. We conducted face-to-face interviews with these professionals through standard video chat service. We sought respondents' consent to record the interview. We went through each of the interviews afterwards and touched base with the interviewee over email in case of any further clarifications. We informed the professionals that the interviews were performed solely for research purposes and that they could benefit from the outcomes of the research. Hence, the participants were forthcoming in sharing their experiences. We designed an interview consisting of open-ended questions to convey a broad discussion led by these questions but not restricted to them. We have provided the questionnaire in Appendix B.

4.4.2. Observations from Field Research: Asset Rearrangement to Manage PPE Demand

Our meeting with the healthcare professionals revealed that the flexibility in managing the PPE inventory enabled the hospitals to conserve PPEs. We learned that the hospitals never really stocked out during the peaks of hospitalizations, once they were past the initial phase of COVID-19. These hospitals were able to leverage its affiliation to a health system to redistribute PPEs and other critical equipment to the location of need. Although the hospitals generally manage their inventories in house, within a few weeks when COVID-19 hit Michigan they adopted a centralized inventory management policy to manage the critical equipment including PPEs. The health systems instituted a centralized incident command team who was responsible for monitoring PPE inventory across hospitals and the procurement and distribution of the equipment, among many other things.

> *"When COVID-19 hit in March 2020, we quickly mobilized incident command structure. On that there were multiple section leader seats, one of which was logistics section seat….All things PPE, equipment etc. would flow though that seat (logistics section seat) as well as through my department (supply chain and logistics department). So, we had, obviously, very intimate knowledge of everything that had occurred which helped us to drive strategy" - Vice President of Supply Chain at case hospital C*

This enabled the supply chain department to gain a system wide view of the PPE usage and load balance PPE inventory to the location of highest equipment demand. One of the hospitals was able to leverage the vast network of hospitals in the health system, centralized warehousing, and logistics to transfer PPEs and other critical resources between facilities (across state) depending on the location of demand.

"…in the state of Michigan our warehouse is down in Fort Wayne, IN. We have trucks going from Fort Wayne to the Michigan facilities (hospitals) every day. So, we had really easy means to move product to them on trucks that are already rolling to them every day."
- Senior Vice President of Supply Chain at case hospital E.

There are two factors that contributes to the incident command team's success in preventing hospitals from potential equipment stock-out during the pandemic. First, they were able to lead the health system to quickly pivot from procuring PPEs from traditional suppliers to a substitution model in which they procured from alternate unorthodox sources. Three hospitals that we interviewed reported that they started working with PPE manufacturers directly to formulate a contract to establish more stable supply of PPEs. We learned that accommodating and providing care services to the patients took precedence over managing the treatment cost. Hence, they followed through such ad hoc partnerships even though such contracts increased the equipment cost. The hospitals often went one step further in the substitution model in case the manufacturers were not able to fill in the demand. These hospitals "*would go from manufacturers to third party black-market retailers*" (Vice President Supply Chain Operations at case hospital B). In case the orders were not filled "*they (the hospitals) would circle back to non-standard manufacturers"*. For example, the case hospital B approached an injection molding company, that manufactured plastic bags, with a request to manufacture isolation gowns for the hospital. The downside of having products manufactured by such non-standardized manufacturers is that the products not always passed the PPE fit-testing standards that the hospitals maintained for their healthcare workers. This often resulted in wastage and higher opportunity costs.

Second, the incident command team was able to rearrange assets internally within the hospitals that enabled the hospitals to attenuate the demand for PPEs. For example, most of the hospitals that we interviewed established brown bag policy. Such policy enabled healthcare workers to store their used facemasks in bags for a certain number of days waiting to decontaminate so that those face masks can be reused in future. In another instance, one hospital repurposed a room into a PPE sanitization room where the used PPEs were sanitized using UV rays. One of the biggest asset rearrangements that the hospitals had undertaken was the creation of isolation wards for COVID-19 patients. Isolation wards were created when hospitals de-pooled (segregated) their resources (infrastructure, equipment, healthcare workers, etc.) and apportioned those resources for COVID-19 patient admission only. Those rooms were access controlled to avoid inter-mixing among virulent and non-virulent patients. General admissions were restricted in those wards. However, any patients showing signs of COVID-19 in the general ward were transferred to the isolation ward.

Two of the five hospitals that we interviewed either never established any isolation wards or never maintained the restricted access of such wards. As such they often admitted COVID-19 patients in the general ward and their policies regarding PPE usage were alike that of a hospital with no isolation wards – the healthcare workers (HCWs) donned PPEs before seeing a patient and doff the set of PPEs after treating the patient. In the next phase of the study, we consider the strategy of not establishing any isolation wards as the baseline strategy – a reference strategy against which other strategies are compared. The remaining three hospitals that we interviewed had established some form of isolation wards on their premises.

The proportion of resource allocation toward isolation wards varied contingent on the health systems. Some health systems chose to dedicate several floors in the hospital complex for the creation of isolation wards. We call these partial COVID-19 hospitals. Few other health systems repurposed the entire hospital complex as an isolation unit and would pool in virulent patients from other affiliated hospitals[28]. We called these hospitals dedicated or full COVID-19 hospitals. The proportion of resource allocation was contingent on virulent patient hospitalization rates. As per our interviews with the clinicians, the hospitals (especially the partial COVID-19 hospitals) chose to vary the proportion of resource allocation between 10% and 80% as COVID-19 patient hospitalization rates varied from low to high, respectively.

Such arrangement of the isolation wards enabled the hospitals to focus their PPE inventory on to these wards and adequately protect the healthcare workers serving the COVID-19 patients in those wards. For example, the hospitals with the isolation wards did not allow the healthcare workers (HCWs) serving in the general wards to wear any PPEs (except gloves). However, the HCWs in the isolation ward were allowed to don a new set of PPEs before seeing a patient and doff the PPEs immediately after treating the patient.

".. it (isolation ward) allowed us to focus our pockets of PPE inventory to those units rather than having them distributed all over the hospital in a decentralized fashion. The ward also helped us to focus where the inventory pockets were held which helped us to conserve masks with higher efficiency" ~ Vice President of Supply Chain at case hospital C

Observation 1: The hospitals that have created the isolation wards, generally, do not let the healthcare workers in the general wards use PPE whereas the healthcare workers in the isolation wards happen to don and doff PPEs after treating every patient.

The policy of creating the isolation wards may help the hospital to reduce the internal demand for PPE, which, in turn, may attenuate the inclination of the procurement managers to bulk up the

[28] https://www.fox2detroit.com/news/detroits-tcf-center-becomes-tcf-regional-care-center-to-treat-covid-19-patients

PPE inventory in case of higher bed occupancy. However, whether the policy can prevent the nosocomial transmission among patients and healthcare workers is not known. The policy defined in observation 1 assumes that the patient COVID-19 testing done prior to the admission procedure was sensitive enough to detect minute traces of viremia in patient and, consequently, report no false negatives. Unfortunately, this is not always the case. Kucirka and Lauer (2020) reported that over the 4 days of COVID-19 infection before symptom onset in a patient the probability that a RT-PCR tests, the golden standard of testing in hospitals, reports false negative is higher than 67%. In other word, the study suggests that RT-PCR tests can detect the viremia in only one third of incoming asymptomatic patients with COVID-19. The healthcare practitioners that we interviewed could not deny of the incidents of asymptomatic COVID-19 patients being admitted in the general wards. As the hospitals did not maintain any record of such incidents it is increasingly difficult for us to understand the severity of such incidents. Hence, healthcare fraternity does not really know whether the policy that observation 1 has outlined is effective enough to prevent nosocomial transmission.

Segregation of infrastructure by creating separate isolation wards may restrict the hospital's capacity to accommodate more patients. For example, isolation wards create a separate service offering channel with a fraction of hospital resource. Hence, during the peak of infected patient hospitalization the hospital with such wards may deny service to COVID-19 patients due to unavailability of beds in isolation wards, whereas the beds in general wards may be available. Hence, isolation wards may incur higher opportunity costs of patient care that can be life-threatening during the pandemic. Existing service OM literature on segregation of capacity or capacity/infrastructure de-pooling is indicative of such decreasing service capacity (Fard et. al. 2019; Eftekhar et. al. 2018). However, creation of such specialized isolation wards may enable the caregivers to treat their patients faster. Benjaafar (2009) has shown that partitioning servers to serve specific customer groups enables the restaurant to provide faster service to the patrons, which improves the service capacity of the restaurant. Currently we do not have any understanding whether hospitals were able to use isolation wards to offer better service capacity in the community during the ongoing pandemic. The hospitals that we interviewed also do not track the patient rejection rates which makes econometric assessment of patient capacity management impossible.

Hence, establishment of isolation wards in the hospitals is indicative of potential tradeoff between the way the hospital administrators manage PPE inventory and patient care quality and capacity. Managing such tradeoff may cause administrative overload as the hospitals scramble to provide critical care services to the community during the ranging pandemic. Arguably, managing such tradeoffs is even more challenging as the hospitals do not track all the required metrices or tracking such data is incredibly difficult. However, this finding related to RQ2, brings to the fore the following research question:

RQ3: How do quality and speed of patient care as well as nosocomial propagation of the virus evolve depending on the type of isolation ward related policies implemented by hospitals?

In order to investigate the aforementioned research question, we develop an agent-based model (AGM) to simulate the interaction between different agents in a generic hospital and to observe the evolution of such interactions due to the establishment of isolation wards. The model is grounded based on the inputs that we derived from the field research. AGMs have been applied extensively to formulate systems characterized by rich and nonlinear dynamics with multiple agents involved (Tong et. al. 2018; Chandrasekaran et al., 2015; Rahmandad and Sterman, 2008). Application of such simulation is critical when empirical data limitations exist. In this study, we use AGM to develop SEIR model of nosocomial transmission in a hospital to represent the landscape of hospital operations during the pandemic (Tong et. al. 2018). The transmission model will help us capture the evolution of quality and speed of patient care, and nosocomial propagation of the virus depending on the type of policies implemented by the hospital. We discuss the model development in the next section.

4.5. The Agent Based Model and Data Analysis

4.5.1. Model Definition

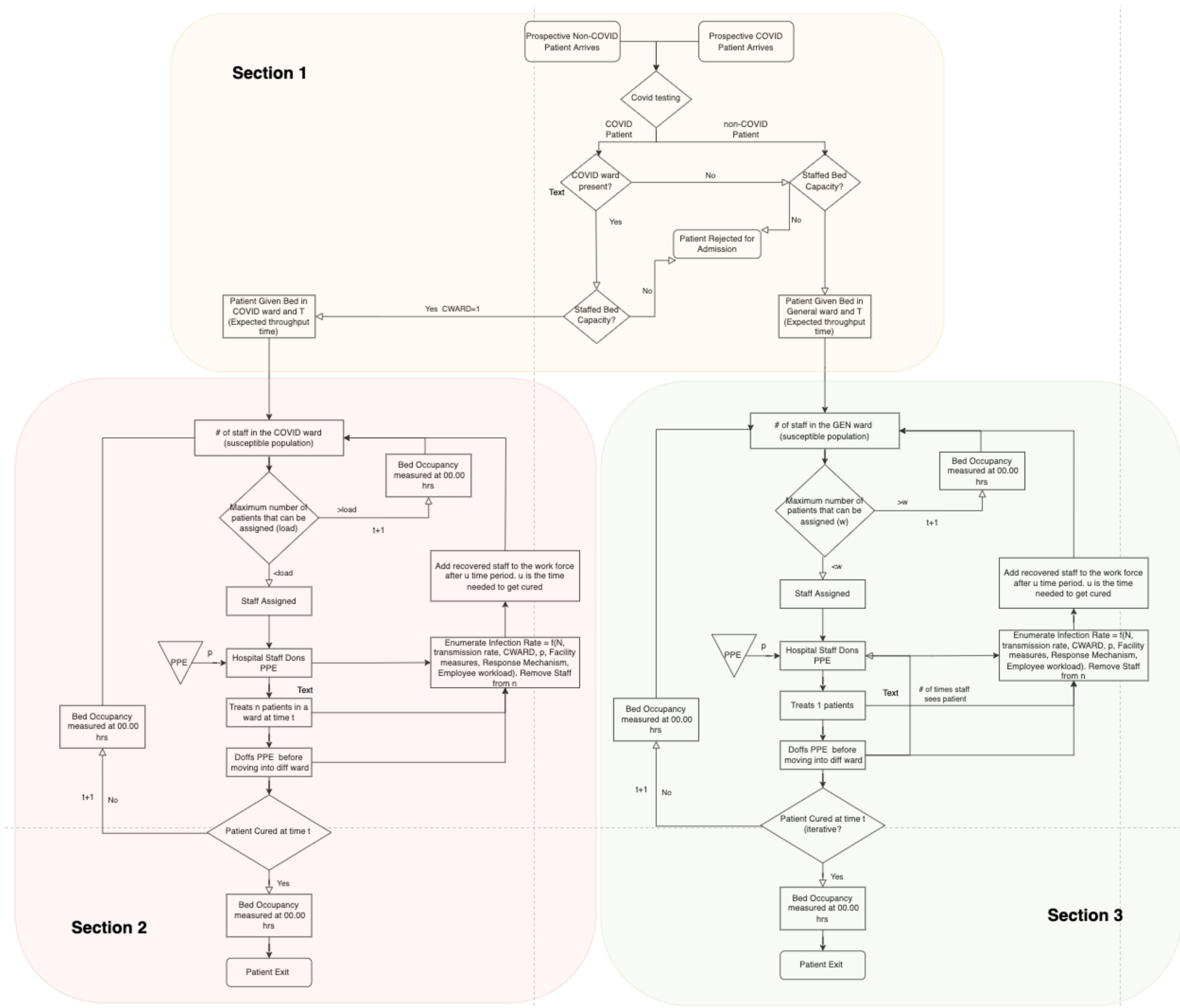
Agent-based models have been applied extensively in OM (Tong et. al., 2018; Chandrasekaran et. al., 2015) and healthcare (Pham et. al., 2021) literatures to formulate a system characterized by rich and nonlinear dynamics with multiple agents involved. Although econometric analysis enables us to understand the simple linear relationship between bed utilization rates and inventory level drawn from statistically significant results based on the available data, such analysis precludes our understanding of the evolution of complex interactions among different hospital agents when different configurations of isolation wards are introduced in the hospital. In such situation an agent-based simulation will aid in modeling the dynamics in a multi-agent care giving system, reminiscent of typical hospital operations, in the context of the introduction of isolation wards and in analyzing policy effect on how the hospital manages its PPE inventory and care services. The multi-agent simulation is particularly useful in modeling the nosocomial virus transmission and how the dynamics evolves over time as the agents' behavior adapts to the introduction of isolation wards.

The first key component of our ABM is to model a typical hospital operation in the context of the pandemic. We followed the ABM modeling presented in Pham et. al. (2021). The study presents the simulation of a hospital in the context of COVID-19 pandemic in UK. We made several modifications in the model to ground it in the US healthcare context based on the key inputs that we derived from our field research. We have presented the process flowchart in Figure 4.2. The entire process can be largely categorized into three sections. In section 1 we describe the process of patient acceptance into the system and describe the process of how a patient is allocated a bed. In section 2 we describe the process of how HCWs interact with PPE inventory and use PPEs to treat patients in an isolation ward. In section 3, we describe the similar process to treat patients in general wards. We simulate multiple scenarios: four different hospital sizes accounted by the number of staffed beds and nurses that the hospital employs, and three different nurse-to-patient ratios. We created scenarios depending on whether the hospital has isolation wards. In case the simulated hospital does not have an isolation ward we define a total of 12 scenarios. The hospital that has isolation wards, we consider a range of values for the proportion of resource allocation from 10% to 100%. Hence, the hospital with isolation wards has a total of 120 simulated scenarios. We iterated each scenario 20 times with different seed values.

In section 1, we assume two patient pools – patients who have COVID-19 and general patients. We assume the stable general patient hospitalization follows Poisson distribution with mean 40 patients (Pham et. al. 2021). We enumerated the COVID-19 patient hospitalization pattern depending on the size of the hospitals. We model the hospital sizes based on different hospitals in the Beaumont health system in Michigan, without the loss of generality. We consider Beaumont system for the information because of two distinct reasons. First, the health system routinely publishes the number of HCWs (nurse practitioners) each hospital employs each year which provides us with suitable information to build the model. Second, the sizes of the eight hospitals that Beaumont has in Michigan vary from the highest 1131 beds to a lowest of 99 beds. As such, this offers us enough variance to model the interactions among the agents across wide spectrum of hospital sizes. We consider four different hospitals in the Beaumont system. We considered the largest hospital in the system in Michigan – Beaumont Royal Oak – that has 1131 beds and 2678 nurse practitioners. Next, we consider a large hospital in the system – Beaumont Dearborn – that has 632 staffed beds and 1235 nurse practitioners. We considered another hospital whose size correspond to the average of the hospital sizes in Michigan – Beaumont Grosse Pointe – that has 280 staffed beds and 527 nurse practitioners. Toward the lower end of the hospital size spectrum, we consider Beaumont Wayne hospital that has only 99 staffed beds and 344 nurse practitioners.

Each hospital belongs to either Oakland or Wayne counties in Michigan. These counties experienced the largest number of COVID-19 infections in Michigan. Such a setup helps us to understand the relationships between agents in the context of high hospitalization demand. We collected the daily new COVID-19 cases data for each of the counties to predict the actual demand that each of hospitals in the model may face daily. We adopted the estimate by Menachemi et. al. (2021) to assess the hospitalization conversion rates of COVID-19 cases, categorized by age groups. We collected the population by age groups in the Oakland and Wayne counties in Michigan to enumerate the total hospitalization cases in these counties. Next, we assume that a hospital will experience total number COVID-19 related patient hospitalization in the county depending on the proportion of staffed beds that the hospital has in the county of operation. Consequently, we estimate the total number of COVID-19 patient hospitalization demand that a hospital (of certain size) may receive. We used 290 days of demand data starting from March 1, 2020, until December 15, 2020. We did not consider data beyond December 15 because after that period HCWs and patients were inoculated which may change the virus reproduction number and hence the overall agent dynamics, which we did not account for in the simulation.

Figure 4.2 Agent Based Modeling Process Flow Diagram



All the patients are tested before the bed allocation process. We assume that the hospital can get the testing results instantaneously. If the isolation wards in the hospital have any vacancy a staffed bed is allocated to the infected patient else the patient is turned away. We learned from the clinicians that patients with the viremia were not accommodated in the general wards in case isolation wards were full. In the absence of any isolation wards, hospitals do not differentiate between the admission process of infected and the general patient. In case of no vacancies the patient is rejected for admission. We record the instances of rejection given any contingencies. We record the expected time (LOS) required to treat the patients. The expected LOS for the COVID-19 patients follows a Gamma distribution with mean and standard deviation of 31.8 days and 30.08 days respectively (Pham et. al. 2021). It has shape and scale of 1.88 and 0.25 respectively (Pham et. al. 2021). The expected throughput time for the general patients follows a Weibull distribution with shape and scale of 0.92 and 4.8 respectively and mean of 4.35 days (Pham et. al. 2021). Please note that the simulated hospital does not have any intensive care units and we assume the patients are low to moderately ill.

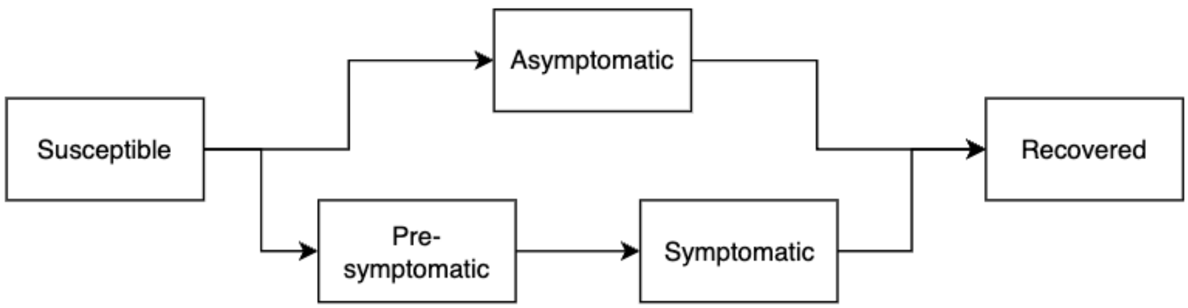
In section 2, we provide information about the HCW assignment process and the PPE don and doff patterns by the HCW in the isolation wards. Based on the discussion with the clinicians, we assume that the hospital ran three shifts, each lasting for at least 8 hours. We assumed each healthcare workers did six rounds of patient visits in each shift (Pham et. al. 2021). Patients are randomly assigned to three different HCWs (each belonging to different shifts). We continue to assign patients randomly to a HCW until it exceeds the load capacity of the HCW (defined by the HCW-to-patient ratio of the scenario). In case a patient cannot be assigned to HCW, the patient waits for another cycle to get assigned. This increases the actual LOS of the patient by another day. During each round of visit each HCW treats all the patients assigned to her. Before treating a patient, she requests a set of PPEs from the inventory. If the request is fulfilled, she dons the PPE and treats patient and doffs PPEs after seeing the patient. After a patient is seen by the assigned HCWs we reduce the LOS by one day. We assume that the patient is fully cured when the LOS equals 0. At this point the hospital discharges the patient and measures the bed occupancy. The process steps in section 3 are identical to that in section 2 with one difference. If the hospital has isolation wards, the HCWs in the general wards are not allowed to access PPEs from the inventory. These HCWs use surgical masks to treat patients. However, if the hospital has no isolation wards the process flow in section 3 is similar to that of section 2.

In both sections 2 and 3, HCWs places request for PPE and an agent responsible for inventory management fulfils the request. We assume the fulfillment happens instantaneously if the requested number of PPEs are in stock. The HCWs in the hospital with no isolation wards requests for several PPEs in a patient visit round that is equal to the number of patients assigned to her. The HCWs in the hospital with isolation wards requests for only one set of PPEs in a patient visit round. We assume the initial inventory count is 10,000. There maybe two possible outcomes depending on the inventory status. The inventory manager may be able to fulfil the entire order, in which case the simulation assigns a factor of 1 to the requesting HCW. The inventory manager may be able to fulfil a part of the request. In such case, the simulation assigns a factor equal to the proportion of the order met to the requesting HCW during the round. This factor is used to discount the effectiveness of the PPE, which simulates the fact that in case of partial fulfilment the HCW must reuse PPEs which has lower effectiveness than a sanitized set of PPEs. Besides, the inventory manager is responsible for procuring PPEs. Based on the suggestions of the practitioners we adopted continuous inventory review process. The inventory manager stores at least 7 days worth of PPE demand data. After the end of day, the manager reviews the inventory status. Based on our discussion with the supply chain professionals we adopt an inventory management policy that lets the inventory manager place replenishment requisition if the level falls below 7 days worth of inventory. The maximum stocking level is 90 days worth of inventory. We adopted exponential smoothening demand forecasting methodology to predict the future PPE inventory burn rate based on which the inventory status is evaluated by the agent. We used 60% as the value of the smoothening constant to capture the uncertainty in the demand for PPEs.

In the simulation, an agent in the hospital can belong to one of the five disease states – Susceptible (S), Asymptomatic (E_A), Presymptomatic (E_P), Infected (I) or Recovered (R). We did not model agent death in the simulation. All susceptible agents have not been infected yet but stand a chance to get exposed to the virus. All the asymptomatic and presymptomatic patients have been exposed to the virus. The asymptomatic agent may never show symptoms during her stay in the hospital. However, a presymptomatic agent, after an incubation period, may start exhibit symptoms. The incubation period is idiosyncratic, and we assume the period follows a Gamma distribution with mean of 5.5 days and standard deviation of 2.29 days (Evans et. al., 2021). The shape and scale of the distribution is 5.807 and 0.948 respectively. An infected agent has the viremia and symptoms. An agent is in recovered state when she has tested negative for COVID-19 and exhibits no symptoms.

A patient may be infected before he is admitted to the hospital or may eventually become infected in the hospital. We model the viral transmission within the hospital using SEIR model (Pham et. al., 2021; Mwalili et. al., 2020) which is commonly used to model viral progression in healthcare literature. We depict the process flow in Figure 4.3. We assume there is no community infection among patients or HCWs. The only difference between transmission patterns in the isolation wards and the general wards is that isolation wards do not have any susceptible patient population unlike the general wards. However, the HCWs in those wards are susceptible to contract the viremia. Viral transmission in the hospital happens only via HCWs as all the patients are assumed to have private room. As such the patients do not encounter another patient. HCWs may get infected as they treat an infected patient, who may belong to either of E_A, E_P and I, and then spread the virus as they continue to treat other susceptible patients until the HCW becomes symptomatic with COVID-19.

Figure 4.3 Agent Based Modeling Disease Progression



We model the reproduction of infection from patient to HCW and from HCW to patients following a Bernoulli distribution. The probability of transmission is modeled following Pham et. al. (2021) with a modification, we assume that the effectiveness of mask usage decreases by a factor that is proportional to mask reuse. We assume no used mask sanitization facility in the hospital. We model HCW to HCW viral transmission may happen as HCWs meet in the breakout rooms. We assume that the HCWs wear normal face masks in the breakout rooms. We characterize the effectiveness of the entire PPE set by the effectiveness of N95 masks. We assume the effectiveness of N95 masks is 95% and that of normal facemasks (surgical masks) are about 50% (Steuart et. al. 2020). We assume that 7.97% and 7.63% of the infected patient population are asymptotic and presymptotic, respectively (He et. al. 2020). These population of patients go undetected and are allocated general patient beds and become viral source in those wards. After the incubation periods the asymptotic and pre-symptotic agents exhibits symptoms and become infected. The infected patients in the general wards are moved to the isolation wards, in case the hospital has an isolation ward, and the expected length of stay is updated accordingly. We validated from our interviews with clinicians that the physicians quarantine themselves for 7 days upon being symptomatic. When a HCW goes to quarantine the hospital clears her patient queue and the patients have to wait until they get assigned to a new HCW. Such assignment may take a few days depending upon bed occupancy of the hospital which may increase the actual length of stay of the patient in the hospital. Consequently, the hospital that witness higher HCWs quarantine rates may experience longer LOS, which may increase the bed occupancy rates. After that HCWs makes recovery, they return to normal operations. We measure the daily rate of new infection among HCWs and patients and the total HCWs in quarantine. We assume that a recovered agent cannot be infected again.

4.5.2. Tradeoffs Associated with the Isolation Wards: Estimation Methodology and Results

As we reported earlier, the simulation has been run for 290 days from March 1, 2020, until December 15, 2020. However, we only consider a subset of the simulation data for subsequent analysis that represent the first two peaks of COVID-19 hospitalization in the state of Michigan. We consider the data at the peaks of COVID-19 hospitalization in our analysis because we expect higher bed occupancy rates during that period and, consequently, higher inventory levels and worsening patient care capacity. Hence, we think such time context would be ideal to study the intended tradeoff of establishing isolation wards in the simulated hospital environment. Hence, we consider simulation data points between April 1, 2020, and May 2, 2020, and between October 1, 2020, and December 15, 2020. We have a panel data structure of 132 simulated scenarios each having 104 days of observations.

Before we present the results, we discuss the summary statistics of the data we retrieved from the simulation. The mean and standard deviation of the daily hospitalization demand (COVID-19 and non-COVID-19 patients) are 50.94 and 13.67, respectively. The mean and standard deviation of the N95 masks inventory level ($Inventory_{it}$) that the average hospital maintains are 159231.2 and 171330.7, respectively. When the hospital does not have isolation wards, the mean and standard deviation of the N95 masks inventory level that the simulated hospital maintains are 307745.6 and 234677.5, respectively. Conversely, the mean and standard deviation of the N95 masks inventory level for an average hospital that has dedicated isolation wards are 144379.7 and 156077.1, respectively. The results of the summary statistics indicate that the hospitals that has isolation wards indeed require almost half of the inventory level to provide care services as compared to its counterpart that has no isolation wards. However, it is critical to understand how the hospitals with isolation wards hold up against the hospitals with no isolation wards from clinical performance perspective. The mean and standard deviation of the bed utilization ($BedUtilization_{it}$) of the hospitals considered in the simulation are 64.97% and 22.88% respectively. The mean and standard deviation of the bed utilization of the hospitals, that do not have an isolation ward, are 75.19% and 19.98% respectively. The mean and standard deviation of the bed utilization of the hospitals, that have isolation wards, are 62.84% and 22.85% respectively, which implies that hospitals with isolation wards experience lower bed occupancy rates as compared to their counterpart. However, such lower bed occupancy may be due to the increasing number of patient rejection by the hospital. We find that the mean and standard deviation of the patient rejections ($Rejection_{it}$) by the hospitals, that do not have an isolation ward, are 12.76 and 13.39 respectively, whereas the metrics for the hospitals, that have isolation wards are 20.78 and

15.08 respectively. This statistic is indicative of lower care capacity that hospitals with no isolation wards offer in the community.

Next, we discuss the summary statistics regarding nosocomial viral transmission in healthcare workers and patients. The mean and standard deviation of the number of infected HCWs being quarantined ($HCWQuar_{it}$) in the entire dataset are 33.35 and 111.14, respectively. The mean and standard deviation of the number of infected HCWs being quarantined in the hospitals with no isolation rooms are 33.28 and 109.23, respectively. The mean and standard deviation of the number of infected HCWs being quarantined in the hospitals with isolation wards are 33.35 and 111.36, respectively. There do not seem to be any observable difference in the metrics. The mean and standard deviation of the patient infection rate ($PatientInfec_{it}$) in the dataset from simulation are 0.3585 and 0.484, respectively. The mean and standard deviation of the patient infection rate in the hospitals with no isolation rooms are 0.3844 and 0.427, respectively. The mean and standard deviation of the patient infection rate in the hospitals with isolation wards are 0.356 and 0.489, respectively. We observe that the infection rates in the patients is slightly less in the hospitals with isolation wards versus in the hospital with no isolation wards. These summary statistics provide initial indication of better inventory and infection prevention performance for the hospitals with isolation wards, in lieu of care capacity the hospital can offer.

Figure 4.4 Descriptive Analysis (Red: Scenarios with No Isolation Wards; Green: Scenarios with Isolation Wards)

Figure 4.5 Descriptive Analysis (Red: Scenarios with No Isolation Wards; Green: Scenarios with Isolation Wards)

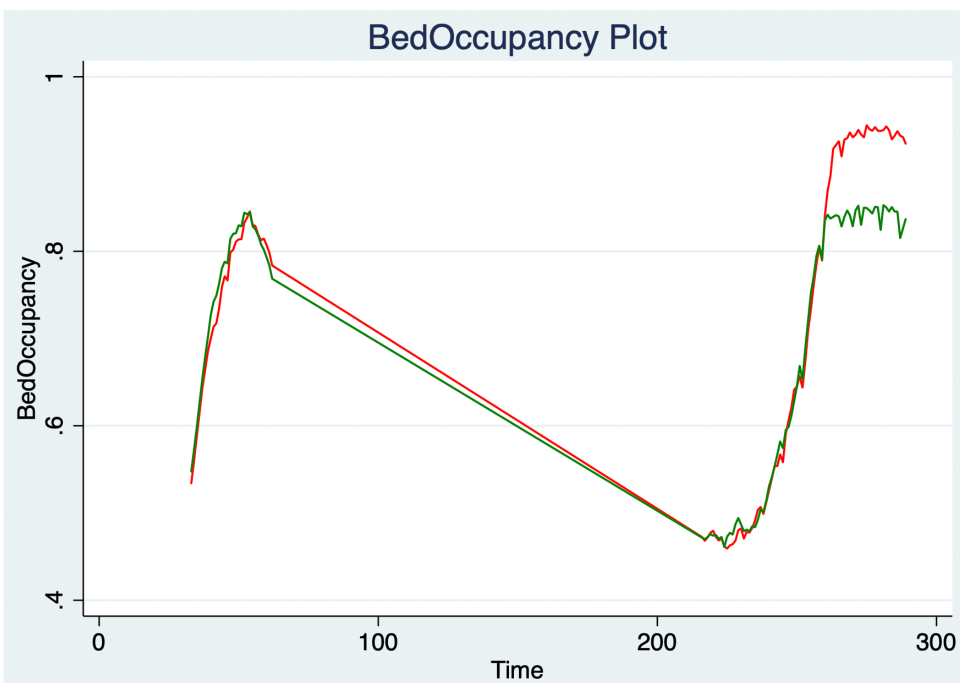


Figure 4.6 Descriptive Analysis (Red: Scenarios with No Isolation Wards; Green: Scenarios with Isolation Wards)

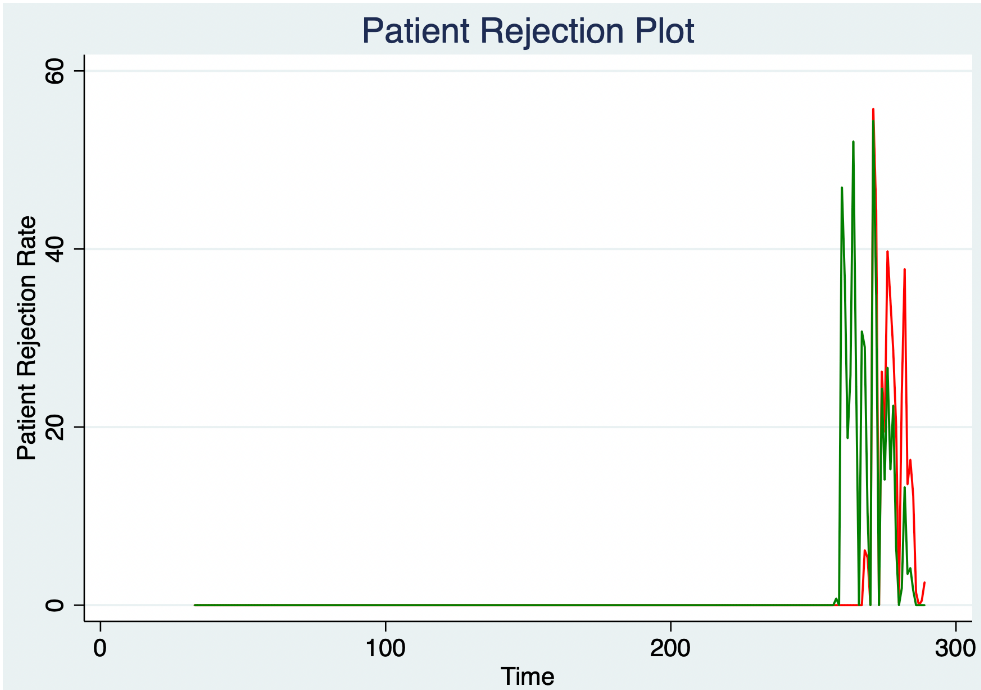


Figure 4.7 Descriptive Analysis (Red: Scenarios with No Isolation Wards; Green: Scenarios with Isolation Wards)

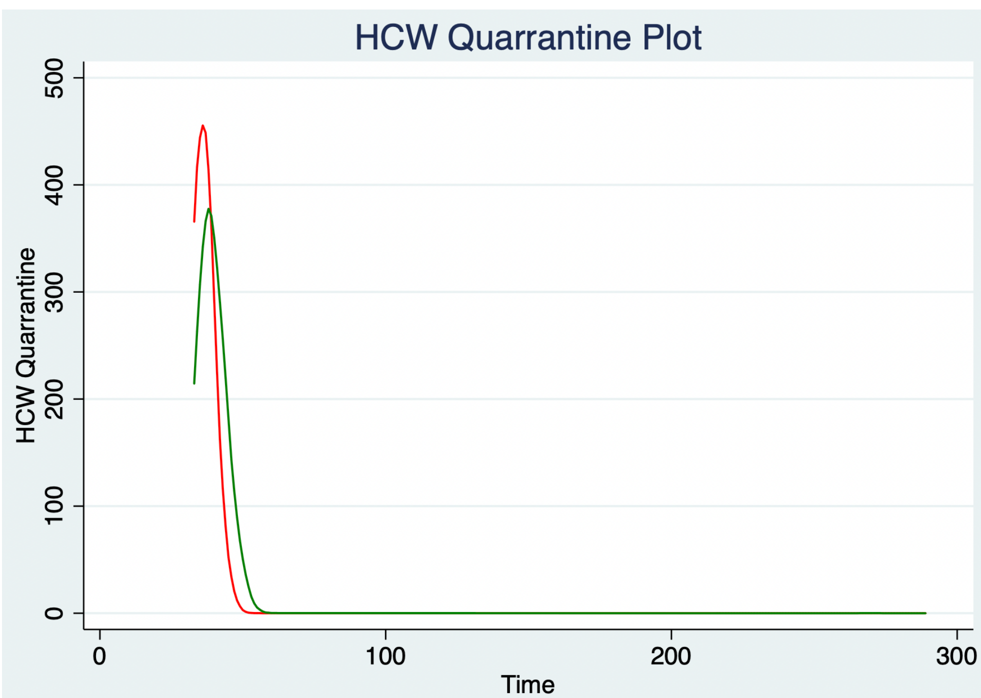
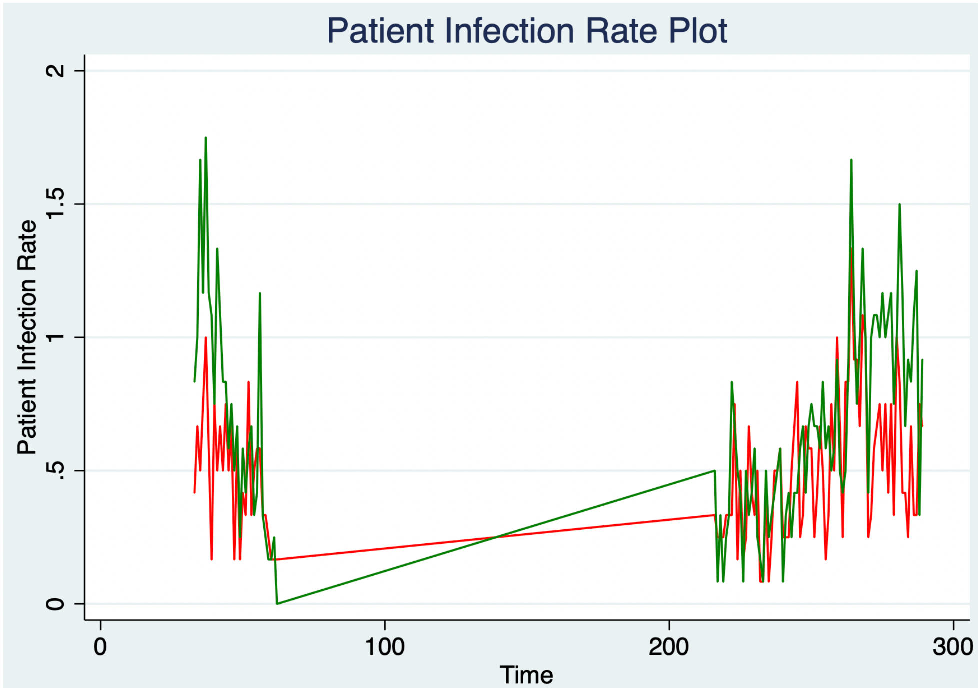


Figure 4.8 Descriptive Analysis (Red: Scenarios with No Isolation Wards; Green: Scenarios with Isolation Wards)



To analyze the simulation data, we use feasible generalized least squares (GLS) panel regression as the estimation methodology since it allows us to model heteroskedasticity across different hospitals and correlation within each hospital panel structure (Wooldridge, 2010; Gao and Hitt, 2012). Additionally, we include controls for demand ($Demand_{it}$) for hospitalization and number of staffed beds ($StaffedBed_i$) to account for the only hospital level heterogeneity in the data. We performed our estimation using the xtgls command in STATA 15. We report effect of the presence of isolation wards ($IsolationWard_i$) on $Inventory_{it}$ in column 1 of Table 4.3. We report that $IsolationWard_i$ has a negative and significant effect on $Inventory_{it}$ (β = -1.3; p < 0.001). We find that with the adoption of isolation wards a hospital experiences 130% lower inventory level as compared to hospitals with no isolation wards. We report the effect of the presence of $IsolationWard_i$ on $BedUtilization_{it}$ in column 2 of Table 4.3. We report that $IsolationWard_i$ has a negative and significant effect on $BedUtilization_{it}$ ($\beta = -0.0607$; $p < 0.001$). We find that with the establishment of isolation wards a hospital experiences 6.07% lower bed utilization as compared to hospitals with no isolation wards. This may be because of higher rejection rates due to the establishment of isolation wards. We report effect of the presence of $IsolationWard_i$ on $Rejection_{it}$ in column 3 of Table 4.3. We report that $IsolationWard_i$ has a positive and significant effect on $Rejection_{it}$ ($\beta = 0.306$; $p < 0.001$). We find that hospitals with isolation wards experience 30.6% higher patient rejection rates as compared to hospitals with no isolation wards. These results suggest that the hospital with isolation wards continue to reject patients even though it experiences lower bed occupancy rates, which is indicative of empty beds in the system that the hospital cannot use toward patient admission. Hence, it seems that having isolation ward in a hospital artificially reduces the hospital's capacity to offer care services to the population.

We report effect of the presence of $IsolationWard_i$ on $HCWQuar_{it}$ in column 4 of Table 4.3. We find that $IsolationWard_i$ has a non-significant effect on $HCWQuar_{it}$ ($\beta = 0.089$; $p > 0.1$). We report effect of the presence of $IsolationWard_i$ on $PatientInfec_{it}$ in column 5 of Table 4.3. We find that $IsolationWard_i$ has a significant and negative effect on $PatientInfec_{it}$ ($\beta = -0.045$; $p < 0.05$). We estimate that with the adoption of isolation wards a hospital experiences 4.5% lower within hospital patient infection rates as compared to hospitals with no isolation wards.

Table 4.3 Regression Analysis of Simulation Data

Variables	(1) $Inventory_{it}$ (F-GLS Model)	(2) $BedUtilization_{it}$ (F-GLS Model)	(3) $Rejection_{it}$ (F-GLS Model)	(4) $HCWQuar_{it}$ (F-GLS Model)	(5) $PatientInfec_{it}$ (F-GLS Model)
$IsolationWard_i$	-1.3*** (0.046)	-0.061*** (0.003)	0.306*** (0.027)	0.089 (0.141)	-0.045*** (0.007)
$Demand_{it}$	-0.01 (0.007)	0.015*** (0.001)	1.426*** (0.016)	-0.001 (0.008)	0.025*** (0.004)
$StaffedBeds_i$	0.794*** (0.025)	-0.096*** (0.001)	-0.84*** (0.013)	0.425*** (0.049)	0.166*** (0.002)
Observations	13,728	13,728	13,728	13,728	13,728
N	132	132	132	132	132
Wald chi-square	1860.22	12403.75	10770.50	76.32	7096.54
p-value	0.00	0.00	0.00	0.00	0.00

The standard error has been reported in the parenthesis.
+. $p < 0.1$ * $p < 0.05$ **. $p < 0.005$ ***. $p < 0.001$

4.6. Discussion and Conclusions

4.6.1. Theoretical Implications

We conduct a multi-method research to explore how different hospitals respond to the growing hospitalization demand during an ongoing exogenous health crisis by managing its PPE inventory. We found econometric evidence that some of the bigger health systems that witness higher hospitalization demand may tend to maintain higher inventory levels. The results are indicative of impulsive decisions by the procurement managers to maintain PPE fill rate in the face of burgeoning demand for PPEs. This result supports the existing theory in OM literature that has investigated inventory management practices in the context of increasing demand (Zepeda et. al. 2016; Fisher and Raman 1996). This practice is unsustainable as it may inflate the price of PPEs or make the equipment even more scarce to procure, making caregiving more expensive service during the period of dire need. Also, there is a risk that a significant portion of such inventory may need to be written off due to small self-life, the portion that could have been otherwise used by hospitals in dire need to such PPEs. Hence, the econometric results indicate toward a more non-equitable distribution of critical resources during the pandemic. The result is surprising given the context of inadequate supply of PPEs. In our opinion, our study is the first of its kind to conduct field research to understand how these hospitals were able to bulk-up on PPEs when most of the hospitals were struggling to procure required PPEs to keep their HCWs safe while treating patients.

We observed that ability of the procurement team to pivot to alternative suppliers enabled the procurement team to maintain consistent supply of PPEs. We further observed that hospitals were able to attenuate the demand for PPEs by internally rearranging assets that enabled them to reduce PPE burn rate and conserve PPEs along the way. We identify these to be tenets of operational flexibility. Hence, the study upholds the importance of flexibility in the operations and supply chain management practice as the hospital combats the uncertain and burgeoning PPE demand patterns. As such our study makes strong contribution to the stream of literature that long debated the importance of operational flexibility in managing organizational performance in the context of environmental uncertainty (Swamidass and Newell 1987; Pagell and Krause 1999; Badri et. al. 2000; Pagell and Krause 2004). Our study informs this stream of literature that healthcare organizations may better prepare themselves as compared to their competitors to provide for their healthcare workers when there is looming crisis of critical equipment because of environmental healthcare crisis.

Going forward we further investigate the impact of the creation of isolation wards in the hospitals, which is a type of asset rearrangement, on the way the hospitals manage their PPE inventory and patient care. We develop an agent-based model, that is grounded in practice, to model the agents – patients, healthcare workers and inventory manager – and to observe the evolution of interactions among them, way they provide care and consequent nosocomial viral transmission. We then use the simulation to observe multi-faceted performance measures of the hospital as we compare different hospital asset rearrangement policies – creation of isolation wards versus the baseline policy when the hospital has no isolation wards. We studied the effect of these policies on PPE inventory levels, resource utilization and nosocomial transmission to understand the tradeoffs among competing priorities of the hospital. The analysis unveils existence of tradeoffs among these metrics that calls for the attention of hospitals to manage. The results indicate that though the hospital can provide equivalent quality of care services with fewer PPE inventory, the hospital experienced lower bed utilization despite higher rejection rates. This is indicative of the higher opportunity costs of de-pooling the hospital infrastructure to create isolation wards as the hospital cannot use empty beds in a type of ward to admit incoming patients in other wards. Additionally, the results show only marginal difference in rates of nosocomial infection under these policies. As such, our study makes strong contribution to the resource de-pooling literature as it lends support to the existing literature which argues that infrastructure de-pooling reduces customer accessibility to the system (Fard et. al. 2019; Eftekhar et. al. 2018; Natarajan and Swaminathan 2014).

4.6.2. Managerial Implications

Our study demonstrates the tradeoff among the objectives of managing PPE inventory levels, resource utilization and nosocomial transmission as the hospital decides to implement isolation ward and calls for the attention of hospital administrators to actively manage the patient care depending on the hospitalization demand. The study serves as a reminder to the administrators to reflect on the priorities of the hospital. For example, the goal of a community hospital may be to make healthcare accessible to the population in the community and may care less about the increasing cost of the care services. In such case, the administrators may consider to not segregate hospital infrastructure into isolation wards as our analysis indicates high opportunity costs of such strategy as the hospitals experience high rejection rates despite having lower bed occupancy levels. On the contrary, a for-profit hospital may consider creating isolation wards as our analysis suggest that hospitals with isolation wards may provide equivalent care services while carrying 130% lower PPE inventory as compared to a peer hospital without isolation wards. Our study suggests that during the start of the pandemic when hospitals experience scarcity of PPEs, the hospitals may consider creation of isolation wards as hospitals can continue to provide care services with lower number of PPE inventories in stock. However, our study indicates that the administrators should have the flexibility to dynamically reserve resource toward isolation wards depending on the hospitalization pattern and demand to lower the opportunity costs of empty patient beds due to segregation. For example, during the peak of COVID-19 patient hospitalization the hospital may decide to allocate higher proportion of resources toward creating isolation ward. However, the hospital may choose to gradually decrease the proportion as the hospital experience lower COVID-19 patient hospitalization rates.

First, the study questions the assumptions based on which the policy has been defined: the hospitals can accurately identify infected people from the non-infected ones using COVID-19 testing. We notice that this assumption may not hold true as almost 15% of the infected patients admitted to the hospital later shows sign of COVID-19, making it difficult to control the nosocomial spread in the general ward. As Kucirka and Lauer (2020) has suggested that the probability of COVID-19 tests reporting false negatives decrease as the number of days passed since the viremia exposure, our study encourages the hospital clinical administrators to conduct ad-hoc testing of the patients in the general wards. As such the hospital will be able to detect asymptomatic cases of COVID-19 before the patients turn symptomatic and hopefully before she spreads the infection to other patients in the wards.

As healthcare workers (HCWs) are carriers of the infection within the hospital, the study suggests that administrators must protect the HCWs from getting affected, especially in the general wards. Currently, the hospitals that have the isolation wards do not let the HCWs use PPEs to treat patients in the general ward, which helps the hospital to conserve the PPE. We suggest that HCWs should use PPEs to treat patient in the general wards too. However, the usage patterns can be different from the HCWs in the isolation wards. The administrators may allocate general ward HCWs a set of PPEs to treat all the patients in a round, which she can doff after every round. Given the low incidence of COVID-19 patients in the general wards such basic protection level might be sufficient to protect the HCWs from contracting the virus. Additionally, the hospitals should consider investing in infrastructure or building partnerships with organizations that can sanitize used PPEs. Such collaboration may enable hospitals to reuse PPEs which may attenuate the internal demand for PPEs. For example, Sparrow Hospital collaborated with Michigan State University to use the university facility of heated forced air to decontaminate used N95 facemasks[29].

4.6.3. Limitations and Directions for Future Research

Though our multi-method study provides robust understanding of research questions and enables us to control endogeneity issues in analysis, our research is not devoid of limitations which opens opportunity for future research. The first limitation of our study is our inability to conduct an extensive field research. We conducted interviews with only five hospitals in Michigan. Within those five we were able to talk to both supply chain and clinical professionals of two hospitals. Though the discussions gave us insight into daily challenges of providing care services during pandemic an extensive field research would have opened us to diverse viewpoints of what the other hospitals (possibly from other states) have been doing. As such, that might have helped in curating the research question more effectively and define the simulation in robust way. Future research should consider a robust fieldwork of hospitals across different states in the country as their operations might be contingent upon varying state policies.

[29] https://www.lansingstatejournal.com/story/news/2020/04/03/msu-michigan-state-university-baking-masks-covid-19/5117840002/

APPENDICES

APPENDIX A

CDC Guidelines

As noted in Table A1, the five categories of guidelines provided by CDC (Worker Safety and Support, Patient Service Delivery, Data Streams for Situational Awareness, Facility Practices and Communications) can be further divided into 10 practical approaches with approach # 1 (Comprehension and execution of IPC practices) divided into four sub-activities and approach # 9 (Extent of enhancing facility's response mechanisms by becoming familiar with pandemic, COVID-19 specific, and crisis standards of care) divided into five sub-activities. Any news item that resonated with one of the approaches was coded under that heading. These approaches are listed in Table A1.

Table A1 Health System Activities/Approaches

Approach Categories	Practical Approaches that Health Systems can follow	Sub-Activities
A. Worker Safety and Support	1. Comprehension and execution of IPC practices	1a. Extent of HCP training on PPE use 1b. Extent of PPE optimization 1c. Extent of implementation of source control 1d. Extent of PPE tracking
	2. Develop protocols for HCP to monitor themselves for infection, and extent of restricting them from work post exposure, and to plan for safely allow return to work	
	3. Extent of provision of extra support for HCP (e.g., support for mental health, parenting, meals, and non-punitive sick policies.)	
B. Patient Service Delivery	4. Extent of help to HCP to become well-versed in evidence-based care	
	5. Comprehension of the guidance for discharging a patient with suspected or confirmed COVID-19 from the hospital to home or to a long-term care facility	

Table A1 (cont'd)

	6. Extent of telehealth usage (e.g., implementation of a phone advice line to triage patients and to address questions and concerns from possible COVID-19 patients)	
C. Data Streams for Situational Awareness	7. Extent of maintaining awareness of the COVID-19 situation in the state, city, and facility	
	8. Extent of reporting hospital capacity data to state administration or registry.	
D. Facility Practices	9. Extent of enhancing facility's response mechanisms by becoming familiar with pandemic, COVID-19 specific, and crisis standards of care	9a. Extent of using hospital preparedness checklist to estimate and respond to the surge in demand for hospital-based services
		9b. Extent of cohorting patients with COVID-19 and assigning dedicated staff.
		9c. Development and implementation of plans to reduce staffing shortages and assessment of need for alternative care sites, such as emergency field hospitals
		9d. Instance of setting up an Emergency Operations Center (EOC) if not already present
		9e. Extent of work towards resuming/maintaining essential healthcare services using a risk/benefit analysis
E. Communications	10. Extent of communication with HCP, patients, and the community (e.g., virtual town halls, daily huddles with local leadership, emails and phone conferences for staff)	

To extract activities of each of the health systems we first used Bert Extractive Summarizer (BERT) (Derek, 2019) to summarize the news contents. The summarizer embeds the sentences, runs a clustering algorithm, and finds the sentences that are closest to the cluster's centroids. These summarization algorithms generally depend on the frequency of words in the news content to form clusters and choose sentences with occurrences of those words as ideal candidates in the summary (Derek, 2019). There are few drawbacks with using the summarization algorithm. First, instances of activities performed by a health system may not have words with the highest frequency and we may lose those sentences in the summarization process. Second, if text reports different activities by more than one health systems then the ones identified in the BERT summarization process, we may lose the context of such activities. As an example, consider the following news item:

> *Michigan Medicine will not open a field hospital as it was initially planned due to the curve "significantly flattening." It continues to plan for a potential need, but there is no definite date on which the field hospital would open at this time. "It appears from current COVID-19 cases and modeling that the curve is significantly flattening," a Michigan Medicine spokeswoman said. Michigan Medicine is still in communication with state officials to coordinate and determine future need. "Our ongoing focus is on our current capacity and readiness to serve patients in our existing hospital facilities." The TCF Regional Care Center is accepting its first 25 patients Friday, and will be staffed by Henry Ford Health System, McLaren Health Care, Beaumont Health and Detroit Medical Center. The Suburban Collection Showplace in Novi has been identified as a second field hospital. It is not expected to be running for several days.*

The corresponding BERT summarization is as follows:

> *Michigan Medicine will not open a field hospital as it was initially planned due to the curve "significantly flattening." "It appears from current COVID-19 cases and modeling that the curve is significantly flattening," a Michigan Medicine spokeswoman said. Michigan Medicine is still in communication with state officials to coordinate and determine future need. "Our ongoing focus is on our current capacity and readiness to serve patients in our existing hospital facilities.*

We notice that the summary drops out the sentence that the hospital system *continues to plan for potential need,* which is an important operational aspect reported in the news. To address this drawback, we developed an algorithm that extracts operational aspects more effectively. The pseudo code is provided below:

```
GET article_text
GET healthsystem_name
DO split article_text into sentence list
SET temporary_list as sentence_list
INITIALIZE summary_list to NULL list
IF healthsystem_name found in article_text THEN
        FOR each sentence in temporary_list
                IF healthsystem_name found in sentence THEN
                        ADD sentence and next two sentences in summary_list
ELSE
        ADD 'Text not found' in summary_list
MERGE items in summary_list to form text
RETURN text
```

As the instances of the activities by the health system generally occur in the news item adjacent to the sentence where the name of the healthcare system name is mentioned, we extract the sentence, where the name of the system appears, along with two following sentences. The resulting summarization is provided below.

> *Michigan Medicine will not open a field hospital as it was initially planned due to the curve "significantly flattening."*
> *It continues to plan for a potential need, but there is no definite date on which the field hospital would open at this time.*
> *"It appears from current COVID-19 cases and modeling that the curve is significantly flattening," a Michigan Medicine spokeswoman said.*
> *Michigan Medicine is still in communication with state officials to coordinate and determine future need.*
> *"Our ongoing focus is on our current capacity and readiness to serve patients in our existing hospital facilities*

The approach adopted in this study preserves all operational activities undertaken by the system. As same events are reported by multiple news channel, even if we missed some of the operational activities in our summarization process from one news source, consideration of multiple channels enables us to ensure that we have captured most of these activities.

APPENDIX B

Interview Questions Directed to the Supply Chain and Clinical Practitioners

Hospital Profile
1. How many beds do the hospital have?
2. How many clinical nurses does the hospital have?
3. How many physicians does the hospital have on payroll?
4. What is the nurse-to-patient ratio during pandemic?

Supply Chain Challenges
1. How did the supply chain department manage PPE inventory during pandemic?
2. How did the hospital manage PPE suppliers during the pandemic?
3. Did the hospital receive any state allocation of PPE?
4. Discuss about the PPE fulfillment policies during the pandemic. What was the maximum inventory that was maintained? What was the reorder point?
5. How did the hospital manage healthcare delivery in case it stock-out on PPEs?
6. How did creation of isolation ward, if any, help in the management of PPE inventory?
7. Discuss the policy about mask usage in both isolation ward, if any, and general wards?

Clinical Procedure and Challenges
1. How many employee shifts did the hospital have during pandemic? How many rounds per shift did the hospital have?
2. Discuss the process of patient admission during the pandemic.
3. Discuss hospital's policy about admitting asymptotic patients during the pandemic.
4. How did the hospital apportion hospital resources toward the creation of isolation wards? In case the reservation is time variant, how was the allocation decided?
5. What were the challenges that hospital faced regarding nosocomial transmission of the virus?
6. In case any patient contracted the virus was she moved to isolation wards if present?
7. Did the hospital perform any ad-hoc COVID-19 testing for the healthcare workers and physicians?

REFERENCES

REFERENCES

Aanestad, M., Jolliffe, B., Mukherjee, A., & Sahay, S. (2014). Infrastructuring work: Building a state-wide hospital information infrastructure in India. Information Systems Research, 25(4), 834-845.

Abdelhady, H., Abdelrazik, M., Abdi, Z., Abdo, D., Abdulle, A., Abel, L., . . . Adams, L. (2021). Effect of Convalescent Plasma on Organ Support–Free Days in Critically Ill Patients With COVID-19: A Randomized Clinical Trial. Jama, 326(17), 1690-1702.

Adbi, A., Chatterjee, C., Drev, M., & Mishra, A. (2019). When the Big One Came: A Natural Experiment on Demand Shock and Market Structure in India's Influenza Vaccine Markets. Production and Operations Management, 28(4), 810-832.

Administration, U. S. F. a. D. (2020). Coronavirus (COVID-19) Update: FDA Coordinates National Effort to Develop Blood-Related Therapies for COVID-19 [Press release]. Retrieved from https://www.fda.gov/news-events/press-announcements/coronavirus-covid-19-update-fda-coordinates-national-effort-develop-blood-related-therapies-covid-19

Agarwal, A., Mukherjee, A., Kumar, G., Chatterjee, P., Bhatnagar, T., & Malhotra, P. (2020). Convalescent plasma in the management of moderate covid-19 in adults in India: open label phase II multicentre randomised controlled trial (PLACID Trial). bmj, 371.

Alcacer, J., & Delgado, M. (2016). Spatial organization of firms and location choices through the value chain. Management Science, 62(11), 3213-3234.

AlQahtani, M., Abdulrahman, A., Almadani, A., Alali, S. Y., Al Zamrooni, A. M., Hejab, A. H., . . . Atkin, S. L. (2021). Randomized controlled trial of convalescent plasma therapy against standard therapy in patients with severe COVID-19 disease. Scientific reports, 11(1), 1-8.

Altay, N., & Pal, R. (2014). Information diffusion among agents: implications for humanitarian operations. Production and Operations Management, 23(6), 1015-1027.

Angrist, J. D., & Pischke, J.-S. (2008). Mostly harmless econometrics: An empiricist's companion: Princeton university press.

Araz, O. M., Galvani, A., & Meyers, L. A. (2012). Geographic prioritization of distributing pandemic influenza vaccines. Health Care Management Science, 15(3), 175-187.

Arifoğlu, K., & Tang, C. S. (2021). A two-sided incentive program for coordinating the influenza vaccine supply chain. Manufacturing & Service Operations Management.

Atasoy, H., Chen, P.-y., & Ganju, K. (2018). The spillover effects of health IT investments on regional healthcare costs. Management Science, 64(6), 2515-2534.

Atasoy, H., Demirezen, E. M., & Chen, P. Y. (2021). Impacts of Patient Characteristics and Care Fragmentation on the Value of HIEs. Production and Operations Management, 30(2), 563-583.

Ateş, İ., Erden, A., Güven, S. C., Gürler, E. K., Çağlayan, A., Güçbey, Ö., . . . Varan, Ö. (2021). Should timing be considered before abandoning convalescent plasma in covid-19? Results from the Turkish experience. Transfusion and Apheresis Science, 60(6), 103238.

Avby, G., Kjellström, S., & Bäck, M. A. (2019). Tending to innovate in Swedish primary health care: a qualitative study. BMC health services research, 19(1), 42.

Avendano-Sola, C., Ramos-Martinez, A., Munez-Rubio, E., Ruiz-Antoran, B., de Molina, R. M., Torres, F., . . . Payares-Herrera, C. (2020). Convalescent plasma for COVID-19: a multicenter, randomized clinical trial. medRxiv.

Axfors, C., Janiaud, P., Schmitt, A. M., van't Hooft, J., Smith, E. R., Haber, N. A., . . . Acosta-Ampudia, Y. (2021). Association between convalescent plasma treatment and mortality in COVID-19: a collaborative systematic review and meta-analysis of randomized clinical trials. BMC infectious diseases, 21(1), 1-23.

Ayer, T., Ayvaci, M. U., Karaca, Z., & Vlachy, J. (2019). The impact of health information exchanges on emergency department length of stay. Production and Operations Management, 28(3), 740-758.

Baker, A. (2001). Crossing the quality chasm: a new health system for the 21st century (Vol. 323): British Medical Journal Publishing Group.

Balcells, M. E., Rojas, L., Le Corre, N., Martínez-Valdebenito, C., Ceballos, M. E., Ferrés, M., . . . Huete, Á. (2021). Early versus deferred anti-SARS-CoV-2 convalescent plasma in patients admitted for COVID-19: A randomized phase II clinical trial. PLoS medicine, 18(3), e1003415.

Barabâsi, A.-L., Jeong, H., Néda, Z., Ravasz, E., Schubert, A., & Vicsek, T. (2002). Evolution of the social network of scientific collaborations. Physica A: Statistical mechanics and its applications, 311(3-4), 590-614.

Batt, R. J., Kc, D. S., Staats, B. R., & Patterson, B. W. (2019). The effects of discrete work shifts on a nonterminating service system. Production and Operations Management, 28(6), 1528-1544.

Bavafa, H., Hitt, L. M., & Terwiesch, C. (2018). The impact of e-visits on visit frequencies and patient health: Evidence from primary care. Management Science, 64(12), 5461-5480.

Beal, J. L., Kadakia, N. N., Reed, J. B., & Plake, K. S. I. (2020). Pharmacists' impact on older adults' access to vaccines in the United States. Vaccine, 38(11), 2456-2465.

Bechini, A., Moscadelli, A., Pieralli, F., Sartor, G., Seravalli, V., Panatto, D., . . . Boccalini, S. (2019). Impact assessment of an education course on vaccinations in a population of pregnant women: a pilot study. Journal of preventive medicine and hygiene, 60(1), E5.

Bégin, P., Callum, J., Jamula, E., Cook, R., Heddle, N. M., Tinmouth, A., . . . Bazin, R. (2021). Convalescent plasma for hospitalized patients with COVID-19: an open-label, randomized controlled trial. Nature medicine, 27(11), 2012-2024.

Bell, D. R., Gallino, S., & Moreno, A. (2018). Offline showrooms in omnichannel retail: Demand and operational benefits. Management Science, 64(4), 1629-1651.

Belloni, A., Lopomo, G., & Wang, S. (2017). Resource allocation under demand uncertainty and private information. Management Science, 63(12), 4219-4235.

Bennett-Guerrero, E., Romeiser, J. L., Talbot, L. R., Ahmed, T., Mamone, L. J., Singh, S. M., . . . Freedenberg, A. T. (2021). Severe acute respiratory syndrome coronavirus 2 convalescent plasma versus standard plasma in coronavirus disease 2019 infected hospitalized patients in New York: a Double-Blind randomized trial. Critical Care Medicine, 49(7), 1015-1025.

Berry, L. L. (2019). Service innovation is urgent in healthcare. AMS Review, 9(1-2), 78-92.

Boschma, R. (2005). Proximity and innovation: a critical assessment. Regional studies, 39(1), 61-74.

Brinck, K., Fischer, R., Groeneveld, J., Lehmann, S., De Paula, M. D., Pütz, S., . . . Huth, A. (2017). High resolution analysis of tropical forest fragmentation and its impact on the global carbon cycle. Nature communications, 8(1), 1-6.

Brodie, D. C. (1981). Pharmacy's societal purpose. American journal of hospital pharmacy, 38(12), 1893-1896.

Bugis, S., N. Caron, S. Kayeand, R. Khotar. (2011). Enhancing Surgical Care in BC: Improving Perioperative Quality, Efficiency, and Access.

Burt, R. S. (1992). Structural holes: Harvard university press.

Burt, R. S. (2017). Structural holes versus network closure as social capital. In Social capital (pp. 31-56): Routledge.

Bushwick, S. (2021). Why COVID Vaccines Are Taking So Long to Reach You. Public Health. Retrieved from https://www.scientificamerican.com/article/why-covid-vaccines-are-taking-so-long-to-reach-you/

CDC. (2020). Ten Ways Healthcare Systems Can Operate Effectively during the COVID-19 Pandemic. Retrieved from https://www.cdc.gov/coronavirus/2019-ncov/hcp/ways-operate-effectively.html

Chen, L., Xiong, J., Bao, L., & Shi, Y. (2020). Convalescent plasma as a potential therapy for COVID-19. The Lancet Infectious Diseases, 20(4), 398-400.

Chen, R., & Wong, E. (2019). The feasibility of universal HPV vaccination program in Shenzhen of China: a health policy analysis. BMC public health, 19(1), 1-10.

Chen, S.-I. (2017). Economic benefits of sharing and redistributing influenza vaccines when shortages occurred. PloS one, 12(10), e0186418.

Chun, Y., Harris, S. L., Chandrasekaran, A., & Hill, K. (2022). Improving care transitions with standardized peer mentoring: Evidence from intervention based research using randomized control trial. Journal of Operations Management.

Chung, L. S., Tkach, A., Lingenfelter, E. M., Dehoney, S. B., Rollo, J., de Havenon, A., . . . Wold, J. J. (2016). Tissue plasminogen activator prescription and administration errors within a regional stroke system. Journal of Stroke and Cerebrovascular Diseases, 25(3), 565-571.

Conlen, M. K., John; Leatherby, Lauren; Smart, Charlie. (2021). How Full Are Hospital I.C.U.s Near You? New York Times. Retrieved from https://www.nytimes.com/interactive/2020/us/covid-hospitals-near-you.html

Converse, P. D. (1949). New laws of retail gravitation. Journal of marketing, 14(3), 379-384.

Cramton, C. D. (2001). The mutual knowledge problem and its consequences for dispersed collaboration. Organization science, 12(3), 346-371.

Dai, T., Cho, S.-H., & Zhang, F. (2016). Contracting for on-time delivery in the US influenza vaccine supply chain. Manufacturing & Service Operations Management, 18(3), 332-346.

Deo, S., & Corbett, C. J. (2009). Cournot competition under yield uncertainty: The case of the US influenza vaccine market. Manufacturing & Service Operations Management, 11(4), 563-576.

Dhanorkar, S., & Muthulingam, S. (2020). Do E-Waste Laws Create Behavioral Spillovers? Quasi-Experimental Evidence from California. Production and Operations Management, 29(7), 1738-1766.

Dobrzykowski, D. D., & Tarafdar, M. (2015). Understanding information exchange in healthcare operations: Evidence from hospitals and patients. Journal of Operations Management, 36, 201-214.

DSHS. (2020). COVID-19 Vaccination Plan. Retrieved from https://dshs.texas.gov/news/updates/Texas-Vaccine-Plan-10-16-2020-DRAFT-CDC-Submission.pdf

Duan, K., Liu, B., Li, C., Zhang, H., Yu, T., Qu, J., . . . Hu, Y. (2020). Effectiveness of convalescent plasma therapy in severe COVID-19 patients. Proceedings of the National Academy of Sciences, 117(17), 9490-9496.

Duan, K., Liu, B., Li, C., Zhang, H., Yu, T., Qu, J., . . . Hu, Y. (2020). Effectiveness of convalescent plasma therapy in severe COVID-19 patients. Proceedings of the National Academy of Sciences, 117(17), 9490-9496.

Duan, W., Gu, B., & Whinston, A. B. (2008). The dynamics of online word-of-mouth and product sales—An empirical investigation of the movie industry. Journal of Retailing, 84(2), 233-242.

Duijzer, L. E., van Jaarsveld, W. L., Wallinga, J., & Dekker, R. (2018). Dose-optimal vaccine allocation over multiple populations. Production and Operations Management, 27(1), 143-159.

Eddy DM. Variations in physician practice: the role of uncertainty. Health Aff (Millwood) 1984

Everson, J. (2017). The implications and impact of 3 approaches to health information exchange: community, enterprise, and vendor-mediated health information exchange. Learning Health Systems, 1(2), e10021.

Facchini, E., Iacovidou, E., Gronow, J., & Voulvoulis, N. (2018). Food flows in the United Kingdom: The potential of surplus food redistribution to reduce waste. Journal of the Air & Waste Management Association, 68(9), 887-899.

Fang, E., Palmatier, R. W., & Steenkamp, J.-B. E. (2008). Effect of service transition strategies on firm value. Journal of marketing, 72(5), 1-14.

Finks, J. F., Osborne, N. H., & Birkmeyer, J. D. (2011). Trends in hospital volume and operative mortality for high-risk surgery. New England Journal of Medicine, 364(22), 2128-2137.

Fitzsimmons, J., & Fitzsimmons, M. J. (1999). New service development: creating memorable experiences: Sage Publications.

Fontaine, P., Ross, S. E., Zink, T., & Schilling, L. M. (2010). Systematic review of health information exchange in primary care practices. The Journal of the American Board of Family Medicine, 23(5), 655-670.

Fortney, J., Rost, K., Zhang, M., & Warren, J. (1999). The impact of geographic accessibility on the intensity and quality of depression treatment. Medical care, 884-893.

Fortney, J. C., Booth, B. M., Blow, F. C., Bunn, J. Y., & Loveland Cook, C. A. (1995). The effects of travel barriers and age on the utilization of alcoholism treatment aftercare. The American journal of drug and alcohol abuse, 21(3), 391-406.

Frisse, M. E., & Holmes, R. L. (2007). Estimated financial savings associated with health information exchange and ambulatory care referral. Journal of biomedical informatics, 40(6), S27-S32.

Frisse, M. E., Johnson, K. B., Nian, H., Davison, C. L., Gadd, C. S., Unertl, K. M., . . . Chen, Q. (2012). The financial impact of health information exchange on emergency department care. Journal of the American Medical Informatics Association, 19(3), 328-333.

Galbraith, J. (1973). Designing complex organizations. Reading, Mass.

Gallagher, C. (2020). Expanded Access Program for Convalescent Plasma discontinues enrollment as FDA authorizes its emergency use. Retrieved from https://newsnetwork.mayoclinic.org/discussion/expanded-access-program-for-convalescent-plasma-discontinues-enrollment-as-fda-authorizes-its-emergency-use/?_ga=2.90801630.576338173.1610647901-1397782561.1610647901

Gao, G., & Hitt, L. M. (2012). Information technology and trademarks: Implications for product variety. Management Science, 58(6), 1211-1226.

Gauri, D. K., Jindal, R. P., Ratchford, B., Fox, E., Bhatnagar, A., Pandey, A., . . . Howerton, E. (2021). Evolution of retail formats: Past, present, and future. Journal of Retailing, 97(1), 42-61.

Gebauer, H., Krempl, R., Fleisch, E., & Friedli, T. (2008). Innovation of product-related services. Managing Service Quality: An International Journal.

Germack, H. D., Fekieta, R., Campbell Britton, M., Feder, S. L., Rosenberg, A., & Chaudhry, S. I. (2020). Cooperation and conflict in intra-hospital transfers: A qualitative analysis. Nursing open, 7(2), 634-641.

Gharbharan, A., Jordans, C. C., GeurtsvanKessel, C., den Hollander, J. G., Karim, F., Mollema, F. P., . . . Koster, A. (2021). Effects of potent neutralizing antibodies from convalescent plasma in patients hospitalized for severe SARS-CoV-2 infection. Nature communications, 12(1), 1-12.

Ghaysouri, A., Nourmohammadi, H., Qasemi, E., Mozafari, A. A., Tavan, H., & Saghari, S. (2021). Evaluation of the therapeutic effect of the plasma of recovered COVID-19 patients for treating the patients admitted to the intensive care unit. In (Vol. 44, pp. 100941): Elsevier.

Giroud, X. (2013). Proximity and investment: Evidence from plant-level data. The Quarterly Journal of Economics, 128(2), 861-915.

Grewal, R., Lilien, G. L., & Mallapragada, G. (2006). Location, location, location: How network embeddedness affects project success in open source systems. Management Science, 52(7), 1043-1056.

Guagliardo, M. F. (2004). Spatial accessibility of primary care: concepts, methods and challenges. International journal of health geographics, 3(1), 1-13.

Gubler, T., Larkin, I., & Pierce, L. (2018). Doing well by making well: The impact of corporate wellness programs on employee productivity. Management Science, 64(11), 4967-4987.

Guo, S., & Fraser, M. W. (2014). Propensity score analysis: Statistical methods and applications (Vol. 11): SAGE publications.

Gutierrez, E., & Rubli, A. (2021). Shocks to hospital occupancy and mortality: Evidence from the 2009 H1N1 pandemic. Management Science.

Hamel, L., Grace, S., & Mollyann, B. (2021). KFF COVID-19 Vaccine Monitor: February 2021. Retrieved from https://www.kff.org/coronavirus-covid-19/poll-finding/kff-covid-19-vaccine-monitor-february-2021/?

Henrich, N., & Holmes, B. (2009). The public's acceptance of novel vaccines during a pandemic: a focus group study and its application to influenza H1N1. Emerging health threats journal, 2(1), 7088.

Hernandez-Boussard, T., Davies, S., McDonald, K., & Wang, N. E. (2017). Interhospital facility transfers in the United States: a nationwide outcomes study. Journal of patient safety, 13(4), 187.

Hirano, K., & Imbens, G. W. (2001). Estimation of causal effects using propensity score weighting: An application to data on right heart catheterization. Health Services and Outcomes research methodology, 2(3), 259-278.

HMS. (2020). Mi-COVID19 Initiative. Retrieved from https://www.mi-hms.org/quality-initiatives/mi-covid19-initiative

Horbar, J. D., Rogowski, J., Plsek, P. E., Delmore, P., Edwards, W. H., Hocker, J., . . . Lewit, E. (2001). Collaborative quality improvement for neonatal intensive care. Pediatrics, 107(1), 14-22.

Horby, P. W., Estcourt, L., Peto, L., Emberson, J. R., Staplin, N., Spata, E., . . . Brunskill, N. E. (2021). Convalescent plasma in patients admitted to hospital with COVID-19 (RECOVERY): a randomised, controlled, open-label, platform trial. medRxiv.

Howells, J. R. (2002). Tacit knowledge, innovation and economic geography. Urban studies, 39(5-6), 871-884.

Hu, Y., & Hoover, D. (2018). Simple Power and Sample Size Estimation for Non-Randomized Longitudinal Difference in Differences Studies. Journal of biometrics & biostatistics, 9(5).

Huff, D. L. (1964). Defining and estimating a trading area. Journal of marketing, 28(3), 34-38.

Ikkersheim, D., Tanke, M., van Schooten, G., de Bresser, N., & Fleuren, H. (2013). Modeling hospital infrastructure by optimizing quality, accessibility and efficiency via a mixed integer programming model. BMC health services research, 13(1), 1-9.

Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. Review of Economics and statistics, 86(1), 4-29.

Imbens, G. W., & Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. Journal of economic literature, 47(1), 5-86.

Jansen, M. C., & Özaltın, O. Y. (2017). Note on cournot competition under yield uncertainty. Manufacturing & Service Operations Management, 19(2), 305-308.

Joyner, M. J., Bruno, K. A., Klassen, S. A., Kunze, K. L., Johnson, P. W., Lesser, E. R., . . . Hodge, D. O. (2020). Safety update: COVID-19 convalescent plasma in 20,000 hospitalized patients. Paper presented at the Mayo Clinic Proceedings.

Joyner, M. J., Carter, R. E., Senefeld, J. W., Klassen, S. A., Mills, J. R., Johnson, P. W., . . . Klompas, A. M. (2021). Convalescent plasma antibody levels and the risk of death from Covid-19. New England Journal of Medicine, 384(11), 1015-1027.

Joyner, M. J., Senefeld, J. W., Klassen, S. A., Mills, J. R., Johnson, P. W., Theel, E. S., . . . Lesser, E. R. (2020). Effect of convalescent plasma on mortality among hospitalized patients with COVID-19: initial three-month experience. medRxiv.

Kabra, A., Belavina, E., & Girotra, K. (2020). Bike-share systems: Accessibility and availability. Management Science, 66(9), 3803-3824.

Kadlec, R. P. (2020). Convalescent Plasma EUA Letter of Authorization. U.S. Food and Drug Administration

Kastalli, I. V., & Van Looy, B. (2013). Servitization: Disentangling the impact of service business model innovation on manufacturing firm performance. Journal of Operations Management, 31(4), 169-180.

Knoben, J., & Oerlemans, L. A. (2006). Proximity and inter-organizational collaboration: A literature review. international Journal of management reviews, 8(2), 71-89.

Kober, C., Manni, S., Wolff, S., Barnes, T., Mukherjee, S., Vogel, T., . . . Gerlach, M. (2022). IgG3 and IgM Identified as Key to SARS-CoV-2 Neutralization in Convalescent Plasma Pools. PloS one, 17(1), e0262162.

Koliba, C. J., Mills, R. M., & Zia, A. (2011). Accountability in governance networks: An assessment of public, private, and nonprofit emergency management practices following Hurricane Katrina. Public Administration Review, 71(2), 210-220.

Korley, F. K., Durkalski-Mauldin, V., Yeatts, S. D., Schulman, K., Davenport, R. D., Dumont, L. J., . . . Jaiswal, S. (2021). Early convalescent plasma for high-risk outpatients with Covid-19. New England Journal of Medicine, 385(21), 1951-1960.

Lan, Y., Massimino, B. J., Gray, J. V., & Chandrasekaran, A. (2020). The effects of product development network positions on product performance and confidentiality performance. Journal of Operations Management, 66(7-8), 866-894.

Landon, B. E., Keating, N. L., Onnela, J.-P., Zaslavsky, A. M., Christakis, N. A., & O'Malley, A. J. (2018). Patient-sharing networks of physicians and health care utilization and spending among Medicare beneficiaries. JAMA internal medicine, 178(1), 66-73.

Lenselink, C. H., Gerrits, M. M., Melchers, W. J., Massuger, L. F., van Hamont, D., & Bekkers, R. L. (2008). Parental acceptance of human papillomavirus vaccines. European Journal of Obstetrics & Gynecology and reproductive biology, 137(1), 103-107.

Letaifa, S. B., & Rabeau, Y. (2013). Too close to collaborate? How geographic proximity could impede entrepreneurship and innovation. Journal of Business Research, 66(10), 2071-2078.

Li, G., Li, L., Choi, T. M., & Sethi, S. P. (2020). Green supply chain management in Chinese firms: Innovative measures and the moderating role of quick response technology. Journal of Operations Management, 66(7-8), 958-988.

Li, L., & Zhang, H. (2008). Confidentiality and information sharing in supply chain coordination. Management Science, 54(8), 1467-1481.

Li, L., Zhang, W., Hu, Y., Tong, X., Zheng, S., Yang, J., . . . Mei, H. (2020). Effect of convalescent plasma therapy on time to clinical improvement in patients with severe and life-threatening COVID-19: a randomized clinical trial. Jama, 324(5), 460-470.

Lim, S. F. W., Rabinovich, E., Park, S., & Hwang, M. (2021). Shopping Activity at Warehouse Club Stores and Its Competitive and Network Density Implications. Production and Operations Management, 30(1), 28-46.

Liu, A. X., Steenkamp, J.-B. E., & Zhang, J. (2018). Agglomeration as a Driver of the Volume of Electronic Word of Mouth in the Restaurant Industry. Journal of Marketing Research, 55(4), 507-523.

Liu, G., Aroean, L., & Ko, W. W. (2022). Power, shared goals and supplier flexibility: a study of the HUB-and-spoke supply chain. International Journal of Operations & Production Management.

Liu, S. T., Lin, H.-M., Baine, I., Wajnberg, A., Gumprecht, J. P., Rahman, F., . . . Bander, J. (2020). Convalescent plasma treatment of severe COVID-19: a propensity score–matched control study. Nature medicine, 26(11), 1708-1713.

Mack, J. (2020). Running out of body bags. People dying in the hallway. Coronavirus has Michigan hospital workers at a breaking point. MLive. Retrieved from https://www.mlive.com/public-interest/2020/04/running-out-of-body-bags-people-dying-in-the-hallway-coronavirus-has-michigan-hospital-workers-at-a-breaking-point.html

Manupati, V. K., Schoenherr, T., Wagner, S. M., Soni, B., Panigrahi, S., & Ramkumar, M. (2021). Convalescent plasma bank facility location-allocation problem for COVID-19. Transportation Research Part E: Logistics and Transportation Review, 156, 102517.

Marani, M., Katul, G. G., Pan, W. K., & Parolari, A. J. (2021). Intensity and frequency of extreme novel epidemics. Proceedings of the National Academy of Sciences, 118(35), e2105482118.

Martin, P., Gupta, D., & Natarajan, K. V. (2020). Vaccine Procurement Contracts for Developing Countries. Production and Operations Management, 29(11), 2601-2620.

McGuire, M., & Silvia, C. (2010). The effect of problem severity, managerial and organizational capacity, and agency structure on intergovernmental collaboration: Evidence from local emergency management. Public Administration Review, 70(2), 279-288.

McQuillan, L., Daley, M. F., Stokley, S., Crane, L. A., Beaty, B. L., Barrow, J., . . . Kempe, A. (2009). Impact of the 2004–2005 influenza vaccine shortage on pediatric practice: a national survey. Pediatrics, 123(2), e186-e192.

Menor, L. J., Tatikonda, M. V., & Sampson, S. E. (2002). New service development: areas for exploitation and exploration. Journal of Operations Management, 20(2), 135-157.

Miles, I. (1995). Innovation in services. Chapters.

Miller, D. (2019). Leveraging BERT for extractive text summarization on lectures. arXiv preprint arXiv:1906.04165.

Mills, A. F., Helm, J. E., Jola-Sanchez, A. F., Tatikonda, M. V., & Courtney, B. A. (2018). Coordination of autonomous healthcare entities: Emergency response to multiple casualty incidents. Production and Operations Management, 27(1), 184-205.

Mølhave, M. (2021). Clinical Management of COVID-19 Patients-An Update. Paper presented at the Seminars in Nuclear Medicine.

Mousa, T. Y., & Freeland-Graves, J. H. (2017). Organizations of food redistribution and rescue. Public Health, 152, 117-122.

Mueller, S., Zheng, J., Orav, E. J., & Schnipper, J. L. (2019). Inter-hospital transfer and patient outcomes: a retrospective cohort study. BMJ quality & safety, 28(11), e1-e1.

Murphy, K. (2021). NC campuses are helping distribute COVID vaccines with clinics and ultra-cold freezers. Retrieved from https://www.newsobserver.com/news/local/education/article248639920.html#storylink=cpy

Neely, A. (2008). Exploring the financial consequences of the servitization of manufacturing. Operations management research, 1(2), 103-118.

O'Donnell, M. R., Grinsztejn, B., Cummings, M. J., Justman, J. E., Lamb, M. R., Eckhardt, C. M., . . . João, E. (2021). A randomized double-blind controlled trial of convalescent plasma in adults with severe COVID-19. The Journal of Clinical Investigation.

Ostermann, M., & Vincent, J.-L. (2019). How much centralization of critical care services in the era of telemedicine? In: Springer.

Pancras, J., Sriram, S., & Kumar, V. (2012). Empirical investigation of retail expansion and cannibalization in a dynamic environment. Management Science, 58(11), 2001-2018.

Perone, G. (2022). The effect of labor market institutions and macroeconomic variables on aggregate unemployment in 1990–2019: Evidence from 22 European countries. Industrial and Corporate Change.

Piyush, R., Rajarshi, K., Khan, R., & Ray, S. (2020). Convalescent plasma therapy: a promising coronavirus disease 2019 treatment strategy. Open Biology, 10(9), 200174.

Prasad, M., Seth, T., & Elavarasi, A. (2021). Efficacy and safety of convalescent plasma for COVID-19: a systematic review and meta-analysis. Indian Journal of Hematology and Blood Transfusion, 1-19.

Prevention, C. f. D. C. a. (2021). CDC COVID-19 Vaccine Allocation Transfer and Redistribution Guidance for IHS and Tribal Facilities. Retrieved from https://www.cdc.gov/vaccines/covid-19/planning/ihs-redistribution.html

Rabøl, L. I., Andersen, M. L., Østergaard, D., Bjørn, B., Lilja, B., & Mogensen, T. (2011). Descriptions of verbal communication errors between staff. An analysis of 84 root cause analysis-reports from Danish hospitals. BMJ quality & safety, 20(3), 268-274.

Rahal, S. B., Karen. (2020). Michigan could receive several hundred thousand doses of Pfizer vaccine next month. Retrieved from https://www.detroitnews.com/story/news/local/michigan/2020/11/25/5-henry-ford-hospitals-approved-covid-19-vaccine-distribution/6421574002/

Ramanathan, U. (2012). Supply chain collaboration for improved forecast accuracy of promotional sales. International Journal of Operations & Production Management.

Reilly, W. J. (1931). The law of retail gravitation: WJ Reilly.

Robusto, C. C. (1957). The cosine-haversine formula. The American Mathematical Monthly, 64(1), 38-40.

Rosenbaum, P. R. (1987). The role of a second control group in an observational study. Statistical Science, 2(3), 292-306.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), 41-55.

Rosso, A., Massimi, A., Pitini, E., Nardi, A., Baccolini, V., Marzuillo, C., . . . Villari, P. (2020). Factors affecting the vaccination choices of pregnant women for their children: a systematic review of the literature. Human vaccines & immunotherapeutics, 16(8), 1969-1980.

Sadahiro, Y. (2021). A method for analyzing the daily variation in the spatial pattern of market area. Journal of Retailing and Consumer Services, 58, 102336.

Sahu, K. K., Jindal, V., Siddiqui, A. D., Cerny, J., & Gerber, J. M. (2020). Convalescent Plasma Therapy: A Passive Therapy for An Aggressive COVID-19. Journal of Medical Virology.

Salazar, M. R., González, S. E., Regairaz, L., Ferrando, N. S., González Martínez, V. V., Carrera Ramos, P. M., . . . Kreplak, N. (2021). Risk factors for COVID-19 mortality: The effect of convalescent plasma administration. PloS one, 16(4), e0250386.

Schartinger, D., Rammer, C., & Fröhlich, J. (2006). Knowledge interactions between universities and industry in Austria: sectoral patterns and determinants. In Innovation, networks, and knowledge spillovers (pp. 135-166): Springer.

Scott, A., Balthrop, A., & Miller, J. W. (2020). Unintended responses to IT-enabled monitoring: The case of the electronic logging device mandate. Journal of Operations Management.

Scott, A., Balthrop, A., & Miller, J. W. (2021). Unintended responses to IT-enabled monitoring: The case of the electronic logging device mandate. Journal of Operations Management, 67(2), 152-181.

Sharma, A., Pathak, S., Borah, S. B., & Adhikary, A. (2020). Is it too complex? The curious case of supply network complexity and focal firm innovation. Journal of Operations Management, 66(7-8), 839-865.

Sharma, L., Queenan, C., & Ozturk, O. (2019). The Impact of Information Technology and Communication on Medical Malpractice Lawsuits. Production and Operations Management, 28(10), 2552-2572.

Shaw, A. T., & Gilly, J.-P. (2000). On the analytical dimension of proximity dynamics. Regional studies, 34(2), 169-180.

Sheldenkar, A., Lim, F., Yung, C. F., & Lwin, M. O. (2019). Acceptance and uptake of influenza vaccines in Asia: a systematic review. Vaccine, 37(35), 4896-4905.

Shen, C., Wang, Z., Zhao, F., Yang, Y., Li, J., Yuan, J., . . . Xing, L. (2020). Treatment of 5 critically ill patients with COVID-19 with convalescent plasma. Jama, 323(16), 1582-1589.

Siemens, D. R., Visram, K., Wei, X., & Booth, C. (2020). Effect of centralization on complex surgical care: A population-based case study of radical cystectomy. Canadian Urological Association Journal, 14(4), 91.

Simonovich, V. A., Burgos Pratx, L. D., Scibona, P., Beruto, M. V., Vallone, M. G., Vázquez, C., . . . Sánchez, M. d. L. (2021). A randomized trial of convalescent plasma in Covid-19 severe pneumonia. New England Journal of Medicine, 384(7), 619-629.

Singh, B., Huang, H.-C., Morton, D. P., Johnson, G. P., Gutfraind, A., Galvani, A. P., . . . Meyers, L. A. (2015). Optimizing distribution of pandemic influenza antiviral drugs. Emerging infectious diseases, 21(2), 251.

Stamm, J. L. H., Serban, N., Swann, J., & Wortley, P. (2017). Quantifying and explaining accessibility with application to the 2009 H1N1 vaccination campaign. Health Care Management Science, 20(1), 76-93.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. Identification and inference for econometric models: Essays in honor of Thomas Rothenberg, 80(4.2), 1.

Suarez, F. F., Cusumano, M. A., & Kahl, S. J. (2013). Services and the business models of product firms: An empirical analysis of the software industry. Management Science, 59(2), 420-435.

Tatikonda, M. V., & Rosenthal, S. R. (2000). Successful execution of product development projects: Balancing firmness and flexibility in the innovation process. Journal of Operations Management, 18(4), 401-425.

Teunter, R. H., & Flapper, S. D. P. (2006). A comparison of bottling alternatives in the pharmaceutical industry. Journal of Operations Management, 24(3), 215-234.

Thornton, R. A., & Thompson, P. (2001). Learning from experience and learning from others: An exploration of learning and spillovers in wartime shipbuilding. American Economic Review, 91(5), 1350-1368.

Toivonen, M., & Tuominen, T. (2009). Emergence of innovations in services. The Service Industries Journal, 29(7), 887-902.

Tong, C., Nagarajan, M., & Cheng, Y. (2016). Operational impact of service innovations in multi-step service systems. Production and Operations Management, 25(5), 833-848.

Torres, A., Sibila, O., Ferrer, M., Polverino, E., Menendez, R., Mensa, J., . . . Anzueto, A. (2015). Effect of corticosteroids on treatment failure among hospitalized patients with severe community-acquired pneumonia and high inflammatory response: a randomized clinical trial. Jama, 313(7), 677-686.

Tucker, A. L., Nembhard, I. M., & Edmondson, A. C. (2007). Implementing new practices: An empirical study of organizational learning in hospital intensive care units. Management Science, 53(6), 894-907.

Tulchinsky, T. H., & Varavikova, E. A. (2014). Planning and Managing Health Systems. The New Public Health, 613.

Vahidnia, M. H., Alesheikh, A. A., & Alimohammadi, A. (2009). Hospital site selection using fuzzy AHP and its derivatives. Journal of environmental management, 90(10), 3048-3056.

Van Walraven, C., Oake, N., Jennings, A., & Forster, A. J. (2010). The association between continuity of care and outcomes: a systematic and critical review. Journal of evaluation in clinical practice, 16(5), 947-956.

Vest, J. R. (2009). Health information exchange and healthcare utilization. Journal of medical systems, 33(3), 223.

Vest, J. R., Unruh, M. A., Freedman, S., & Simon, K. (2019). Health systems' use of enterprise health information exchange vs single electronic health record vendor environments and unplanned readmissions. Journal of the American Medical Informatics Association, 26(10), 989-998.

Walker, D. M. (2018). Does participation in health information exchange improve hospital efficiency? Health Care Management Science, 21(3), 426-438.

Westerink-Duijzer, L. E., Schlicher, L. P., & Musegaas, M. (2020). Core allocations for cooperation problems in vaccination. Production and Operations Management, 29(7), 1720-1737.

Wiengarten, F., & Longoni, A. (2018). How does uncertainty affect workplace accidents? Exploring the role of information sharing in manufacturing networks. International Journal of Operations & Production Management.

Witell, L., Snyder, H., Gustafsson, A., Fombelle, P., & Kristensson, P. (2016). Defining service innovation: A review and synthesis. Journal of Business Research, 69(8), 2863-2872.

Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data: MIT press.

Xue, L., Song, P., Rai, A., Zhang, C., & Zhao, X. (2019). Implications of application programming interfaces for third-party new app development and copycatting. Production and Operations Management, 28(8), 1887-1902.

Ye, M., Fu, D., Ren, Y., Wang, F., Wang, D., Zhang, F., . . . Lv, T. (2020). Treatment with convalescent plasma for COVID-19 patients in Wuhan, China. Journal of Medical Virology.

Zaheer, A., & Soda, G. (2009). Network evolution: The origins of structural holes. Administrative Science Quarterly, 54(1), 1-31.

Zepeda, E. D., Nyaga, G. N., & Young, G. J. (2016). Supply chain risk management and hospital inventory: Effects of system affiliation. Journal of Operations Management, 44, 30-47