Simulating COVID-19 Personal Protective Equipment Use in Acute Care Hospitals

by

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Abstract

America faced crippling shortages of Personal Protective Equipment (PPE) during the COVID-19 pandemic from 2020-2021. In response to these recent shortages, policy makers, emergency responders, public health agencies and private healthcare facilities are investing significant time and money to ensure America is better equipped to meet the need for PPE in the next pandemic. As America pours money into larger stockpiles and increased domestic manufacturing, it is crucial that decision makers understand PPE demand during COVID-19-type pandemics so they can allocate resources appropriately. This thesis aims to answer two central questions: 1) How can planners forecast PPE use in acute care hospitals for future COVID-19-type pandemics? 2) How can the model used to develop these forecasts contribute to a robust PPE preparedness plan?

This thesis presents a simulation that can be used by planners to forecast PPE use in acute care hospitals. The simulation is then applied in a case study to demonstrate potential applications and identify opportunities to shape PPE demand through hospital policy. By implementing conservation policies, policy makers can decrease N95 facepiece respirator use by 47%, and gown and glove use by over 50% in acute care hospitals during a COVID-19-type pandemic. In an environment where significant attention is being paid to increasing supply capacity, a focus on shaping demand at the source is an often neglected, but critical, aspect of enabling supply capacity to meet pandemic demand.

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Table of Contents

Table of Figures

Table of Tables

List of Acronyms

AGP	Aerosol generating procedure
ASPR	Assistant Secretary for Preparedness and Response
CDC	Center for Disease Control and Prevention
DPA	Defense Production Act
ED	Emergency department
EM-DAT	Emergency Events Database
EMS	Emergency Medical Services
EMSC	Emergency Medical Services for Children
EUA	Emergency Use Authorization
FDA	Food and Drug Administration
FEMA	Federal Emergency Management Agency
ICU	Intensive care ward
IHME	Institute for Health Metrics and Evaluation
JHU	Johns Hopkins University
MD	Medical doctor
MDPH	Massachusetts Department of Public Health
N95	N95 filtering facepiece respirator
PCA	Patient care assistant
PPE	Personal protective equipment
PUI	Person under investigation
RN	Registered nurse
UCLA	University of California Los Angeles

1. Motivation

1.1 PPE shortages during COVID-19

At the onset of COVID-19, hospitals across the country reported inadequate access to PPE, leaving them unable to provide sufficient supplies to support their staff (Grimm, 2020). As internal PPE stockpiles ran out, healthcare facilities were left to fend for themselves in a marketplace that was said to resemble the "Wild West", where prices were exorbitant and quality assurance was unreliable (Lagu et al., 2020). Many healthcare facilities were forced to turn to the public to ask for donations, although the quality and quantity of donations was insufficient to meet the rising PPE demand (Goldberg, 2020). The federal government stepped in to assist, but the strategic national stockpile (SNS) was woefully insufficient to meet national demand for PPE, especially demand for N95 respirators. This was to be expected, since by design, the SNS is meant to provide a temporary stopgap in short lived emergencies, not provide a steady stream of supply for the duration of a pandemic (Khazan, 2020). SNS administrators were forced to prioritize requests from states that were in dire need, and even then, requests from those states were only partially filled (R. Crawford, 2020). By April 1, 2020, well before the worst national level COVID-19 caseloads, N95s in the SNS were nearly depleted (Miroff, 2020). In the face of these shortages, acquiring PPE during COVID-19 was left largely to the states, who were forced to hastily assemble state level stockpiles, often competing in the market with the healthcare facilities they were trying to assist (Altman, 2020).

Despite rapidly rising demand and market shortages in 2020, potential new PPE producers, large and small, reported they were hesitant or unable to enter the market. Starting production involved investing in equipment and raw goods that had skyrocketed in price, such as the blowers needed to make the melt-blown polypropylene used to make N95s or the elastic needed for the ear loops that allow the mask to seal tightly to the face. Even if producers had capital to procure the raw goods and equipment, they feared that by the time they received production equipment, much of which needed to be shipped from China, the COVID-19 demand surge would be over, and they would be left with expensive manufacturing plants that would lay dormant until the next pandemic (Lessons from COVID, 2021). In the absence of a clear understanding of PPE demand, producers that could help relieve PPE shortages did not have the information they needed to enter the market.

1.2 Efforts to increase preparedness

In response to the PPE shortages in COVID-19, government responders at all levels have increased investment in PPE stockpiles to prevent shortages in the next pandemic. The federal government plans to vastly increase the PPE stored in the SNS, including increasing stockpiled N95s from the 24 million held in January 2020 to 300 million and increasing stockpiled nitrile gloves from 22 million pairs held in November 2020 to 4.5 billion pairs (Evstatieva, 2020). States are also investing in increased PPE preparedness. Nine out of twelve states surveyed in July 2020 by the National Governors Association reported building or enhancing their own PPE stockpile (National Governors Association, 2020). In December 2020, Washington state had more than 30 million N95s stockpiled and California announced plans to stockpile 100 million N95s and 200 million surgical masks (Reicher, 2020; Office of Governor Gavin Newsom, 2020). Some states are passing legislation to mandate PPE stockpiles in hospitals, including a 90-day PPE requirement in California and New York (Anderson, 2020; Smith, 2020).

In addition to buying time to respond by building PPE stockpiles, the federal government is attempting to address the underlying vulnerability in the PPE supply chain. President Biden laid the foundation for this effort in his Executive Order on a Sustainable Public Health Supply Chain, published January 21, 2021. This order directs the government to identify points of failure in PPE supply chains and develop a multi-year implementation plan for domestic PPE production. It also directs authorities to use the Defense Production Act (DPA) to encourage PPE production by domestic firms that may be unwilling or unable to provide PPE to government agencies (Presidential Actions, 2021).

1.3 Increased understanding of pandemic PPE demand is needed to drive these preparedness efforts

The national trauma from COVID-19 has encouraged the deployment of massive resources for PPE stockpiles and supply chain interventions. This increased funding and attention has the potential to prevent suffering caused by widespread PPE shortages in the next pandemic. However, these resources are bound to be inefficiently allocated or wasted without a thorough understanding of the underlying PPE demand during a pandemic like COVID-19. This thesis attempts to further understanding of pandemic PPE demand so policy makers can best prepare for the next pandemic. This is this thesis' first central research question:1) How can planners forecast PPE use in acute care hospitals for future COVID-19-type pandemics?

Even with an understanding of pandemic demand, policy makers cannot prepare for every pandemic possibility. They will inevitably have to make trade-offs with limited resources that will leave the United States under prepared for the most extreme future pandemic scenarios. In light of this possibility, policy makers, public health officials, and healthcare leaders need to understand what levers they can pull to decrease PPE demand when there are PPE shortages. This thesis attempts to provide policy makers with that understanding through its second central research question: 2) How can the model used to develop these forecasts contribute to a robust PPE preparedness plan?

To answer these research questions this thesis 1) presents a simulation model to predict PPE use in acute care hospitals given daily hospitalizations, 2) presents a case study of PPE use in acute care hospitals in Massachusetts from April 4, 2020 to April 3, 2021 to understand the key variable relationships in the simulation and provide an example for future application, and 3) discusses how policy makers can use this simulation and the PPE use process it illuminates to create a robust preparedness plan given limited resources. For the purposes of this thesis, PPE will include N95 filtering facepiece respirators (N95s), surgical/procedural disposable masks (surgical/procedural masks), nitrile exam gloves (gloves), level II and above disposable isolation gowns (gowns), and re-usable plastic eye protection (eye protection).

1.4 Thesis format

The format for this thesis is outlined below:

The **Relevant Literature** section reviews previous work published on the topics related to this thesis. It also identifies the gaps in this current literature that this thesis aims to fill.

The **Methods** section presents the simulation and demonstrates potential use of the simulation through a case study. The case study consists of four parts: 1) a simulation run where all variables are deterministic, 2) sensitivity analysis on the deterministic case study, 3) a simulation run using multiple epidemiological forecasts to produce an array of results, and 4) a Monte Carlo simulation where select variables are changed from deterministic to stochastic.

The **Discussion** section reviews potential applications and limitations of the simulation. It then discusses the key lessons learned in the case study. Finally, this section explores how the simulation and lessons learned from the case study can be used as part of a holistic approach to a PPE preparedness plan and where future work is needed to further understanding of PPE demand in acute care hospitals.

2. Relevant literature

This section addresses literature that is relevant to this thesis and is broken into six sections: Demand forecasting in humanitarian logistics, pandemic PPE forecasting, publicly available PPE calculators, PPE conservation, demand planning for COVID-19, and Monte Carlo simulation. The literature was identified through Google Scholar key word searches including "demand forecasting humanitarian logistics", "pre-positioned stock humanitarian logistics", "COVID-19 PPE supply chain", "flattening the curve", "PPE calculator", "PPE influenza pandemic", "PPE conservation" and "Monte Carlo simulation". Subsequently, a further search of papers that had been cited in the initial literature was conducted. This section concludes with a summary of the gaps in current literature that this thesis attempts to address.

2.1 Demand forecasting in humanitarian logistics

Demand forecasting is widely addressed in emergency response literature and is typically presented in two parts. First, there is a forecast for the total affected population by a future disaster. Second, there is a forecast for the supplies required by that affected population over time. Demand forecasting literature in humanitarian logistics focuses primarily on environmental disasters as opposed to pandemics. Pandemic forecasting literature will be addressed in the next section.

There have been varying efforts to forecast the total affected population for natural disasters. There is abundant research in fields such as climate science, geophysics, and fluid dynamics that discuss forecasting future extreme weather events (Done et al. 2015; Dore, 2003; Du et al., 2014; Jin et al., 2008; Musa et al., 2018; Vere-Jones, 1995; Zhang et al., 2018). The United States Federal Emergency Management Agency (FEMA) uses its Hazus Program to estimate the risk of earthquakes, floods, tsunamis, and hurricanes in the United States (FEMA, 2021). There is also significant use of past disaster data to inform future disaster forecasts. The International Disaster Database (EM-DAT) provides information on the affected population of past disasters and has been relied upon in stockpile pre-positioning literature to model future disaster impact (Acimovic & Goentzel, 2016; Duran et al., 2011; Taskin & Lodree, 2010). Japan International Cooperation Agency and Tehran Red Crescent Society also have published information on possible earthquake scenarios that have been used by humanitarian logistics researchers (JICA, 2000; RCS, 2005).

Once the affected population is determined, researchers then forecast emergency supply use per affected individual to determine an overall needs forecast. Acimovic & Goentzel determine their per-person demand calculations by consulting the Sphere Handbook, which provides guidelines on typical relief supply use (2016; The Sphere Project, 2018). Duran et al. utilize operational guidelines published by the International Federation of the Red Cross (2000). There is limited research that uses historical demand data and more closely fits the demand forecasting conducted in private industry: Davis et al. (2016) analyzed food donation behavior to forecast future food donations, Holguin-Veras and Jaller (2011) utilized historical demand data to forecast relief supply demand for hurricanes and van der Laan et al. (2016) analyzed demand forecasting efforts at Médecins Sans Frontieres.

This simulation will focus on the second step in humanitarian supply chain forecasting, determining the supplies required by a pre-defined affected population. Epidemiological forecasting is out of the scope of this thesis. The simulation instead uses COVID-19 hospitalizations as a deterministic input that is used to determine PPE use. Although outside of the current scope, epidemiological forecasts can easily be integrated into the model for future applications.

2.2 Pandemic PPE forecasting

Pandemic PPE demand forecasting appears to have fallen outside the scope of traditional humanitarian supply chain literature, which focuses mainly on natural environmental disasters such as hurricanes, earthquakes, and tsunamis. There have, however, been prior attempts to forecast PPE use in hospitals and other healthcare facilities for disease outbreaks and pandemics that are published in medical or public health focused journals. These follow the same general approach to forecasting as the above referenced natural disaster supply forecasts. They begin by forecasting the total population that will become infected or the total workforce interacting with infected personnel, they then forecast total PPE use per individual.

In 2015, Carias et al. published the heavily cited prediction of 1.7 – 3.5 billion N95 respirators needed for a hypothetical influenza pandemic in the United States (2015). This paper utilized a spreadsheet-based calculation to predict N95 and surgical mask use across the United States for the entirety of a pandemic by using percentage of the United States population that would ultimately be infected as its patient input and combining this with respirator and surgical mask use per worker and per patient per day. Hashikura & Kizu used a different approach when they published a tool to assist hospitals in deciding a PPE stockpile (2009). They recommended hospitals multiply total sets of PPE used by different healthcare worker types each day by the population of their healthcare workforce to determine the PPE needed to cover an eight week pandemic. Finally, Radonovich et al. utilized scenarios based off the United States 1918 pandemic influenza event to estimate total population seeking medical care and length of stay. They combined those assumptions in a spreadsheet-based model with estimated patient encounters per patient day to determine total PPE needed for the United States Veterans Association medical system in a hypothetical influenza pandemic (2009).

The simulation presented in this thesis builds off the work of Carias et al. and Radonovich et al. but differs significantly in approach and inputs. Notably, the simulation presented here calculates daily PPE use as opposed to aggregate demand for the entire pandemic, includes more inputs based around hospital policy, and allows for dynamic calculations of staff interacting with the infected population based on the extent of patient concentration. Additionally, instead of using a hypothetical future outbreak, the case study in this thesis will utilize the historical data from actual COVID-19 cases and hospitalizations in Massachusetts from April 2020 – April 2021.

2.3 Publicly available PPE calculators

In addition to the traditional peer-reviewed pandemic PPE forecasts referenced above, there was a push to create publicly available PPE calculators and predictions specific to COVID-19 at the onset of the pandemic. The most notable publicly available aggregate calculator came out of Johns Hopkins Bloomberg School of Public Health Center for Health Security (PPE Assumptions, 2020). This spreadsheet-based model used attack rate, length of stay, and PPE changes per patient per day to calculate total expected PPE use for a 100-day pandemic wave in the United States. Similar to Carias et al. and Hashikura & Kizu,, this model produces an aggregate prediction for PPE use over the entire 100-day period based on total population attack rate.

In addition to the United States aggregate prediction from Johns Hopkins University, the office of the Assistant Secretary for Preparedness and Response (ASPR), the Center for Disease Control and Prevention (CDC), the Emergency Medical Services for Children (EMSC) Program, the University of Pennsylvania Perelman School of Medicine, and the Covid Staffing Project created tools to assist individual hospitals in predicting their own PPE use during COVID-19 (JHU, 2020; ASPR, 2020; CDC, 2020; EMSC, 2020; UPenn, 2020; Covid Staffing Project, 2020). These models did not use epidemiological case predictions but instead utilized data available to hospitals in real time such as staffing numbers, current hospitalized cases, PPE conservation strategies, and historic PPE burn rates to provide hospitals daily predictions of PPE use.

Although these calculators corroborate the logic of the simulation presented in this thesis, the simulation model presented here more closely follows the previously published PPE forecasting techniques than the publicly available calculators because it forecasts PPE use for multiple facilities based on epidemiological forecasts and is meant to inform emergency planners and policy makers. These calculators are tools primarily meant for day to day use by hospital operators.

2.4 PPE conservation

PPE conservation research is limited and only became available after the onset of COVID-19. Although there have been suggestions in published research and broad guidelines published from the CDC, PPE conservation guidance is still in no way comprehensive because the safety of PPE conservation is still being researched. As the CDC states on its website, “at this time, there is not known a maximum number of uses (donnings) the same facemask could be re-used”. This holds true for other PPE types as well. The CDC provides broad guidance on prioritizing PPE when faced with a shortage and potentially using expired PPE, but generally leaves PPE conservation decisions to healthcare providers (CDC Strategies for Optimizing the Supply of Facemasks, 2021).

Although 54% of acute care hospitals reported implementing PPE conservation policies by March 2020 (Premier Inc, 2020), PPE conservation practices are not currently a part of published surgery guidelines. During COVID-19, PPE conservation practices were mainly left up to hospital discretion based on the severity of their shortage and their internal infection control guidelines (Agrawal et al., 2021). A range of research has been published recommending PPE conservation policies since the onset of COVID-19. Sampathkumar et al. recommended conserving PPE by classifying COVID-19 patients as “modified droplet precaution”, allowing staff to only wear N95s when treating those patients for aerosol generating procedures (AGP) (2020). Steuart et al. presented a list of conservation recommendations, including limiting large group rounds, dismissing non-essential personnel, clustering care, utilizing telemedicine when possible, identifying COVID-19 care teams, reusing PPE, and suspending PPE use for certain non-COVID-19 procedures (2020). Yorio et al. further validated the recommendation to reuse PPE, when possible, by creating a model showing the linear effect of PPE reuse policies on decreasing PPE demand (2020). Crosby et al., however, warned against the widespread use of aggressive conservation measures and instead recommended applying the precautionary principle when deciding the required PPE needed to treat each patient (Crosby et al., 2020).

The safety of different PPE conservation methods is the subject of ongoing research and is out of scope of this thesis. Instead, the case study explores how different PPE conservation policies that were utilized during COVID-19 affect total use so they can be prioritized for future implementation and research. This is an important contribution, because other than the model built by Yorio et al., there has been no published research on the quantitative effect of implementing PPE conservation practices, including cohorting, limiting patient contacts, and decreasing staff to patient ratios on total PPE demand.

2.5 Decreasing PPE shortages during the COVID-19 pandemic

There has been ample research surrounding the failure of PPE supply chains to meet COVID-19 pandemic demand. This research offers potential solutions on both the demand and supply side. Govindan et al. offer a solution to decrease healthcare facility demand by classifying the population into groups that are then given different mitigation measures to prevent the spread of disease (2020). This falls into the general realm of literature that focuses on “flattening the curve” to decrease demand in the healthcare system by decreasing hospitalizations (Kenyon, 2020; Ng et al., 2020; Kosir & Sorensen, 2020; Tarrataca et al., 2021; Thunstrom et al., 2020; Block et al., 2020). Public health interventions are out of the scope of this thesis. Instead, this thesis takes a different approach to decreasing pandemic PPE demand by instead focusing on decreasing PPE use through hospital policy, as opposed to through decreased community transmission.

There is also a diverse field of research surrounding increasing supply chain capability to meet pandemic demand. Mehrotra et al. presents a stochastic optimization model to allocate limited ventilators to high demand areas (2021). Shokrani et al. explores the possibility of retooling existing supply chains to meet demand for face shields (2020). Zhu et al. advocates that medical supply chains should be nationalized to allow for government control of medical resources (2020). Although this is an important area for further research, increasing supply chain capabilities is not within the scope of this thesis.

2.6 Monte Carlo simulation

Monte Carlo simulations can be used to represent a dynamic system when inputs include uncertainty (Vitoriano et al., 2013). This technique has been used across many fields, including finance, construction, and operations management to inform decision makers and planners. Monte Carlo simulations model an event or series of events by running through multiple iterations, sometimes hundreds of thousands, drawing one or more of its input variables from a probability distribution. This simulation technique aims to represent the full range of possible outcomes and present a distribution of possible outcomes to decision makers so they can accurately assess risk. The goal of Monte Carlo simulations is to take a situation with uncertain inputs and produce an assessment of what could happen and what is likely to happen (Banomyong & Sopadang, 2010).

Monte Carlo simulations have been used widely in operation management but have not had significant usage in humanitarian logistics and have not been used in previously published pandemic PPE forecasting. This is surprising, because humanitarian logistics consistently has uncertain inputs, including the severity of the event, the timing of the event, the extent of damage and the population affected (Behl & Dutta, 2018). In response to this uncertainty, Banomyong & Sopadang advocate increased usage of Monte Carlo simulation to select appropriate emergency response models to use in disasters (Banomyong & Sopadang, 2010). Behl & Dutta agree in their

2018 literature review of existing humanitarian supply chain research that simulation modeling is severely lacking in current humanitarian supply chain literature (Behl & Dutta, 2018). An exception to the generally scarce use of Monte Carlo simulations for humanitarian logistics research is Garrido et al. who incorporate uncertainty into their research on flood emergency response by utilizing a Monte Carlo simulation to determine possible flood relief demand scenarios.

Monte Carlo simulations have gained more traction in traditional logistics and operations management. Examples of Monte Carlo simulations use include estimating the reliability of supply chain networks, identifying potential supply chain disruptions, solving vehicle routing problems, assisting in demand forecasting for products, and estimating the impacts of severe weather events (Ozkan & Kilic, 2019; Schmitt & Singh, 2009; Juan et al., 2009; Klug, 2011; Strader et al., 2016). This thesis utilizes a Monte Carlo simulation as part of its case study in section 4 and contributes to current PPE forecasting literature by using the Monte Carlo simulation to explore the effect of uncertain inputs on total PPE use.

2.7 Gaps in current literature

This thesis aims to fill the gaps identified in the literature review above. Although there is ample forecasting literature in the field of humanitarian logistics, this does not typically include forecasting for pandemics. The PPE demand forecasting that has been conducted for pandemics either aggregates use over an entire period, therefore preventing planners from making day by day decisions, or does not investigate the effect of policy decisions such as cohorting, decreasing patient contacts, or decreasing staff ratios on PPE use. PPE conservation methods have been recommended in a broad sense but have not been sufficiently researched to investigate their quantitative effect on total PPE demand. Finally, although many solutions have been presented to ease the shortage of PPE during COVID-19, most address decreasing demand through the lens of decreasing case load, whereas this thesis explores decreasing PPE demand through hospital PPE conservation policies. To address these gaps, this thesis presents a novel simulation model to forecast PPE demand that outputs daily PPE use in acute care hospitals and allows for varying epidemiological inputs and policy interventions (such as reuse, cohorting, etc.). It then applies this simulation model to an exploratory case study to understand the factors that affect PPE use in hospitals, provide an example of potential future simulation applications, and explore the effect of uncertainty in the simulation. Finally, it discusses next steps for policy makers to use this simulation to create a robust preparedness plan with limited resources.

3. Methods

This section describes the methods used to address the two central research questions for this thesis: 1) How can planners forecast PPE use in acute care hospitals for future COVID-19-type pandemics? 2) How can the model used to develop these forecasts contribute to a robust PPE preparedness plan? This section starts discusses the research design and the simulation formulation.

3.1 Research design

This thesis presents a Python based simulation model to predict PPE use in acute care hospitals given daily hospitalization data for a contagious respiratory illness similar to COVID-19. A simulation is used because the glass box nature of simple simulation allows for buy in from stakeholders who can understand the logic behind the results. It also lends itself to a step-by-step exploration of the PPE use process, which can be used to understand how different input modifications effect the final output. As will be shown in the exploratory case study, the relationship between COVID-19 hospitalizations and PPE use is not linear. This is because COVID-19 patients concentrated in one location can be treated by fewer unique staff members than COVID-19 patients that are widely spread across different facilities. For example, as COVID-19 hospitalizations increase and multiple COVID-19 patients inhabit one floor in one hospital, the same N95 can be used by a single staff member to treat multiple patients. Simulation was determined to be the best way to explore this relationship along with other variable interactions, like the effect of COVID test turnaround time, which are best understood through multiple simulation runs. Ultimately, simulation allows policy makers to understand intuitively, not just mathematically, how COVID-19 hospitalizations and hospital policies combine to affect PPE use.

Alternate methods for forecasting PPE were considered, such as utilizing more traditional time series analysis of historical PPE ordering history during COVID-19, but were ultimately not chosen due to a lack of reliable PPE consumption data from COVID-19 and an inability to impact future use predictions by changing hospital policy. A machine learning forecasting approach was also considered but was not selected due to concerns about obtaining reliable input data in a rapidly changing context and selecting appropriate input variables without the insights gained from a simulation.

In order to demonstrate the simulation and explore how different variables impact PPE use, an exploratory case study is used to predict acute care hospital PPE use in Massachusetts during the COVID-19 pandemic. The case study contains four steps: 1) All variables are held as deterministic inputs to create a base case output. 2) Certain input variables are altered to conduct sensitivity testing and explore alternate COVID-19 severity scenarios. 3) The simulation is run for the period of December 15, 2020 – January 11, 2021 using five different Massachusetts hospitalization forecasts made on December 13, 2020 as hospitalization inputs. 4) Certain variables are changed to stochastic variables with conditional triangular probability distributions in a Monte Carlo simulation approach with 5,000 iterations.

The deterministic base case and sensitivity analysis uses COVID-19 case and hospitalization data in Massachusetts from April 4, 2020 to April 3, 2021 and selects input variables from reported Massachusetts hospital capacity, typical Massachusetts hospital policy collected from 30 interviews with subject matter experts, and PPE reuse guidelines published by the state. This approach is chosen because the recent lived experience with COVID-19 helps add intuitive understanding to the results and provide an accessible example for non-academic policy makers. It also allows for sensitivity analysis that reveals important interactions in the simulation and identifies policy levers that can decrease PPE use.

Although applying previously reported actual COVID-19 hospitalization data to the simulation is useful to understand and analyze PPE use, it is unlikely that there will be one definitive epidemiological forecast in the next pandemic. To illustrate possible applications of this simulation model to future disease events with conflicting epidemiological forecasts, multiple four-week-ahead COVID-19 hospitalization forecasts made on December 13, 2020 for the period of December 15, 2020 – January 11, 2021 for the state of Massachusetts are used instead of the actual COVID-19 hospitalizations numbers. The simulation is run using the hospitalization numbers reported in five different forecasts: Columbia University, Google-Harvard School of Public Health, Institute for Health Metrics and Evaluation (IHME), Johns Hopkins University (JHU), and University of California Los Angeles (UCLA). These results are then graphed to show the range of possible PPE use values for that four-week period that decision makers could use to inform purchasing and stockpiling choices. This approach of using multiple epidemiological forecasts in the simulation to produce a range of values demonstrates a realistic and viable future application of this simulation.

Finally, the simulation is slightly modified by changing select variables with inherent uncertainty from deterministic to stochastic. A Monte Carlo simulation is then used to explore the effect of those uncertain inputs on total PPE use. The Monte Carlo approach allows for a presentation of thousands of iterations and presents the distribution of possible PPE use outcomes. This allows decision makers to understand the range of possible outcomes and gauge risk. Monte Carlo simulation is a useful tool for the purposes of this thesis but has notable setbacks. First, it requires significant computational power when the simulation is complex. Monte Carlo simulation is a viable option for this thesis because the simulation is computationally simple enough for execution time to remain low. Second, the outcome probability distributions that are produced may not appropriately communicate the risk of low-probability events. As applied to this model, that could mean not adding sufficient weight to iteration with very large PPE demand. This thesis attempts to counteract this by presenting the entire outcome distribution, including the most extreme simulation outcomes, not just the distribution mean (Paolo, 2014).

The goal of this thesis is to both present a simulation that can be tailored to future pandemics and to use insights from the simulation case study to help inform a robust PPE preparedness plan. The case study section uses different approaches to using the simulation in order to illustrate possible applications of the simulation and illuminate lessons learned from its application to the COVID-19 pandemic in Massachusetts.

3.2 The simulation

The simulation outlined in this section calculates daily PPE use in acute care hospitals given each day’s COVID-19 hospitalizations. The simulation takes in all epidemiological inputs, including COVID-19 intensive care unit (ICU) hospitalizations, COVID-19 inpatient hospitalizations, daily persons under investigation (PUI) in ICU, daily PUI in inpatient, and daily AGPs performed as deterministic inputs. This simulation is in no way meant to predict the severity of a future pandemic but instead is meant to be combined with epidemiological scenarios to produce PPE use forecasts for a COVID-19-type pandemic given those disease scenarios.

The structure of the simulation, including variable selection and simulation logic, was created during a yearlong intensive collaboration between the MIT Humanitarian Supply Chain Lab and the Massachusetts General Hospital Center for Disaster Medicine that took place from June 2020 to June 2021. The simulation incorporates the healthcare process and treatment protocol expertise provided by members of the Massachusetts General Hospital Center for Disaster Medicine. The simulation is meant to capture the variables in healthcare settings that determine PPE use and to provide an understanding of the PPE used each day in acute care hospitals given that day's COVID-19 hospitalization and PUI numbers.

The simulation takes in the static, stochastic, dynamic variables listed in Table 3.3.1 and runs through the five steps illustrated in Figure 3.3.2 for every day (i) of the simulation run to return the gloves, gowns, N95s, eye protection, and surgical/procedural masks used on that day. The static inputs are selected on day 0 of the simulation and stay as deterministic values for the duration of the simulation. The stochastic inputs are selected each day of the simulation from a defined probability distribution. Dynamic inputs are deterministic values that vary for each day of the model run depending on COVID-19 hospitalizations that day. Finally, the calculated values are held within the simulation and updated each day.

The simulation operates under the following assumptions:

- **Contact precaution and droplet precaution patients are treated with the same PPE:** Contact precaution and droplet precaution patients are combined into one single patient type referred to as "contact/droplet" and are treated with the same PPE.
- **PPE is used appropriately:** It is assumed staff will use pre-defined PPE for each patient type. Staff treating standard precaution patients will wear gloves and a surgical/procedural mask. Staff treating contact/droplet precaution patients will wear a gown, gloves, and a surgical/procedural mask. Staff treating COVID-19 or PUI patients will wear a gown, gloves, eye protection, and an N95. Staff treating airborne precaution patients will wear eye protection, gloves, and an N95. It is assumed there will be perfect adherence to these PPE use policies and no staff members will over- or under-protect themselves for the patient type they are treating.

- **All PPE lasts for the duration of the reuse policy:** It is assumed no PPE is broken, spoiled, or disposed of before the end of its reuse policy.
- **Staffing protocols remain static:** It is assumed that the staff to patient ratios will remain the same regardless of the number of COVID-19 cases. There is no implementation of emergency staffing protocols or crisis standards of care.
- **PUI treatment precautions:** It is assumed that PUI patients are treated with COVID-19 level PPE until they have received a negative COVID-19 test, which only occurs after the completion of the COVID-19 test turnaround time.
- **Care is not deferred and demand for services remains at typical levels:** It is assumed non-COVID-19 patients, both inpatient and ICU, will seek hospital care at a constant rate, regardless of the severity of COVID-19 hospitalizations.
- **Concentration/Dispersion of cases in and among facilities:** It is assumed there are no cohorting policies that purposefully segregate COVID-19 and PUI patients into their own facilities or wings of facilities. The concentration/dispersion of COVID-19 and PUI patients in the acute care hospital population is approximated as the ratio of COVID-19 and PUIs to the entire patient/resident population. This ratio will be referred to as the concentration coefficient.
- **Efficient staffing for contact/droplet and standard precaution patients:** It is assumed that contact/droplet and standard precaution patients are ubiquitous enough to ensure they are treated by the least number of staff possible. For example, if a single nurse can care for four patients, it is assumed that the same nurse will be able to care for four different contact/droplet patients in the simulation. For that to be true, it must be assumed that those four patients are all within the same facility and on the same floor.
- **Inefficient staffing for airborne precaution patients:** It is assumed that airborne precaution patients are rare enough so that the same staff member would not care for more than one airborne patient at a time. For that to be true, it must be assumed that all airborne patients on each day are in different facilities or are on different hospital floors.
- **N95s and eye protection are not single use except for when conducting aerosol generating procedures (AGP):** It is assumed that N95s and eye protection are subject to a reuse policy that is specified as a certain number of shifts in the static inputs. The only

exception is when N95s are used for AGPs. N95s used for AGPs are discarded after the AGP is complete.

- **Gowns and gloves are single use:** It is assumed there are no reuse policies for gowns and gloves. All gowns and gloves are disposed of after each patient contact.
- **Surgical masks are sometimes single use:** Surgical masks are single use only when used to treat contact/droplet precaution patients. All other surgical mask uses are specified as a certain number of shifts in the static inputs.
- **Hospitals continue to operate past their typical bed and staff capacity.** The simulation will run for as long as input data is available and has no artificial stops built in, even when hospital capacity is surpassed. This choice was based on the assumption that in dire circumstances hospitals will allow themselves to surge well past typical capacity (Searle, 2020). Therefore, setting an artificial cap on capacity may underestimate PPE use.

Table 4.1.1: Simulation variables by function

Static Variable Inputs	
Variable	**Variable_name**
k	Percent_typical_sick_requiring_airborne_precautions
K	Percent_typical_sick_requiring_contact_droplet_precautions
t	COVID_test_turnaround_time
g	Specialists
y	ED_Staff_per_day
z	HCWs_per_AGP
U	Shifts_per_day_clinical
u	Shifts_per_day_non_clinical
S	Daily_inpatient_typical_sick
E	Daily_patients_presenting_to_ED
b	Shifts_per_eye_protection
τ	Shifts_per_N95
ρ	Shifts_per_surgical_mask
ω	Misc_non_clinical_entering_hospital
d_{ICU}	Typical_sick_ICU_occupancy
$d_{Inpatient}$	Typical_sick_Inpatient_occupancy
x	Non_Clinical_per_patient
μ	HCW_visits_per_patient_ED

Stochastic Variable Inputs	
Variable	**Variable_name**
θ	HCW_daily_visits_ICU
λ	HCW_daily_visits_Inpatient
$V_{RN, ICU}$	RNs_per_ICU_patient
$V_{MD,ICU}$	MDs_per_ICU_patient
$V_{PCA,ICU}$	PCA_per_ICU_patient
$V_{Student,ICU}$	Student_per_ICU_patient
$V_{RN, Inpatient}$	RNs_per_Inpatient
$V_{MD, Inpatient}$	MDs_per_Inpatient
$V_{PCA, Inpatient}$	PCA_per_Inpatient
$V_{Student, Inpatient}$	Student_per_Inpatient
$V_{PCA, Inpatient}$	PCA_per_Inpatient
$V_{Student, Inpatient}$	Student_per_Inpatient

Dynamic Variable Inputs	
Variable	**Variable_name**
$C_{0,ICU}$	COVID_in_ICU
$C_{0,Inpatient}$	COVID_in_Inpatient
$H_{0,ICU}$	New_PUI_in_ICU
$H_{0,Inpatient}$	New_PUI_in_Inpatient
κ	Percent_ED_patient_COVID_risk
I	AGPs_performed

Variables Calculated within the Simulation	
Variable	**Variable_name**
$P_{0,ICU}$	PUI_in_ICU
$P_{0,Inpatient}$	PUI_Inpatient
J	Patients_requiring_COVID_precautions
O	Patients_requiring_contact_droplet_precautions
Q	Patients_requiring_airborne_precautions
R	Patients_requiring_standard_precautions
V	Staff_per_patient
N	Patients_by_type
W	Clinical_staff_working
X	Non_clinical_staff_working
Z	Clinical_staff_perfoming_AGPs
α	N95s_used
β	Eye_protection_used
γ	Gowns_used
δ	Gloves_used
ε	Surgical_or_procedural_masks_used
ϕ	Concentration_coefficient

Sets		
Variable	**Variable_name**	**Values**
i	Day	{1,.....,365}
a	Location	{ICU, Inpatient}
j	Staff_type	{RN, MD, PCA, Student}
h	Patient_type	{C+P,O,Q,R}

Table 3.3.2: Simulation variables by type

Patient Related Variables	
k	Percent_typical_sick_requiring_airborne_precautions
K	Percent_typical_sick_requiring_contact_droplet_precautions
d_{ICU}	Typical_sick_ICU_occupancy
$d_{Inpatient}$	Typical_sick_Inpatient_occupancy
ω	Misc_non_clinical_entering_hospital
J	Patients_requiring_COVID_precautions
O	Patients_requiring_contact_droplet_precautions
Q	Patients_requiring_airborne_precautions
R	Patients_requiring_standard_precautions
N	Patients_by_type
$C_{0,ICU}$	COVID_in_ICU
$C_{0,Inpatient}$	COVID_in_Inpatient
$H_{0,ICU}$	New_PUI_in_ICU
$H_{0,Inpatient}$	New_PUI_in_Inpatient
κ	Percent_ED_patient_COVID_risk
l	AGPs_performed
$P_{0,ICU}$	PUI_in_ICU
$P_{0,Inpatient}$	PUI_Inpatient
ϕ	Concentration_coefficient
S	Daily_inpatient_typical_sick
E	Daily_patients_presenting_to_ED

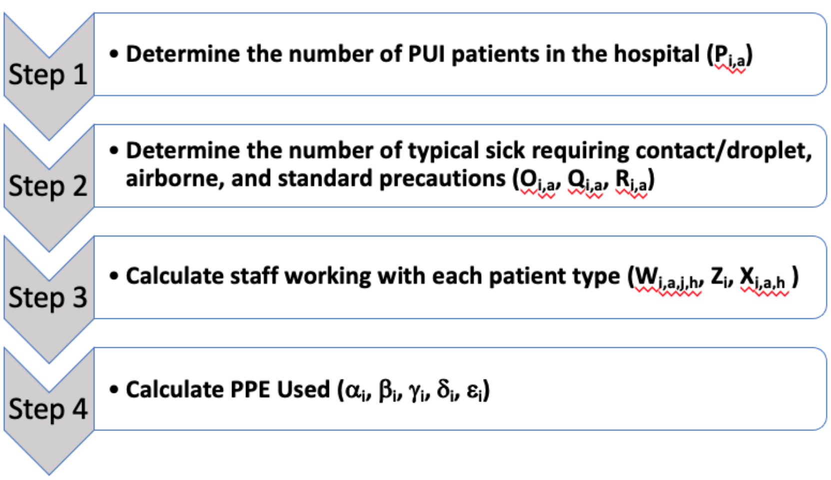
Staff Related Variables	
θ	HCW_daily_visits_ICU
λ	HCW_daily_visits_Inpatient
$V_{RN, ICU}$	RNs_per_ICU_patient
$V_{MD,ICU}$	MDs_per_ICU_patient
$V_{PCA,ICU}$	PCA_per_ICU_patient
$V_{Student,ICU}$	Student_per_ICU_patient
$V_{RN, Inpatient}$	RNs_per_Inpatient
$V_{MD, Inpatient}$	MDs_per_Inpatient
$V_{PCA, Inpatient}$	PCA_per_Inpatient
$V_{Student, Inpatient}$	Student_per_Inpatient
$V_{PCA, Inpatient}$	PCA_per_Inpatient
$V_{Student, Inpatient}$	Student_per_Inpatient
x	Non_Clinical_per_patient
μ	HCW_visits_per_patient_ED
g	Specialists
y	ED_Staff_per_day
z	HCWs_per_AGP
U	Shifts_per_day_clinical
u	Shifts_per_day_non_clinical
V	Staff_per_patient
W	Clinical_staff_working
X	Non_clinical_staff_working
Z	Clinical_staff_perfoming_AGPs

Infection Control Related Variables	
t	COVID_test_turnaround_time
b	Shifts_per_eye_protection
τ	Shifts_per_N95
ρ	Shifts_per_surgical_mask

Sets		
Variable	**Variable_name**	**Values**
i	Day	{1,.....,365}
a	Location	{ICU, Inpatient}
j	Staff_type	{RN, MD, PCA, Student}
h	Patient_type	{C+P,O,Q,R}

PPE Related Variables	
α	N95s_used
β	Eye_protection_used
γ	Gowns_used
δ	Gloves_used
ε	Surgical_or_procedural_masks_used

Figure 4.1.1: Simulation process



Step 1: Determining the Number of PUI Patients ($P_{i,a}$)

PUI patients are defined as patients who enter the hospital and are either exhibiting COVID-19 symptoms or are at risk of COVID-19 exposure. It is assumed PUI patients will be treated with COVID-19 precautions until they have received a negative COVID-19 test. PUI patients are a part of the typical sick population and are not considered COVID-19 patients until they receive a negative test result. In this step, the number of daily PUI patients in the hospital is calculated by determining how many of the previous day's PUI patients have been cleared by a test and how many new PUI patients are entering care. Because the population of PUI patients cannot exceed the total number of non-COVID patients in the hospital, a constraint is then enforced to ensure PUIs do not exceed the total number of typical sick patients.

Equation 3.2.1: Determining the number of PUI patients

$$P_{i,a} = P_{i-1,a} - (P_{i-1,a} / t) + H_{i,a}$$

$$\text{If } P_{i,a} > d_{i,a},$$

$$\text{then } P_{i,a} = d_{i,a}$$

Step 2: Determining the Number of Typical Sick Requiring Contact/Droplet, Airborne, and Standard Precautions

It is important to capture the PPE used when treating typical sick in addition to the PPE used for COVID patients. Since PPE use depends on the precaution level for the patient that is being treated, the number of typical sick that fall into each precaution category each day is calculated.

Equation 3.2.2: Determining the typical sick requiring contact/droplet, airborne, and standard precautions

$$J_{i,a} = C_{i,a} + P_{i,a}$$

$$O_{i,a} = (d_{i,a} - P_{i,a}) * K$$

$$Q_{i,a} = (d_{i,a} - P_{i,a}) * k$$

$$R_{i,a} = d_{i,a} - P_{i,a} - O_{i,a} - Q_{i,a}$$

Step 3: Calculate Staff Working with Each Patient Type

This step calculates how many staff members will be treating each type of patient in order to calculate how many staff members will be wearing an N95 or eye protection at some point during their shift. First, the concentration coefficient (ϕ_i) is calculated by determining the fraction of COVID plus PUI patients over the total hospital patient population. This coefficient is then used to determining the staff treating COVID-19 precaution patients. A concentration coefficient of 1 means that COVID and PUI patients are perfectly concentrated in one location so can be treated by the fewest possible staff members. A concentration coefficient of 0 means COVID and PUI patients are entirely spread out in different locations so must be treated by different staff members. As the concentration coefficient moves between 0 and 1, the number of unique staff members treating COVID and PUI patients moves proportionally between 1 staff member for each COVID or PUI patient and the fewest staff members possible for the group of COVID and PUI patients. Contact/droplet precaution patients and standard precaution patients are assumed to be optimally located to allow for the most efficient staff to patient ratios. Airborne patients are assumed to be inefficiently located due to their rare occurrence, and therefore all interact with unique staff members

Equation 3.2.3: Calculate staff working with each patient type

$$\phi_i = (C_{i,a} + P_{i,a}) / (C_{i,a} + P_{i,a} + (d_{i,a} - P_{i,a}))$$

$$W_{i,a,j,COVID} = N_{i,a,COVID} * (V_{a,j} + ((1 - \phi_i) * (1 - V_{a,j}))) * U$$

$$X_{i,a,COVID} = N_{i,a,COVID} * (x + ((1 - \phi_i) * (1 - x))) * u$$

$$W_{i,a,j,contact/droplet} = N_{h,i,contact/droplet} * V_{a,j} * U$$

$$X_{i,a,contact/droplet} = N_{h,i,contact/droplet} * x * u$$

$$W_{i,a,j,airborne} = N_{h,i,airborne} * U$$

$$X_{i,a,airborne} = N_{h,i,airborne} * u$$

$$W_{i,a,j,standard} = N_{h,i,standard} * V_{a,j} * U$$

$$X_{i,a,standard} = N_{h,i,standard} * x * u$$

$$Z_i = I_i * z$$

Step 4: Calculate PPE Use

N95s and Eye Protection: It is assumed all staff working with COVID-19, PUI, and airborne precaution patients will require an N95 and eye protection during their shift. It also assumes that on every day, regardless of the number of COVID-19 hospitalizations, every emergency room staff member and specialists likely to consult on a COVID-19 hospitalization (cardiologist, nephrologist, pulmonologist, infectious disease specialist, and rheumatologist) will wear an N95 and eye protection during their shift. To determine daily N95 or eye protection use, the daily use by staff members is divided by the reuse policy (shifts per N95 or eye protection). The small number of N95s used for aerosol generating procedures (AGPs), which are always single use, is also calculated.

Equation 3.2.4: Calculate N95s and eye protection used

$$\alpha_i = ((\sum_0^a \sum_0^j W_{i,a,j,COVID} + \sum_0^a \sum_0^j W_{i,a,j,airborne} + \sum_0^a X_{i,a,j,COVID} + \sum_0^a X_{i,a,airborne} + y + g) / \tau\ ) + Z_i$$

$$\beta_i = (\sum_0^a \sum_0^j W_{i,a,j,COVID} + \sum_0^a \sum_0^j W_{i,a,j,airborne} + \sum_0^a X_{i,a,j,COVID} + \sum_0^a X_{i,a,airborne} + y + g) / b$$

Gowns: It is assumed that gowns are always single use and are disposed after each patient contact. Gown use is calculated by multiplying the number of COVID-19, PUI, and contact/droplet patients in the hospital that day by the number of daily contacts expected for each patient depending on their location (ED, ICU, Inpatient).

Equation 3.2.5: Calculate gowns used

$$\gamma_i = ((O_{i,ICU} + C_{i,ICU} + P_{i,ICU}) * \theta) + ((O_{i,Inpatient} + C_{i,Inpatient} + P_{i,Inpatient}) * \lambda) + (E * \kappa * \mu) + Z_i$$

Gloves: Similar to gowns, it is assumed gloves are always single use and therefore use is determined by total patient contacts per day. Gloves are used for every patient type, so total daily glove use is calculated by multiplying the number of patients by the number of contacts expected for each patient depending on their location (ED, ICU, Inpatient).

Equation 3.2.6: Calculate gloves used

$$\delta_i = 2 * (((C_{i,ICU} + d_{i,ICU}) * \theta) + ((C_{i,Inpatient} + d_{i,Inpatient}) * \lambda) + (E * \mu) + Z_i$$

Surgical/Procedural Masks: It is assumed that every staff member who works in the hospital is given a new surgical mask each day to wear in their office and that every patient in the hospital is given a surgical mask each day to wear in their room. We also assume staff treating patients with contact/droplet precautions will dispose of their mask after each patient contact and pick up a new one.

Equation 3.2.7: Calculate surgical/procedural masks used

$$\varepsilon_i = ((\sum_0^a \sum_0^j \sum_0^h W_{i,a,j,h} + \sum_0^a \sum_0^h X_{i,a,h} + \omega) / \rho) + E + A_i + (\sum_0^j W_{i,ICU,j,contact/droplet} * \theta) + (\sum_0^j W_{i,Inpatient,j,contact/droplet} * \lambda)$$

4. Case study

The case study consists of four parts: 1) a simulation run where all variables are deterministic, 2) sensitivity analysis on the deterministic case study, 3) a simulation run using multiple epidemiological forecasts to produce an array of results, and 4) a Monte Carlo simulation where select variables are changed from deterministic to stochastic. The case study uses COVID-19 hospitalization published by the Massachusetts Department of Public Health (MDPH) from April 4, 2020 – April 3, 2021. This case study applies the simulation to predict the amount of PPE used in all acute care hospitals in Massachusetts during the specified time period. The static and stochastic inputs were determined through background research in nursing and medical journals, CDC provided resources, reports from the Bureau of Labor and Statistics, and extensive interviews with medical providers and support staff. This case study is presented as follows: First, all variables are held as deterministic inputs to create a base case output. Second, certain input variables are altered to conduct sensitivity testing and explore alternate COVID-19 severity scenarios. Third, to demonstrate potential future applications of the simulation, the simulation is run for the period of December 15, 2020 – January 11, 2021 using five different

Massachusetts hospitalization forecasts made on December 13, 2020 as hospitalization inputs. The results are presented to show the range of values that would result from uncertain epidemiological inputs. Finally, certain variables are changed to stochastic variables with conditional triangular probability distributions in a Monte Carlo simulation approach with 5,000 iterations. These iterations are then analyzed to identify the effects of input uncertainty. The end result is a thorough exploration of multiple applications of the simulation.

4.1 Simulation with Deterministic Inputs

In this simulation run, all variables are held as deterministic for the entirety of the simulation run. Although it is likely there is some uncertainty in the inputs, as described in sections 4.2 and 4.3, the deterministic run is important to explore the variables that affect PPE use and conduct sensitivity analysis.

4.1.1 Simulation Variables

There are two types of inputs in this simulation run, static inputs that remain the same for each day of the simulation and dynamic inputs containing epidemiological inputs such as COVID-19 hospitalization that change each day. The variables that were previously labeled in Table 3.3.1 as stochastic are held as deterministic and changed to static variables.

4.1.1.1 Static Inputs

A full list of static input data used in this case study is available in Appendix A. Select variables and their sources are described below.

- **Percent of typical sick population requiring airborne and contact/droplet precautions:** Data on typical percentage of patients requiring airborne and contact/droplet precautions were obtained from historical infection control records from a Massachusetts hospital (Hospital system data analyst, 2020).
- **COVID-19 test turnaround time:** COVID-19 test turnaround time was determined through historical records at a major Massachusetts hospital system (Hospital system data analyst, 2020).
- **Daily specialist and ED staff:** This case study assumed all registered specialists in the fields of nephrology, pulmonology, cardiology, infectious disease, and rheumatology work with at least one COVID-19 patient each day. Total specialist numbers come from

the Massachusetts Board of Registration in Medicine (2021). Daily ED staff was determined through historical 2019 staffing records provided by Patient Care Link (2021).

- **Shifts per day for clinical and non-clinical staff:** Shifts per day were chosen to match common healthcare staffing practices (Disaster Medicine Specialist, 2020).
- **Daily typical sick ED, inpatient, and ICU patients:** Daily patients presenting to the ED was determined by the 2017 National Hospital Ambulatory Medical Care Survey published by the CDC (2017). This survey contained historic yearly ED visits in the United States. Daily inpatient population in Massachusetts was determined by historic United States hospital admission data from 1975 – 2016 published by the Center for Disease Control (Hospital admission, 2016). Finally, the daily ICU patient population was taken from a ventilator use study for the United States by Wunsch et al. These sources all reported values for the entire United States. To determine the value for Massachusetts, the United States aggregate value was multiplied by 0.021 to adjust for Massachusetts' percentage of the total population as reported in 2019 (United States Population, 2019).
- **Shifts per N95, eye protection, and surgical masks:** Shifts per N95 mask was determined by published guidance by the Massachusetts Department of Public Health (Comprehensive Personal Protective Equipment (PPE) Guidance, 2021). Following consultation with disaster medicine experts, shifts of use per eye protection and surgical mask were set to match the N95 reuse guidance (Disaster Medicine Specialist, 2020).
- **HCW visits per patient in ED, Inpatient, and ICU:** Healthcare worker daily visits per inpatient and ICU patient were set to match the PPE assumptions in the Johns Hopkins University model (JHU, 2020). Healthcare worker daily visits per ED patient were determined through consultation with Massachusetts ED staff and disaster medicine experts (Disaster Medicine Specialist, 2020).
- **Staff per ICU and Inpatient:** Medical doctor (MD), Registered Nurse (RN), Patient Care Assistant (PCA), and student ratios per ICU patient and Inpatient were determined using a combination of pandemic preparedness guidelines published by the University of Minnesota and publicly available Massachusetts hospital staffing data from 2019 from

Patient Care Link (Pandemic Influenza Planning Guidance for Healthcare Institutions, 2007; Patient Care Link, 2019).

4.1.1.2 Dynamic Inputs

Dynamic input data used in this case study containing daily COVID-19 hospitalization and PUI populations is available in Appendix B. Select variables and their sources are described below.

- **Daily COVID-19 hospitalizations:** Daily COVID-19 hospitalization data was obtained from publicly available data published by the Massachusetts Department of Public Health (Dashboard of Public Health Indicators, 2021).
- **New PUI in ICU and inpatient**: PUI population data was extrapolated from data provided by a major Massachusetts hospital system (Hospital system data, 2021). This data showed that for every new COVID positive patient entering the hospital, roughly one additional patient was admitted as a PUI. To determine daily PUI patients entering inpatient, the total COVID-19 inpatient population was divided by 8 (the estimated length of stay for COVID-19 inpatients), to approximate the new COVID-19 inpatients that day. Since every new inpatient generates one new PUI, that number was used as the new inpatient PUI for that day. The same was done for ICU using a length of stay of 13 days determined by published findings from Lapidus et al. (Massachusetts Hospital System Data Analyst, 2021; 2020).
- **AGPs performed**: Daily AGPs performed were approximated by taking the new daily ICU patients (as described above) and multiplying by 2. This represents the population being put on and taken off ventilators each day.
- **Percent of ED patients who are considered COVID-19 risk**: The percent of ED patients who are considered COVID-19 risk was determined through historical ED records for a major Massachusetts hospital system obtained on December 14, 2020. Although it is likely this number should be more dynamic, it was kept constant for each day of the simulation due to lack of data availability (Hospital system data analyst, 2020).

4.1.2 Results

The data described in the previous section was used in the simulation outlined in section 3.3 to calculate the PPE used each day in acute care hospitals in Massachusetts from April 4th, 2020 to April 3rd, 2021. The sum of the PPE use for that entire period is summarized in Table 4.1.2.1 below along with the average day's use and the use on the worst day of COVID-19 hospitalizations. These results will be the base for the sensitivity analysis conducted in section 4.1.4.

Table 4.1.2.1: Massachusetts deterministic case study results

Year Cumulative	
N95s	5,657,829
Gowns	61,358,122
Gloves	392,028,164
Eyepro	5,626,297
Surg/proc masks	40,424,394

Average Day	
N95s	15,501
Gowns	168,104
Gloves	1,074,050
Eyepro	15,415
Surg/proc masks	110,752

Worst Day	
N95s	28,552
Gowns	471,692
Gloves	1,654,508
Eyepro	28,228
Surg/proc masks	120,711

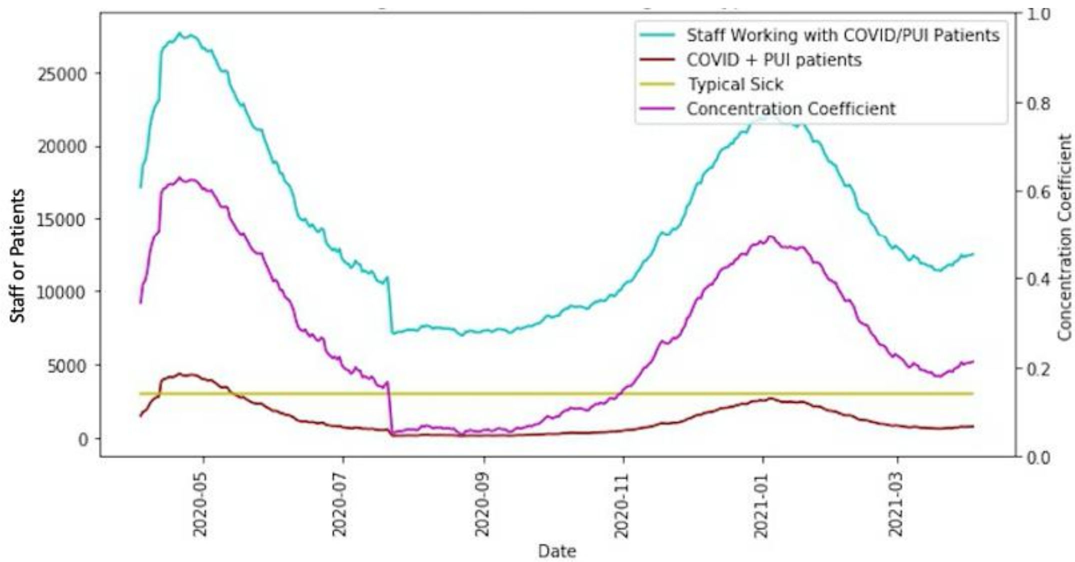
4.1.3 Variable relationships identified in the deterministic simulation

The initial deterministic simulation run helps identify the non-policy related variables that drive PPE use, such as COVID-19 hospitalizations and total patient population. Key drivers of use for each PPE type are described below along with a brief discussion of the concentration coefficient. The effect of policy-related variables on PPE use will be explored in the sensitivity analysis.

4.1.3.1 The concentration coefficient increases with COVID-19 and PUI patients

The concentration of COVID-19 and PUI patients within hospitals increases as COVID-19 cases increase. This approximates the natural phenomenon of COVID-19 and PUI patients becoming widespread enough that multiple end up in the same hospitals and wards. See Figure 4.1.3.1 below. The effect on the concentration coefficient on PPE use is significant and will be discussed in the sensitivity analysis.

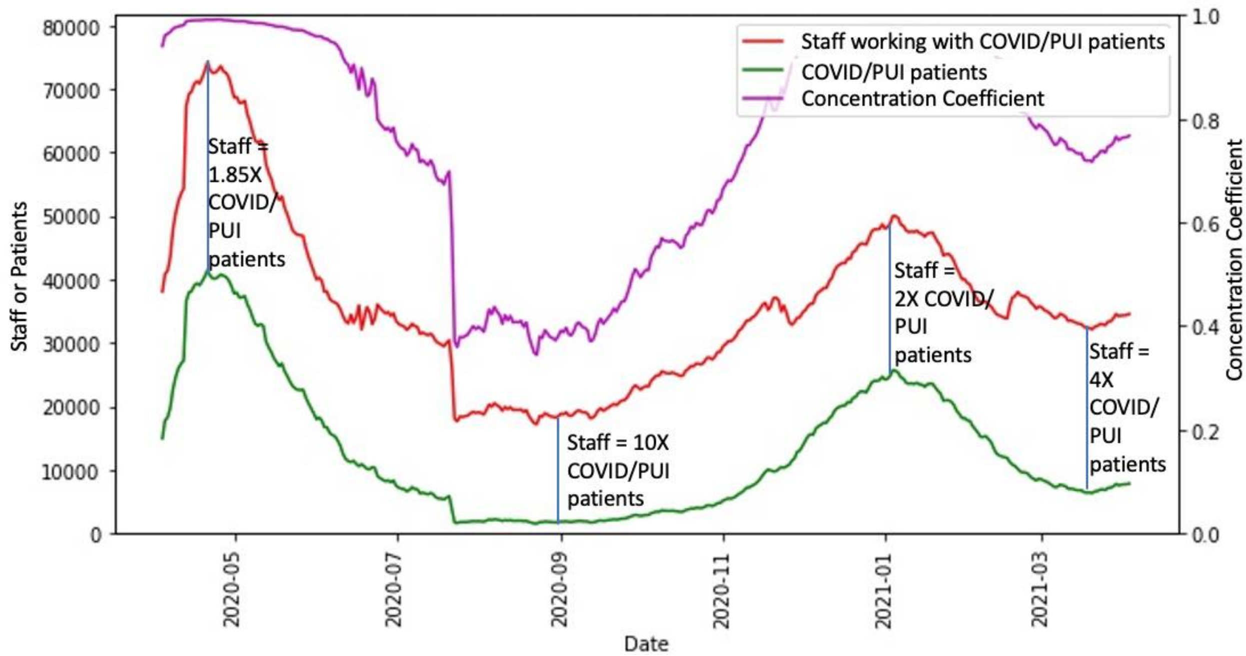
Figure 4.1.3.1: Concentration coefficient in the Massachusetts deterministic case study



4.1.3.2 The concentration coefficient is a key driver for the number of staff working with COVID-19 and PUI patients

As the concentration coefficient increases, COVID-19 and PUI patients become concentrated within hospital wards. This allows a single staff member to treat multiple COVID-19 and PUI patients during his or her shift. Although this effect is also seen in the current case study, in order to more easily visualize the dramatic effect of high concentration coefficients, the simulation was run with COVID-19 hospitalizations equal to 10X the rate seen in Massachusetts from April 4th, 2020 to April 3rd, 2021. At these high hospitalization levels, it is visually apparent how the rising concentration coefficient results in staff members treating COVID and PUI patients increasing non-linearly with COVID and PUI patient hospitalizations.

Figure 4.1.3.2: The effect of concentration coefficient as shown in a 10X COVID-19 scenario



4.1.3.3 Number of staff working with COVID-19 and PUI patients daily determines N95 and eye protection use

N95s and eye protection use is directly related to the number of staff working with COVID-19 and PUI patients. The fewer unique staff members interacting with these patients, the less N95s and eye protection will be used. The slight gap between total N95 use and staff working with COVID/PUI patients is a result of the small number of AGPs that require a single use N95 and staff working with airborne patients. The slight gap between total eye protection use and staff working with COVID/PUI patients also comes from staff working with airborne patients. See Figure 4.1.3.3 and Figure 4.1.3.4 below.

Figure 4.1.3.3: Massachusetts deterministic case study daily N95 use

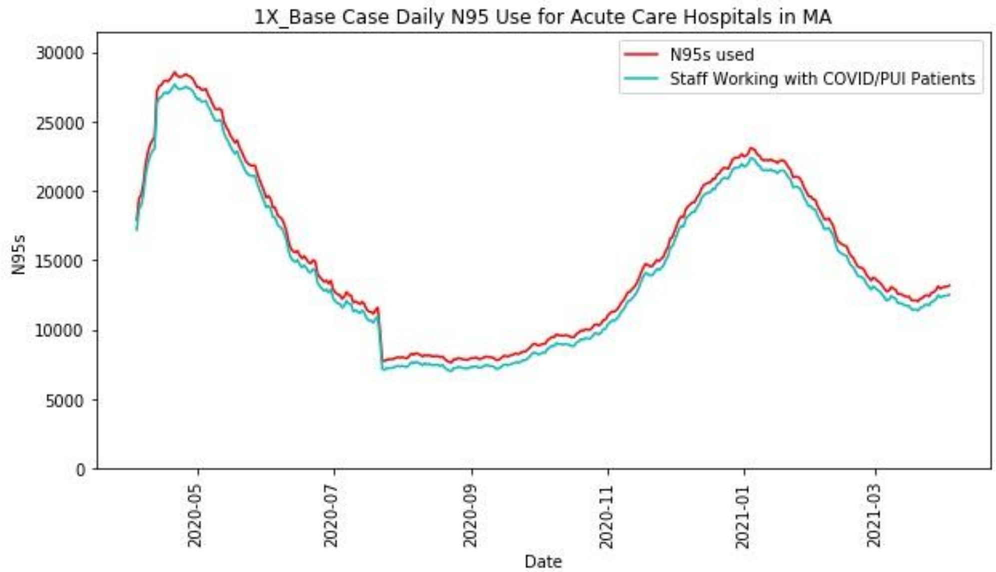
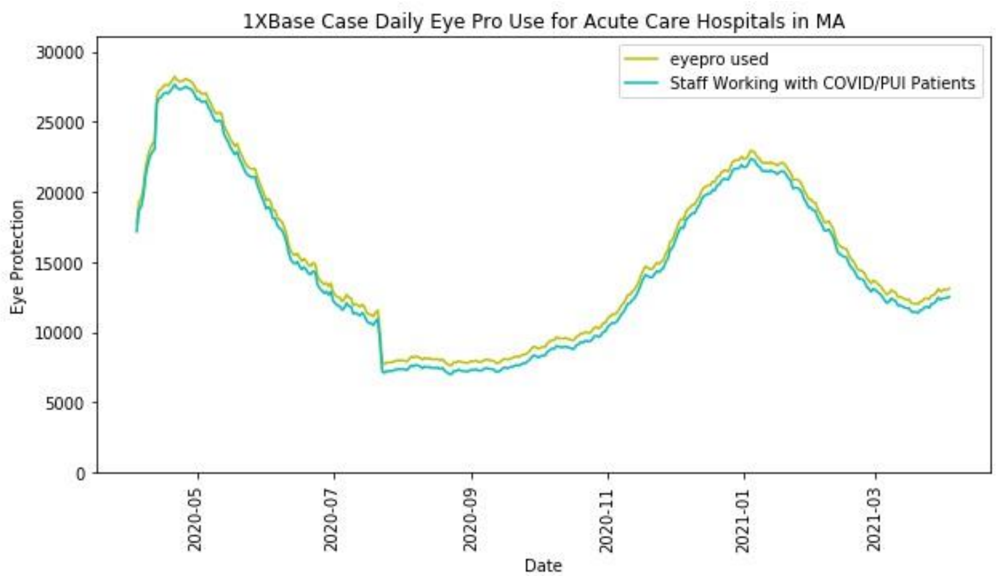


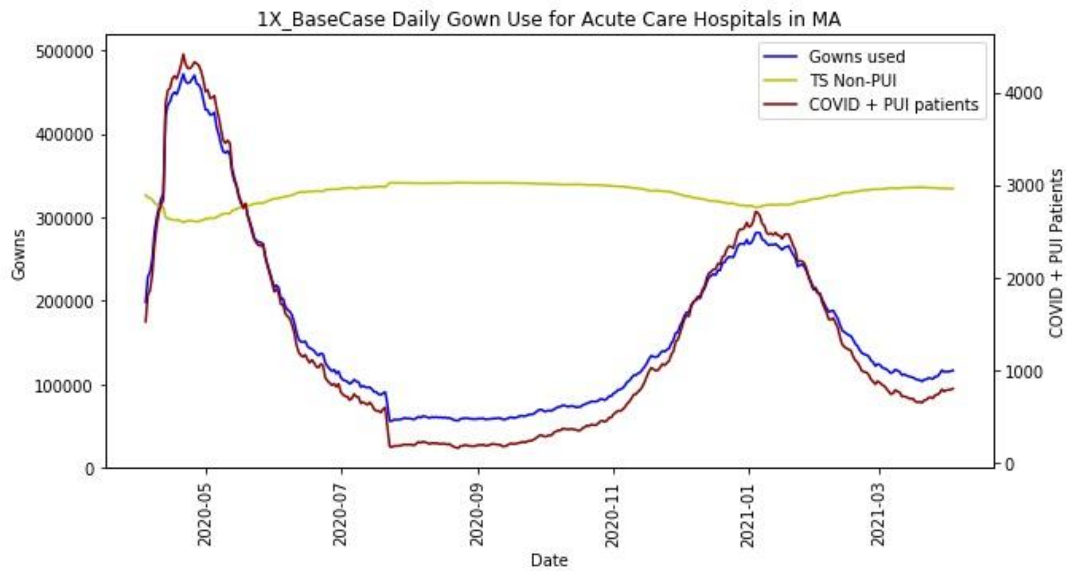
Figure 4.1.3.4: Massachusetts deterministic case study daily eye protection use



4.1.3.4 Total COVID-19 and PUI patients daily is the key driver of gown use

Gown use is heavily dependent on COVID-19 and PUI patients. It is also affected slightly by the typical sick population due to the gown use for typical sick contact/droplet patients. Figure 4.1.3.5 shows this effect clearly at the two peaks at 2020-05 and 2021-01 and at the trough at 2020-09. At the two peaks the large number of COVID patients result in more of the typical sick population being treated as PUI patients, as seen by the dip in the typical sick non-PUI population. This dip accounts for why the gown use at this period does not exactly align with the COVID and PUI trend. The trough at 2020-09 shows the opposite effect, where gown use well exceeds COVID and PUI patient use due to the gown use by the large typical sick non-PUI patient population.

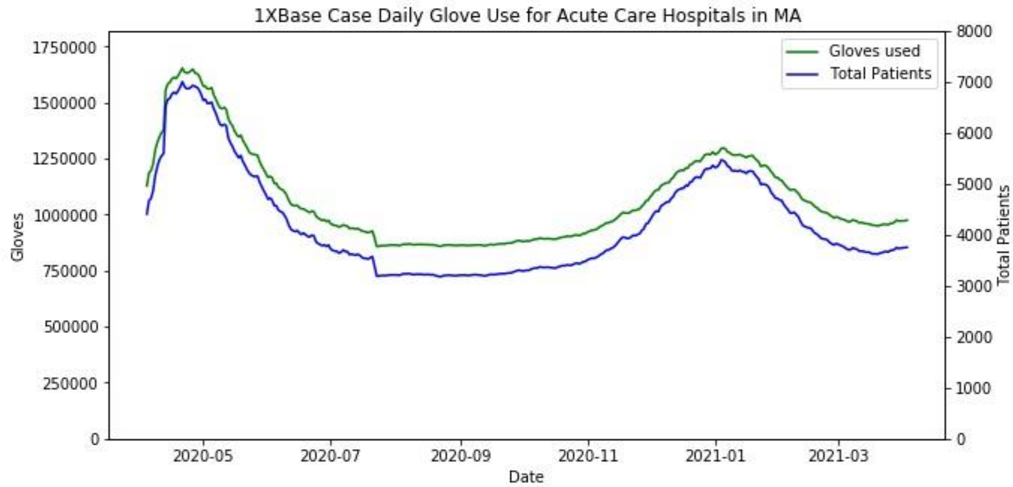
Figure 4.1.3.5: Massachusetts deterministic case study daily eye gown use



4.1.3.5 Total patient volume is the key driver of glove use

Gloves are used across the patient population when interacting with all patient types, so glove use is directly related to the total patient population. See Figure 4.1.3.6 below.

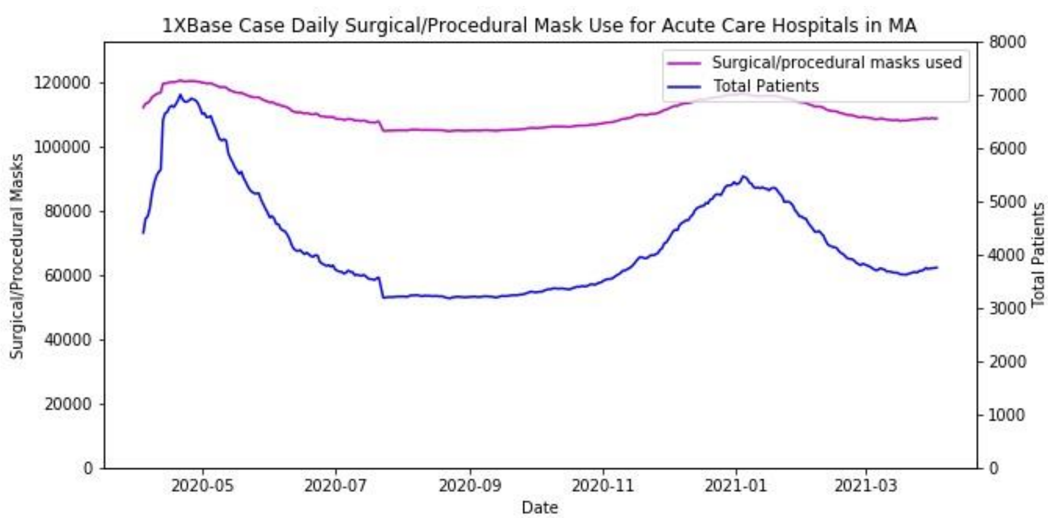
Figure 4.1.3.6: Massachusetts deterministic case study daily glove use



4.1.3.6 Surgical/procedural mask use has a high, almost constant base rate

Surgical/procedural masks have a high base level use due to their use by all staff and visitors in the hospital daily. Surgical/procedural mask use above this base rate is determined by patient population. Increased patient population results in more surgical/procedural masks being given to patients each day and more surgical mask changes that occur after interactions with contact/droplet precaution patients. See Figure 4.1.3.7 below.

Figure 4.1.3.7: Massachusetts deterministic case study daily surgical/procedural mask use



4.1.4 Sensitivity Analysis

Sensitivity analysis was conducted to explore the effects of slower COVID-19 diagnostic test turnaround times, increased reuse policies, decreased daily patient contacts by healthcare workers, implemented COVID-19 and PUI cohorting, and more extreme COVID-19 scenarios. This analysis is critical to identify policy-related variables that can decrease PPE use and potentially be incorporated into pandemic preparedness and response plans.

4.1.4.1 COVID-19 diagnostic test turnaround time

The longer the COVID-19 diagnostic test turnaround time, the longer it takes to clear PUI patients with a negative test result. Increased diagnostic test turnaround times result in increased use of N95s, gowns, and eye protection. It does not affect glove use, as gloves are used across patient type and do not depend on precaution level. Counterintuitively, longer diagnostic test turnaround times actually decrease surgical mask use. This is due to more healthcare workers wearing N95s with PUIs who would otherwise have been cleared by a negative COVID-19 test and treated as contact/droplet patients using only a surgical mask. Although the impact of increased testing times is not severe, it is important to note that this impact would be significantly higher in scenarios where more than one PUI was produced for every new COVID-19 case. This would be the case in very densely populated areas or during a strong influenza season. See Table 4.1.4.1 below.

Table 4.1.4.1: COVID-19 diagnostic test turnaround time sensitivity analysis

	Base Case (1 Day Turnaround)	2 Day Turnaround		3 Day Turnaround		7 Day Turnaround	
PPE Type	Year Cumulative	Year Cumulative	% Increase from Base Case	Year Cumulative	% Increase from Base Case	Year Cumulative	% Increase from Base Case
N95s	5,657,829	5,786,669	2.3%	5,876,079	3.9%	5,920,461	4.6%
Gowns	61,358,122	63,089,359	2.8%	64,807,847	5.6%	71,675,637	16.8%
Gloves	392,028,164	392,028,164	0.0%	392,028,164	0.0%	392,028,164	0.0%
Eye protection	5,626,297	5,755,137	2.3%	5,844,547	3.9%	5,888,929	4.7%
Surg/proc masks	40,424,394	40,232,900	-0.5%	40,007,436	-1.0%	38,944,202	-3.7%

4.1.4.2 Increased reuse policies

Increasing the length of reuse policies has a linear effect on decreasing eye protection use, meaning increasing reuse from 1 shift to 5 shifts will decrease PPE use by 80%. The effect of increasing reuse policies for N95s is close to linear but varies slightly because N95s used during AGPs are considered single use and are not affected by the reuse policy. Increasing reuse policies for surgical masks has a small effect due to the assumption that patients will continue to be issued a new surgical mask every day regardless of reuse policy. Therefore, only staff are able to reuse their surgical masks. Gowns and gloves are considered single use and are not affected by the reuse policy. See Table 4.1.4.2 below.

Table 4.1.4.2: Reuse policy sensitivity analysis

	Base Case (1 Shift Reuse)	5 Shifts Reuse	
PPE Type	Year Cumulative	Year Cumulative	% of Base Case
N95s	5,657,829	1,156,788	20.4%
Gowns	61,358,122	61,358,122	100.0%
Gloves	392,028,164	392,028,164	100.0%
Eye protection	5,626,297	1,125,256	20.0%
Surg/proc masks	40,424,394	15,986,507	39.5%

4.1.4.3 Decreased healthcare worker patient contacts

Reducing healthcare worker patient contacts has a linear effect on use for gowns and gloves, meaning if healthcare workers visit a patient 10 times instead of 20 times per day, glove and gown use will be cut in half. It has a much smaller effect on surgical masks due to the high base rate of surgical mask use for all patients and employees. Reducing patient contacts only affects surgical mask use for contact/droplet precaution patients. Healthcare worker daily visits does not affect N95 or eye pro use. See Table 4.1.4.3 below.

Table 4.1.4.3: Healthcare worker patient contacts sensitivity analysis

	Base Case (Typical Daily Patient Contacts)	Half Daily Patient Contacts	
PPE Type	Yearly Cumulative	Yearly Cumulative	% of Base Case
N95s	5,657,829	5,657,829	100.0%
Gowns	61,358,122	30,694,827	50.0%
Gloves	392,028,164	196,045,614	50.0%
Eye protection	5,626,297	5,626,297	100.0%
Surg/proc masks	40,424,394	37,482,084	92.7%

4.1.4.4 Implemented cohorting of COVID-19 and PUI patients

In the simulation it is assumed the concentration/dispersion of COVID-19 cases across and within acute care hospitals can be approximated by the ratio of COVID-19 and PUI patients to the entire patient population. This is meant to approximate how COVID-19 and PUI cases would occur without any intervention to segregate or cluster patients into a single facility or wing in a facility. As the concentration coefficient increases, each COVID-19 and PUI patient is treated by fewer unique staff members. This is intuitive, because as wards are overwhelmed with COVID-19 and PUI patients, staff members are treating multiple COVID-19 and PUI patients on their shift, which allows them to use the same N95 for multiple patients. This sensitivity analysis explores the possible decrease in PPE that occurs if there is perfect cohorting, meaning every COVID-19 and PUI case is put into a single facility in order to be treated by the fewest staff members possible. Although this is an unlikely scenario, it shows the potential impact of implemented cohorting policies. Cohorting patients only affects use of PPE items that are reused by staff members between patients, namely N95s and eye protection. Because patients are cohorted, the same staff member can use the same N95 or eye protection between patients without changing it. Additionally, because patients are treated efficiently, fewer total staff are working each day, resulting in slightly less surgical/procedural mask use. See Table 4.1.4.4 below.

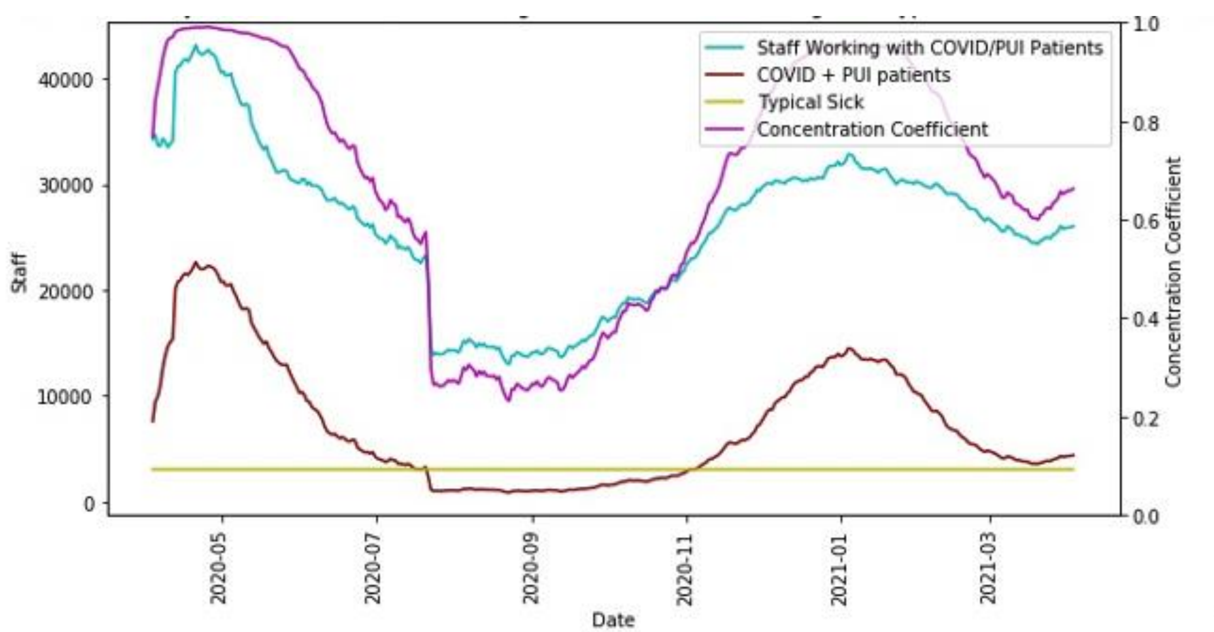
Table 4.1.4.4: Implemented cohorting sensitivity analysis

	Base Case (Concentration Coefficient Approximation)	Implemented Perfect Cohorting	
PPE Type	Yearly Cumulative	Yearly Cumulative	% of Base Case
N95s	5,657,829	2,953,060	52.2%
Gowns	61,358,122	61,358,122	100.0%
Gloves	392,028,164	392,028,164	100.0%
Eye protection	5,626,297	2,921,528	51.9%
Surg/proc masks	40,424,394	38,521,978	95.3%

4.1.4.5 Higher COVID-19 hospitalization scenarios

Increasing the severity of the COVID-19 pandemic has a non-linear effect on PPE use. In a scenario that is exactly 5X worse than COVID-19, meaning every day has 5X more COVID-19 hospitalizations than was reported during the actual COVID-19 pandemic, the concentration coefficient approaches 1. This means that there are so many COVID-19 patients that they naturally concentrate within hospitals. When the concentration of COVID-19 and PUI patients is high, the same healthcare worker is treating multiple COVID-19 and PUI patients. Since we assume healthcare workers can wear the same N95 and eye protection between patients during their shift, this means additional COVID-19 and PUI patients do not always require the use of additional N95s and eye protection by staff. This effect was shown clearly in the 10X COVID-19 scenario shown in Figure 4.1.3.2, but is also evident in the 5X COVID-19 scenario shown in Figure 4.1.4.1.

Figure 4.1.4.1: Concentration coefficient in 5X COVID-19 Massachusetts deterministic case study scenario



A 5X COVID-19 scenario has a non-linear effect on gowns, gloves, and surgical masks due to their use with typical sick patients. Gowns are used with contact/droplet patients, which do not increase when COVID-19 patients increase. Gloves are used with all typical sick patients, which also stay constant in this scenario. Finally, surgical/procedural masks have a high base rate from being issued to staff and patients daily, so are not strongly affected by increases in COVID-19 cases.

Table 4.1.4.5: 5X COVID-19 scenario sensitivity analysis results

Year Cumulative

PPE type	Base Case	5X COVID-19 Severity	% of Base Case
N95s	5,657,829	10,692,755	189%
Gowns	61,358,122	246,105,412	401%
Gloves	392,028,164	747,668,964	191%
Eyepro	5,626,297	10,535,223	187%
Surg/proc masks	40,424,394	44,552,302	110%

Worst Day

PPE	Base Case	5X COVID-19 Severity	% of Base Case
N95s	28,552	49,442	173%
Gowns	471,692	2,191,974	465%
Gloves	1,654,508	4,950,692	299%
Eyepro	28,228	47,766	169%
Surg/proc masks	120,711	140,047	116%

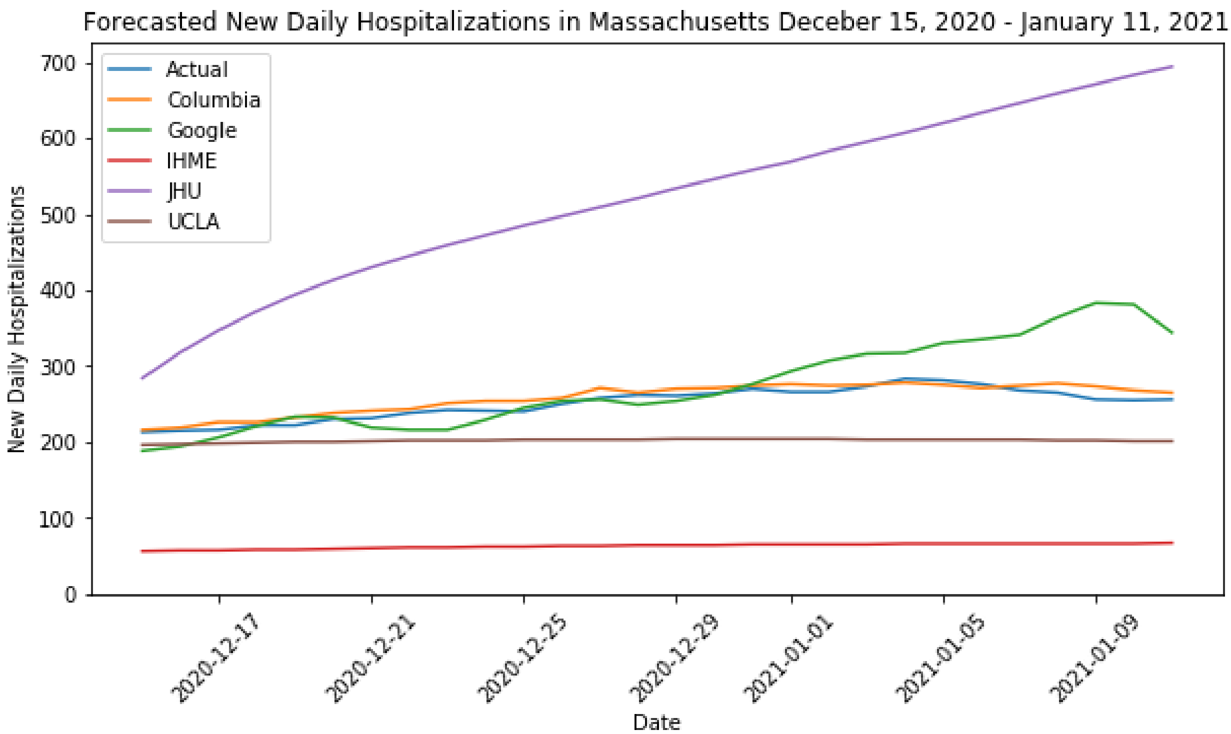
4.2 Example simulation application when faced with conflicting epidemiological forecasts

The previous case study simulation application used actual reported COVID-19 hospitalizations in Massachusetts for the purposes of demonstrating the simulation and identifying how different variables affect PPE use. In future real-world applications of this simulation, it is unlikely that there will be one definitive epidemiological model that provides hospitalization numbers for the dynamic inputs. It is much more likely that, like in COVID-19, there will be multiple, often conflicting, epidemiological forecasts being reported. In this section, an example application of five reported COVID-19 hospitalization forecasts for the state of Massachusetts from December 15, 2020 – January 11, 2021 is used to create a range of possible PPE outputs. This output range could then be used by decision makers to weigh risk and make informed PPE purchasing and stockpile decisions.

4.2.1 Epidemiological input data

Every week starting June 1, 2020 to present, forecasters from across the country submitted COVID-19 forecasts to the COVID-19 forecast hub and the CDC. These forecasts included four-week-ahead state-level forecasts on new COVID-19 hospitalizations (CDC Forecasting, 2021). For this portion of the case study, five different submitted forecasts covering the period of December 15, 2020 – January 11, 2021 in Massachusetts were used as the dynamic inputs for daily COVID-19 hospitalizations. The week of December 15, 2020 – January 11, 2021 was chosen due to the presence of significant disagreement between forecasts, allowing for a wide range of results. The simulation is run using the hospitalization numbers reported in five different forecasts: Columbia University, Google-Harvard School of Public Health, Institute for Health Metrics and Evaluation (IHME), Johns Hopkins University (JHU), and University of California Los Angeles (UCLA). These were chosen out of 11 possible choices because they best represented a diverse range of forecasts with little overlap. The forecasts are shown in Figure 4.2.1.1 below along with the actual reported Massachusetts hospitalizations for that period.

Figure 4.2.1.1: Submitted forecasts for December 15, 2020 – January 11, 2021



4.2.2 Results

Figure 4.2.2.1 through 4.2.2.5 show the PPE outputs produced for the specified four-week period using the inputs from each of the five forecasts and the actual Massachusetts COVID-19 hospitalizations. These forecasts produce a wide range of predictions. The largest N95 daily predictions are over twice as large as the smallest N95 daily predictions. For gowns, the largest daily predictions are over six times as large as the smallest gown daily predictions. These varying results make it clear that the simulation is only as accurate as its epidemiological inputs and is not robust against error in COVID-19 hospitalization predictions. Although this large spread in outputs makes it difficult to identify the "correct" PPE prediction, seeing an array of output possibilities allows decision makers to weigh risk and make an informed choice in the face of uncertainty in disease progression. It is also worth noting that despite dependence on epidemiological inputs for PPE output accuracy, the simulation can still be used to explore the magnitude of the effects of different interventions as shown in previous sensitivity analysis.

The five forecasts used for this analysis only forecasted new daily hospitalizations, not current hospitalizations. The simulation was initiated with the actual COVID-19 hospitalizations on December 14, 2020. The simulated PPE use for the IHME forecast, which had very low predictions for new COVID-19 hospitalization, decreases over the first eight days of the simulation because the simulation is initiated with higher current hospitalizations than forecasted by IHME. Those current hospitalizations leave the hospital over their eight-day length of stay and are not fully replaced by the low IHME new hospitalizations. After eight days, all of the initial hospitalizations have left the hospital and hospitalizations are only provided by the IHME forecast, hence the leveling off of PPE use. This effect is seen in all five forecasts but since the other four forecasts align more with the actual COVID-19 reported hospitalization the effect is not as stark.

Figure 4.2.2.1: Daily N95 use predicted from multiple forecasts

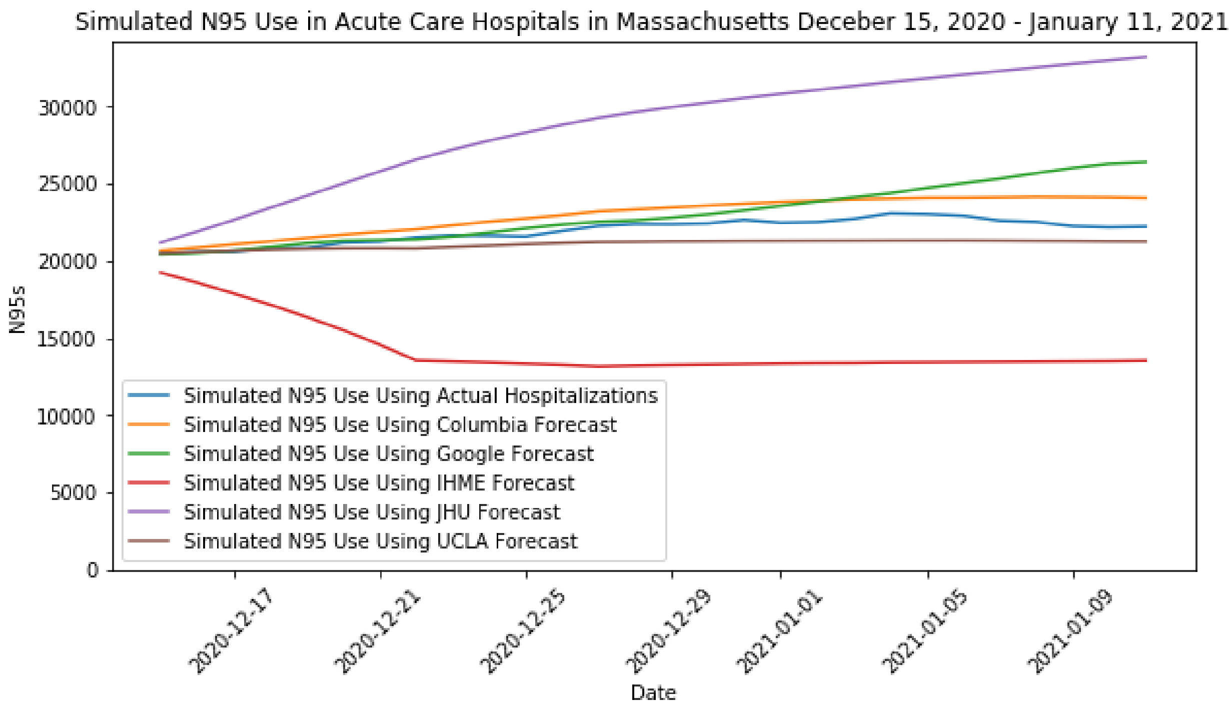


Figure 4.2.2.2: Daily eye protection use predicted from multiple forecasts

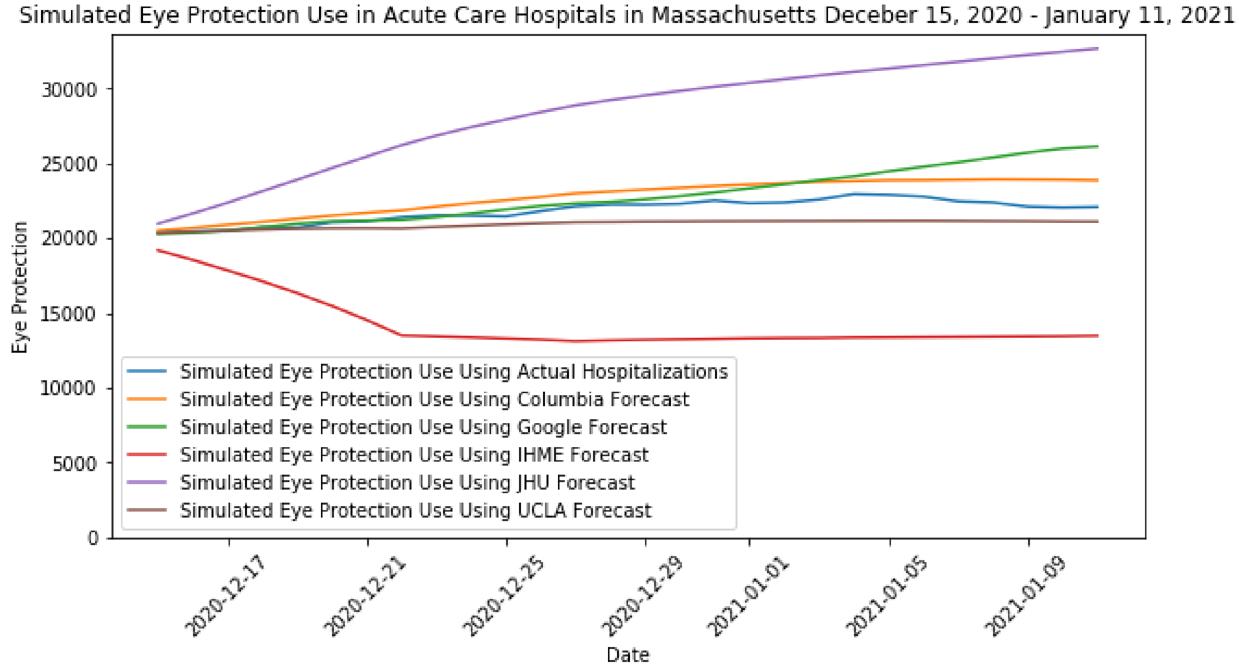


Figure 4.2.2.3: Daily gown use predicted from multiple forecasts

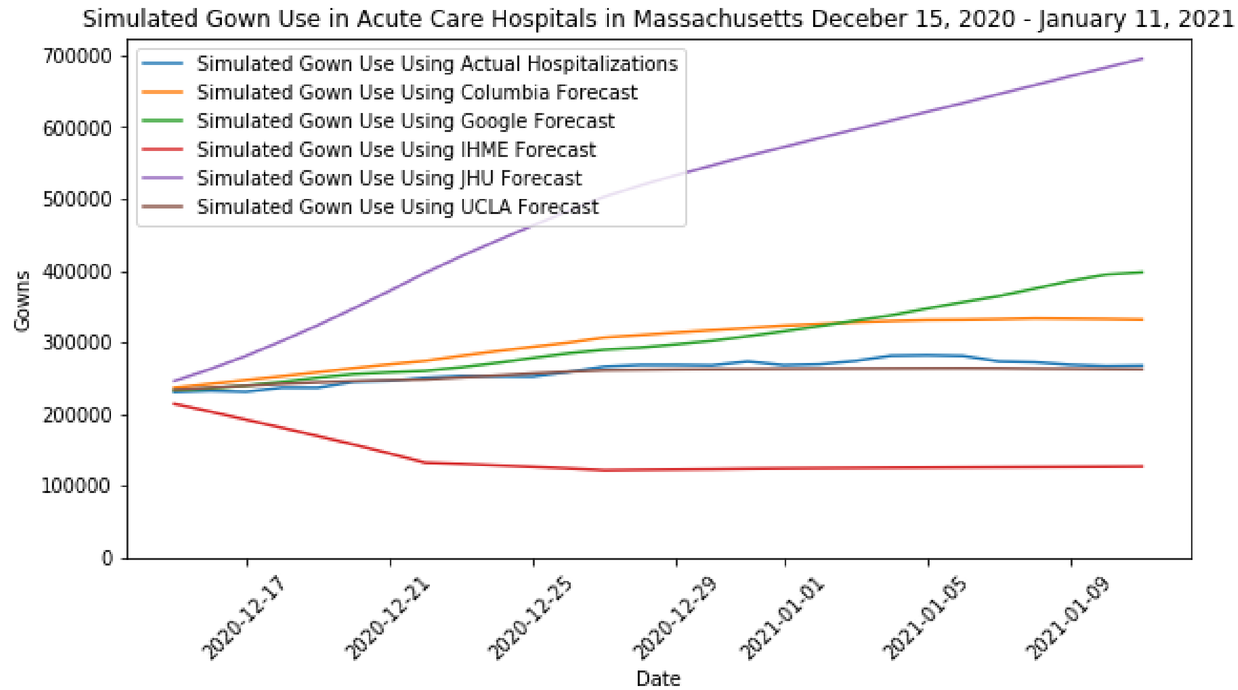


Figure 4.2.2.4: Daily glove use predicted from multiple forecasts

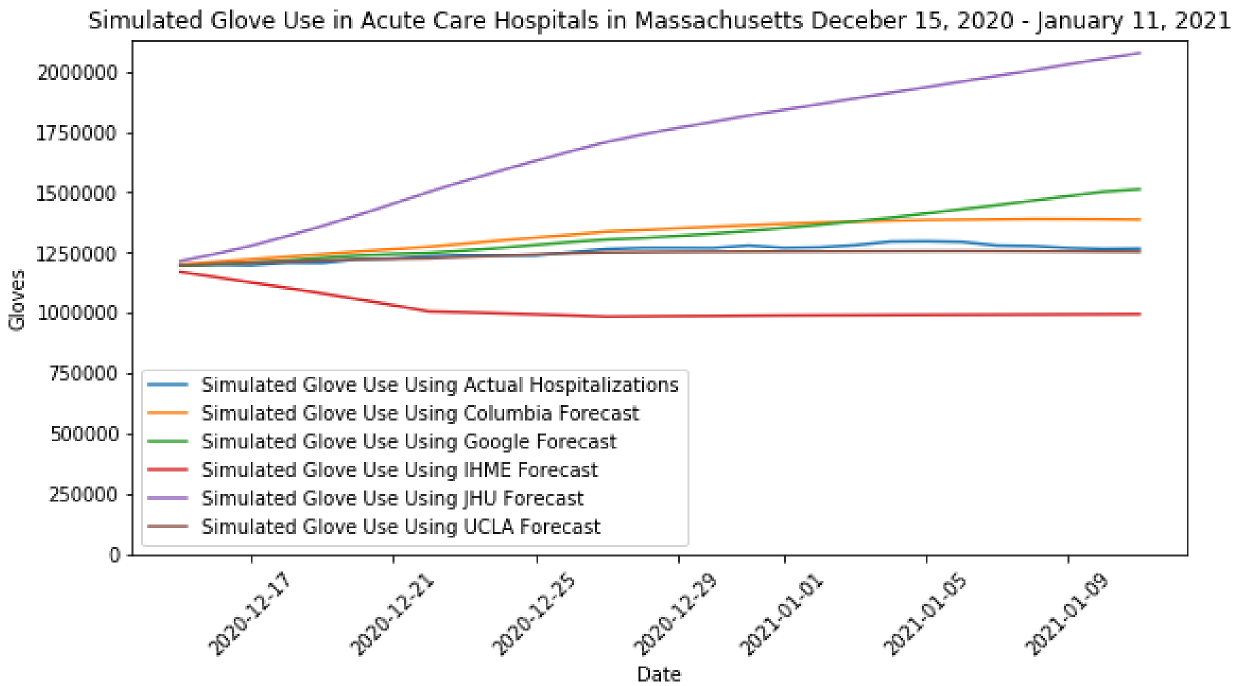
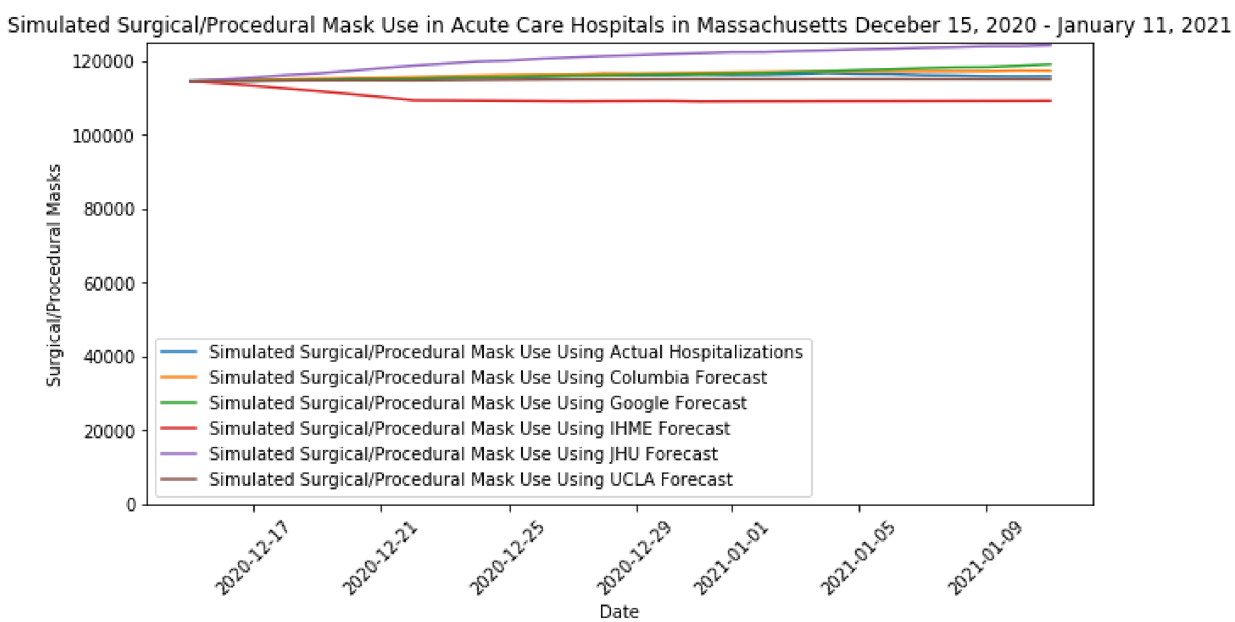


Figure 4.2.2.5: Daily surgical/procedural mask use predicted from multiple forecasts



4.3 Understanding the effect of uncertainty with a Monte Carlo simulation

The deterministic simulation runs using actual reported COVID-19 hospitalizations and COVID-19 hospitalization forecasts fail to account for uncertainty inherent in the static input variables. In this section, certain input variables are changed from deterministic to stochastic and a Monte Carlo simulation is used to produce a range of PPE use outputs. Running a deterministic case study is important to identify key interactions between variables in the simulation and to conduct sensitivity analysis that can inform future policy. However, Monte Carlo simulation may be a better application for real time decision making because it allows for uncertainty in key variables that better reflects actual variation in use on the ground.

4.3.1 Stochastic variables

Table 4.3.1.1 below shows the variables that were converted to stochastic inputs along with their minimum, maximum, and starting mean values for their conditional triangle probability distributions. Two primary types of variables were chosen: 1) Healthcare worker daily visits to patients and 2) Staff per patient. These two variable types were chosen because they are dependent on hospital specific practices and on patient severity and care needs. Keeping them as set deterministic values would fail to capture the natural variations between hospitals and patients. Secondly, changes in these input variables have non-trivial effects on total PPE output as shown in the sensitivity analysis conducted in section 4.1.4.

Table 4.3.1.1: Stochastic variables for Monte Carlo simulation

Variable	Variable_name	Description	Min	Mean	Max	Units	Source for Mean Values	Source for Min/Max Values
θ	HCW_daily_visits_ICU	How many times a healthcare worker sees an ICU patient per day (requiring a PPE change)	60	170	220	visits	PPE Assumptions. Johns Hopkins Bloomberg School of Public Health Center for Health Security website. Updated April 18, 2020. Accessed December 15, 2020. https://www.centerforhealthsecurity.org/resources/COVID-19/PPE/PPE-assumptions	Disaster Medicine Specialist, PhD, oral communication, July 30, 2021
λ	HCW_daily_visits_Inpatient	How many times a healthcare worker sees an inpatient per day (requiring a PPE change)	20	80	120	visits	PPE Assumptions. Johns Hopkins Bloomberg School of Public Health Center for Health Security website. Updated April 18, 2020. Accessed December 15, 2020. https://www.centerforhealthsecurity.org/resources/COVID-19/PPE/PPE-assumptions	Disaster Medicine Specialist, PhD, oral communication, July 30, 2021
$V_{RN, ICU}$	RNs_per_ICU_patient	Number of RNs who would be assigned to treat an ICU patient. For example, .5 would mean 1 RN treats 2 ICU patients	0.5	0.73	2	RNs	2019 Reports. PatientCareLink website. Accessed December 3, 2020. https://patientcarelink.org/2019-plans/	Disaster Medicine Specialist, PhD, oral communication, July 30, 2021
$V_{MD, ICU}$	MDs_per_ICU_patient	Number of MDs who would be assigned to treat an ICU patient. For example, .5 would mean 1 MD treats 2 ICU patients	0.07	0.13	0.2	MDs	Pandemic Influenza Planning Guidance for Healthcare Institutions, Table 9. Center for Infectious Disease and Research Policy, University of Minnesota webiste. Updated September 2007, Accessed November 17, 2020. https://www.cidrap.umn.edu/sites/default/files/public/php/340/340_guidance.pdf	Disaster Medicine Specialist, PhD, oral communication, July 30, 2021
$V_{PCA, ICU}$	PCA_per_ICU_patient	Number of PCAs who would be assigned to treat an ICU patient. For example, .5 would mean 1 PCA treats 2 ICU patients	0.07	0.14	0.2	PCAs	2019 Reports. PatientCareLink website. Accessed December 3, 2020. https://patientcarelink.org/2019-plans/	Disaster Medicine Specialist, PhD, oral communication, July 30, 2021
$V_{Student, ICU}$	Student_per_ICU_patient	Number of students who would be assigned to treat an ICU patient. For example, .5 would mean 1 student treats 2 ICU patients	0	0.15	0.15	student	Disaster Medicine Specialist, PhD, oral communication, December 8, 2020	Disaster Medicine Specialist, PhD, oral communication, July 30, 2021
$V_{RN, Inpatient}$	RNs_per_Inpatient	Number of RNs who would be assigned to treat an inpatient. For example, .5 would mean 1 RN treats 2 ICU patients	0.11	0.27	0.5	RNs	2019 Reports. PatientCareLink website. Accessed December 3, 2020. https://patientcarelink.org/2019-plans/	Disaster Medicine Specialist, PhD, oral communication, July 30, 2021
$V_{MD, Inpatient}$	MDs_per_Inpatient	Number of MDs who would be assigned to treat an inpatient. For example, .5 would mean 1 MD treats 2 ICU patients	0.03	0.04	0.1	MDs	Pandemic Influenza Planning Guidance for Healthcare Institutions, Table 9. Center for Infectious Disease and Research Policy, University of Minnesota webiste. Updated September 2007, Accessed November 17, 2020. https://www.cidrap.umn.edu/sites/default/files/public/php/340/340_guidance.pdf	Disaster Medicine Specialist, PhD, oral communication, July 30, 2021
$V_{PCA, Inpatient}$	PCA_per_Inpatient	Number of PCAs who would be assigned to treat an inpatient. For example, .5 would mean 1 PCA treats 2 ICU patients	0.05	0.12	0.17	PCAs	2019 Reports. PatientCareLink website. Accessed December 3, 2020. https://patientcarelink.org/2019-plans/	Disaster Medicine Specialist, PhD, oral communication, July 30, 2021
$V_{Student, Inpatien}$	Student_per_Inpatient	Number of students who would be assigned to treat an inpatient. For example, .5 would mean 1 student treats 2 ICU patients	0	0.1	0.1	student	Disaster Medicine Specialist, PhD, oral communication, December 8, 2020	Disaster Medicine Specialist, PhD, oral communication, July 30, 2021

Minimum and maximum values were determined through guidance from a disaster medicine subject matter expert. Minimum values represent the lowest possible values that could be reached while still achieving required patient care standards. Minimum values would be accurate in either low acuity patients or in situations where resources are scarce and must be rationed. Maximum values represent the most resources and time that would be needed to treat a single patient. Maximum values would be accurate when treating extremely sick patients with maximum resources available.

These stochastic variables follow a conditional triangle distribution instead of a typical triangle distribution because each variable is correlated with the percent of hospital capacity that is being used. The mean values listed in Table 4.3.1.1 above represent the mean values when hospitals are operating at their typical volumes without the addition of COVID-19 patients. As hospitals become more crowded, these mean values will shift as healthcare workers and resources are strained. For example, as hospital patient populations move towards their maximum capacity, healthcare workers will be assigned to provide treatment to more patients at one time, therefore lowering the staff to patient rations. As these staff to patient ratios decrease, daily healthcare worker visits to patients will also decrease as healthcare staff have less time to check in on each patient. The minimum and maximum values never change as these are considered the extreme minimum and maximum for ethical patient care. To account for this correlation between hospital capacity and the mean values of the triangle distribution, a conditional triangle distribution was used where the mean shifts continuously towards the minimum values as percent of used hospital capacity increases. Once hospitals reach 100% used capacity, mean values are all equal to the minimum values in the distribution, making the triangle distribution one tailed to the right. The equation to shift the mean conditionally on hospital capacity is shown in Equation 4.3.1 below. Although only HCW visits per patient is shown, the same process is used for all staff per patient variables as well.

Table 4.3.1.2: Variables for the mean adjustment process for the conditional triangle distributions

Variable	Variable_name	Description	Value	Units	Source
a	Typical ICU Occupancy in MA	ICU occupancy on an average day in Massachusetts prior to COVID-19	1023	patients	Wunsch H, Wagner J, Herlim M, Chong DH, Kramer AA, Halpern SD. ICU occupancy and mechanical ventilator use in the United States. Crit Care Med. 2013;41(12):2712-2719. doi:10.1097/CCM.0b013e318298a139
b	Total ICU Capacity in MA	Total reported ICU beds across all acute care hospitals in Massachusetts	1458	beds	Dashboard of Public Health Indicators. Massachusetts Department of Public Health website. December 29, 2020. Accessed December 30 2020. https://www.mass.gov/info-details/archive-of-covid-19-cases-in-massachusetts#december-2020-
d	Typical Inpatient Occupancy in MA	Inpatient occupancy on an average day in Massachusetts prior to COVID-19	2017	patients	Table 82. Hospital admission, average length of stay, outpatient visits, and outpatient surgery, by type of ownership and size of hospital: United States, selected years 1975–2015. Center for Disease Prevention and Control Website. Accessed November 17, 2020.
e	Total Inpatient Capacity in MA	Total reported inpatient beds across all acute care hospitals in Massachusetts	9061	beds	Dashboard of Public Health Indicators. Massachusetts Department of Public Health website. December 29, 2020. Accessed December 30 2020. https://www.mass.gov/info-details/archive-of-covid-19-cases-in-massachusetts#december-2020-

Equation 4.3.1: The mean adjustment process for the conditional triangle distribution – healthcare worker visits per patient example

$$h = a / b$$

$$f = (a + C_i) / b$$

$$k = d / e$$

$$g = (d + C_i) / e$$

$$\theta_{mean,\, i} = \theta_{mean} - ((\theta_{mean} - \theta_{min}) * ((f - h)/ (1 - h))$$

$$if\ \theta_{mean,\, I} < \theta_{min}:$$

$$\theta_{mean,\, I} = \theta_{min}$$

$$\lambda_{mean,\, i} = \lambda_{mean} - ((\lambda_{mean} - \lambda_{min}) * ((g - k) / (1 - k))$$

$$if\ \lambda_{mean,\, i} < \lambda_{min}:$$

$$\lambda_{mean,\, i} = \lambda_{min}$$

4.3.2 Results

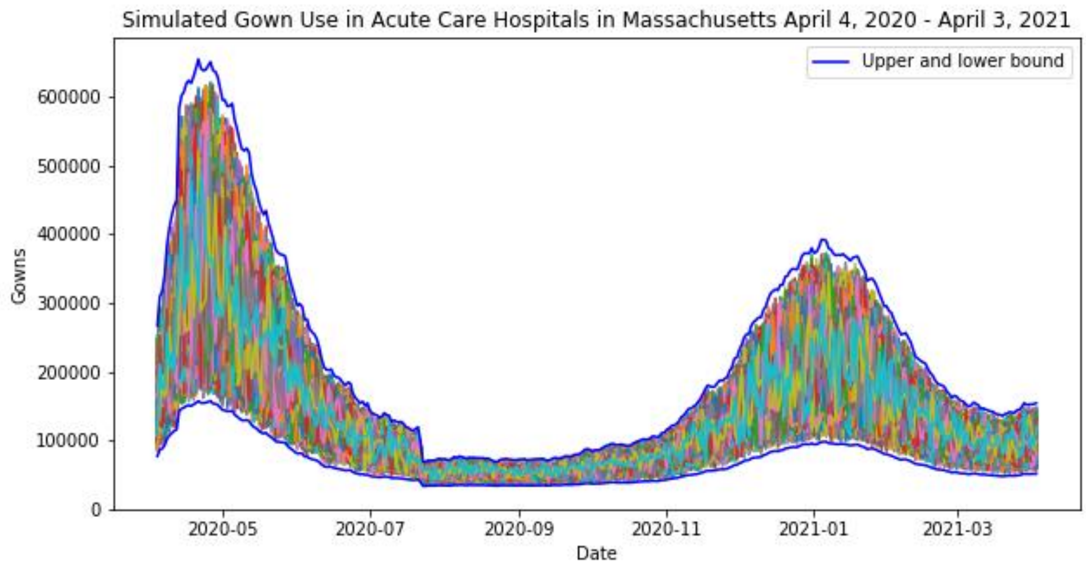
A Monte Carlo simulation was run for 5,000 iterations using the stochastic variables with conditional triangle probability distributions described above. Table 4.3.2.1 shows the minimum, maximum, and average simulated PPE use across all iterations in acute care hospitals in Massachusetts for April 4, 2020 to April 3, 2021.

Table 4.3.2.1: Monte Carlo simulation results

	Min Year Cumulative	Average Year Cumulative	Max Year Cumulative	Standard Deviation	Standard Deviation % of Mean
N95s	5,649,159	5,662,571	5,676,647	3,771	0.07%
Gowns	48,924,341	51,026,901	53,054,550	591,947	1.16%
Gloves	320,516,250	331,662,412	342,610,698	1,695,586	0.51%
Eye protection	5,617,627	5,631,039	5,645,115	3,771	0.07%
Surg/proc masks	39,346,796	39,532,806	39,729,829	52,557	0.13%

The addition of uncertainty in the form of stochastic variables has the strongest effect on gowns and gloves as shown in Figure 4.3.2.1 and 4.3.2.2.

Figure 4.3.2.1: Gown daily use Monte Carlo results



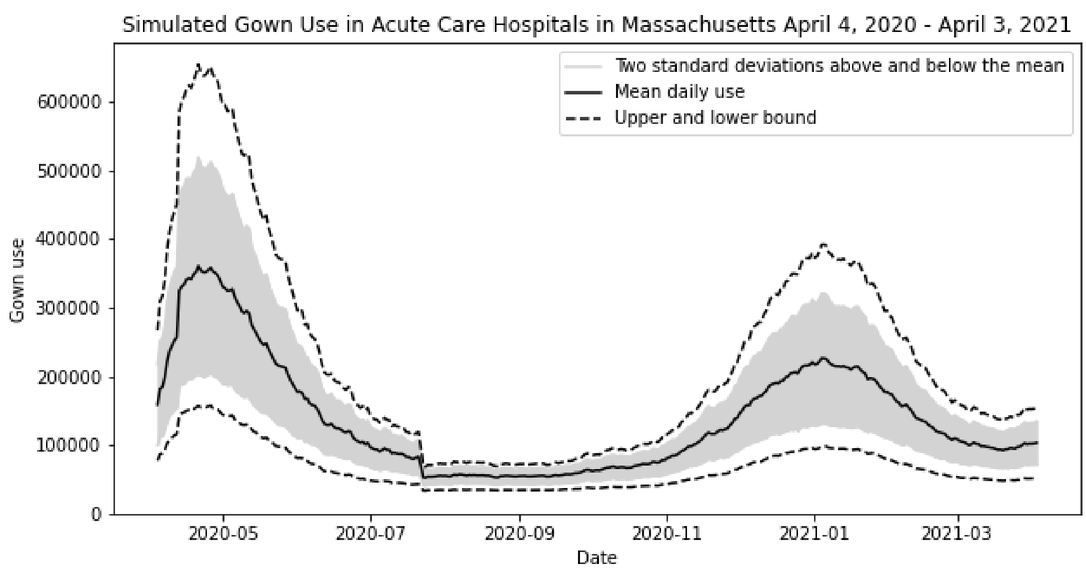
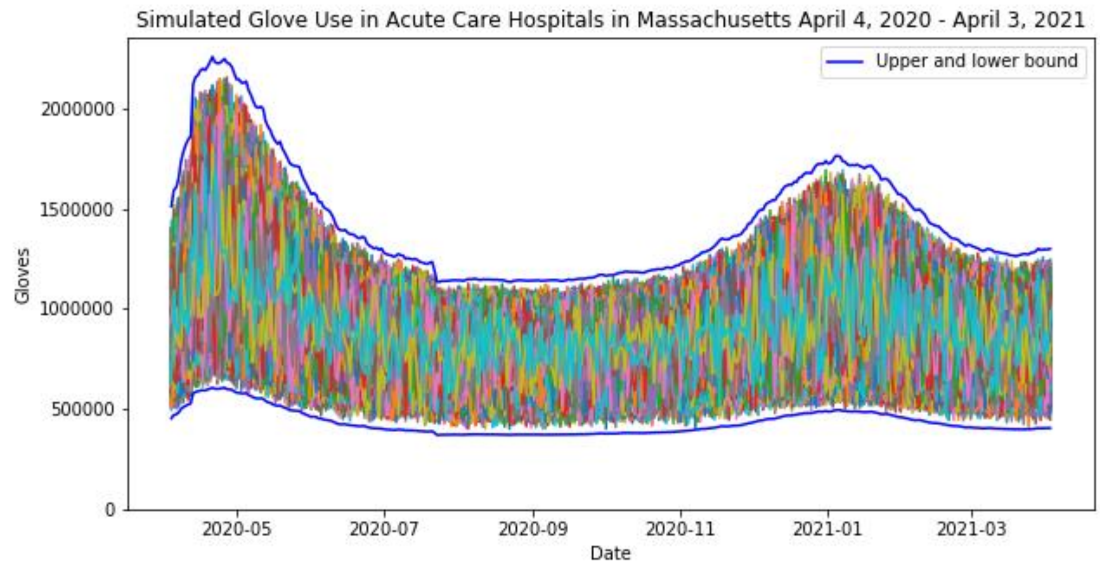
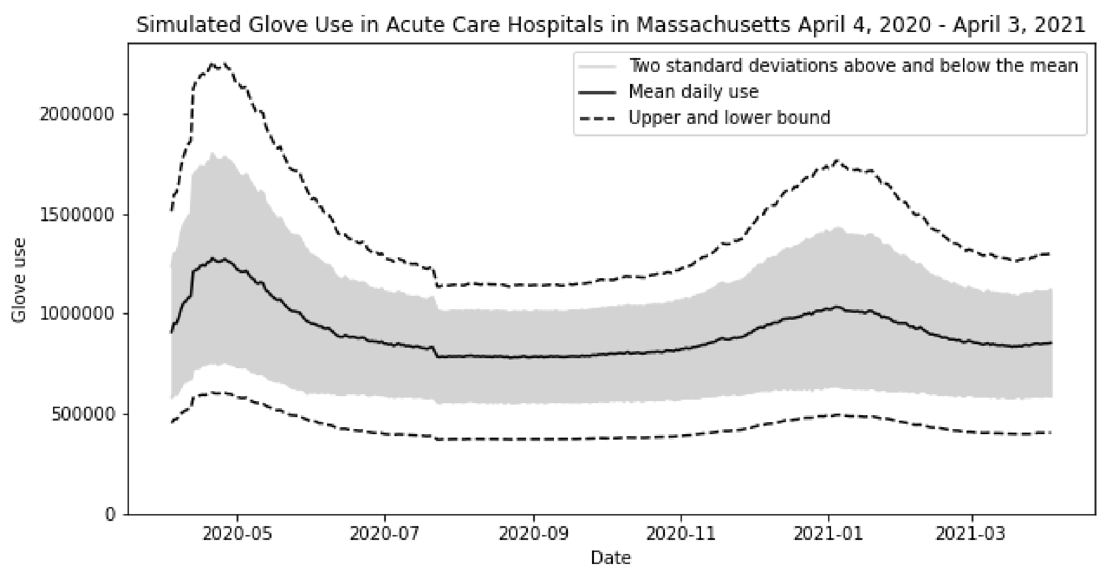


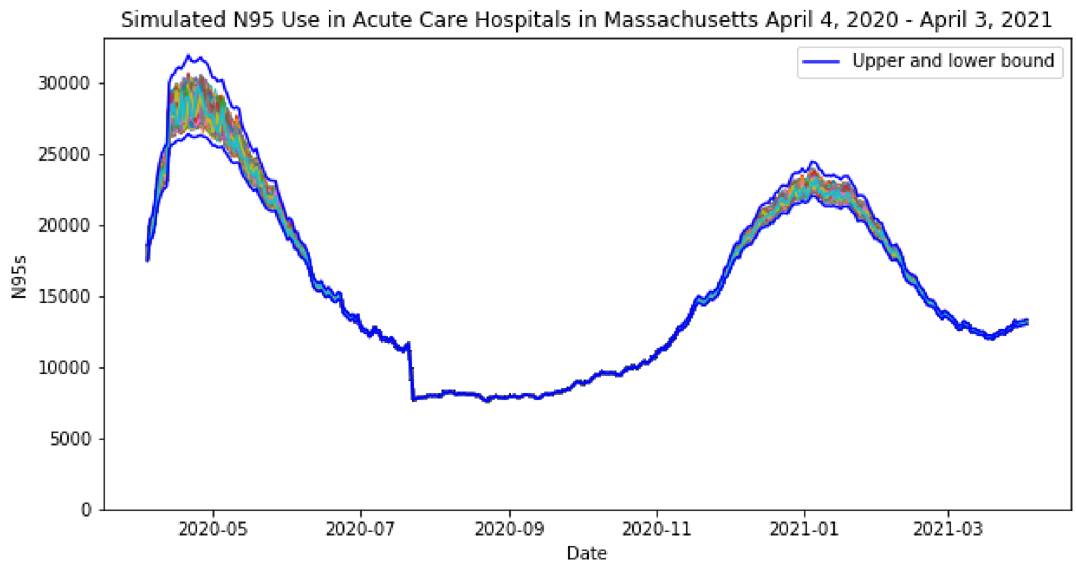
Figure 4.3.2.2: Glove daily use Monte Carlo results





N95s and eye protection outputs show less variability as a result of the introduction of the stochastic variables. See Figure 4.3.2.3 and 4.3.2.4.

Figure 4.3.2.3: N95 daily use Monte Carlo results



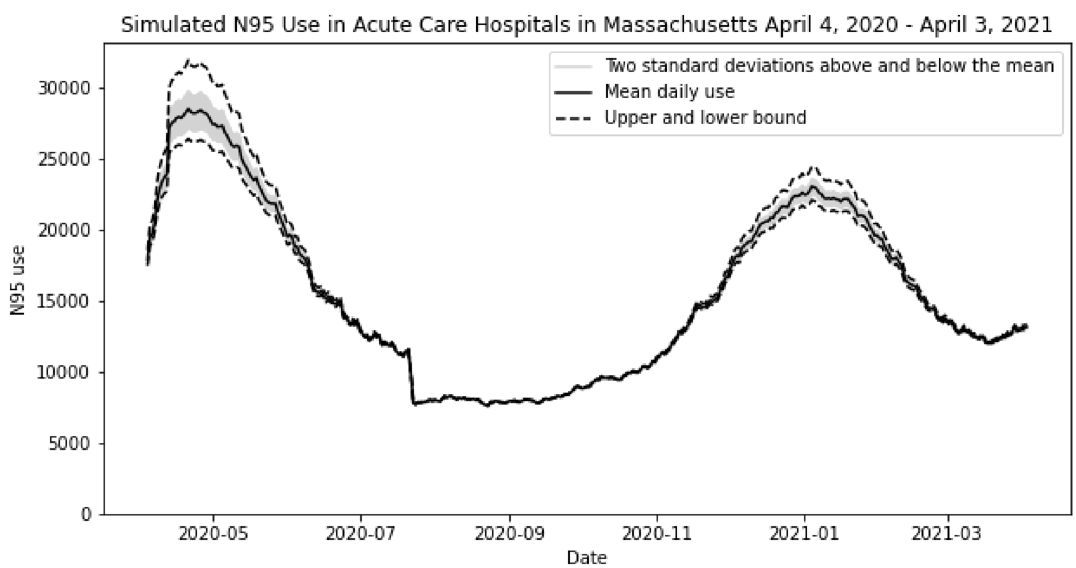
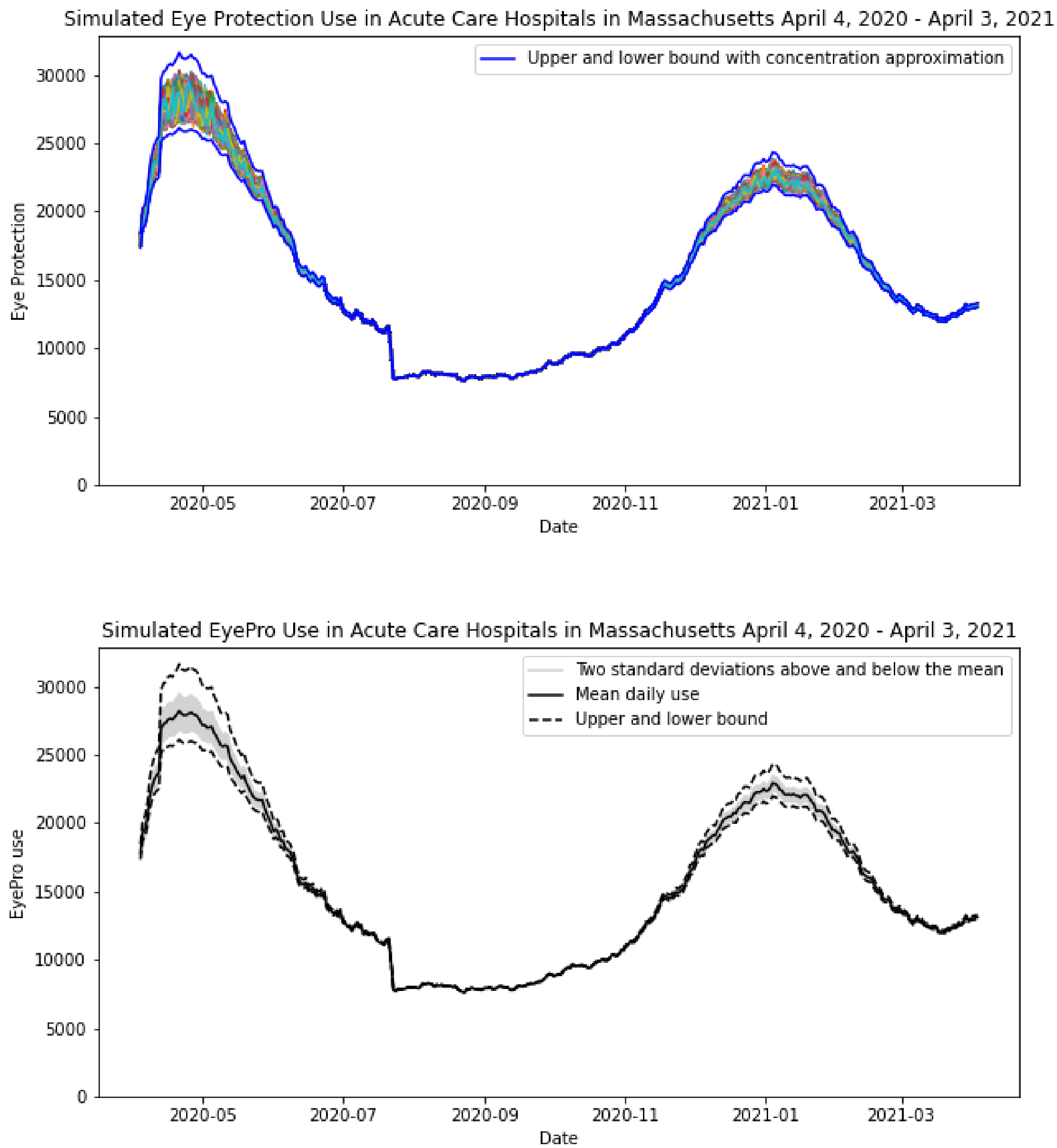


Figure 4.3.2.4: Eye protection daily use Monte Carlo results



The relatively small effect of the stochastic variables on total N95 and eye protection use is due to two factors: 1) the low concentration coefficient and 2) a baseline use from emergency room, specialist, and nonclinical staff that is held static in the Monte Carlo simulation. The low concentration coefficient keeps variability low because when COVID-19 cases are spread across facilities and within hospitals, changes in staff per patient ratios do not linearly decrease N95 and eye protection use. Even if staff to patient ratios are low, COVID-19 cases are being treated alongside typical sick patients, meaning many unique staff members still use N95 and eye protection. To demonstrate this effect, Figure 4.3.2.5 and 4.3.2.6 below shows the effect of the introduction of stochastic variables when there is perfect cohorting, meaning every COVID-19 patient is treated in one location.

Figure 4.3.2.5: N95 daily use Monte Carlo simulation results with and without perfect cohorting

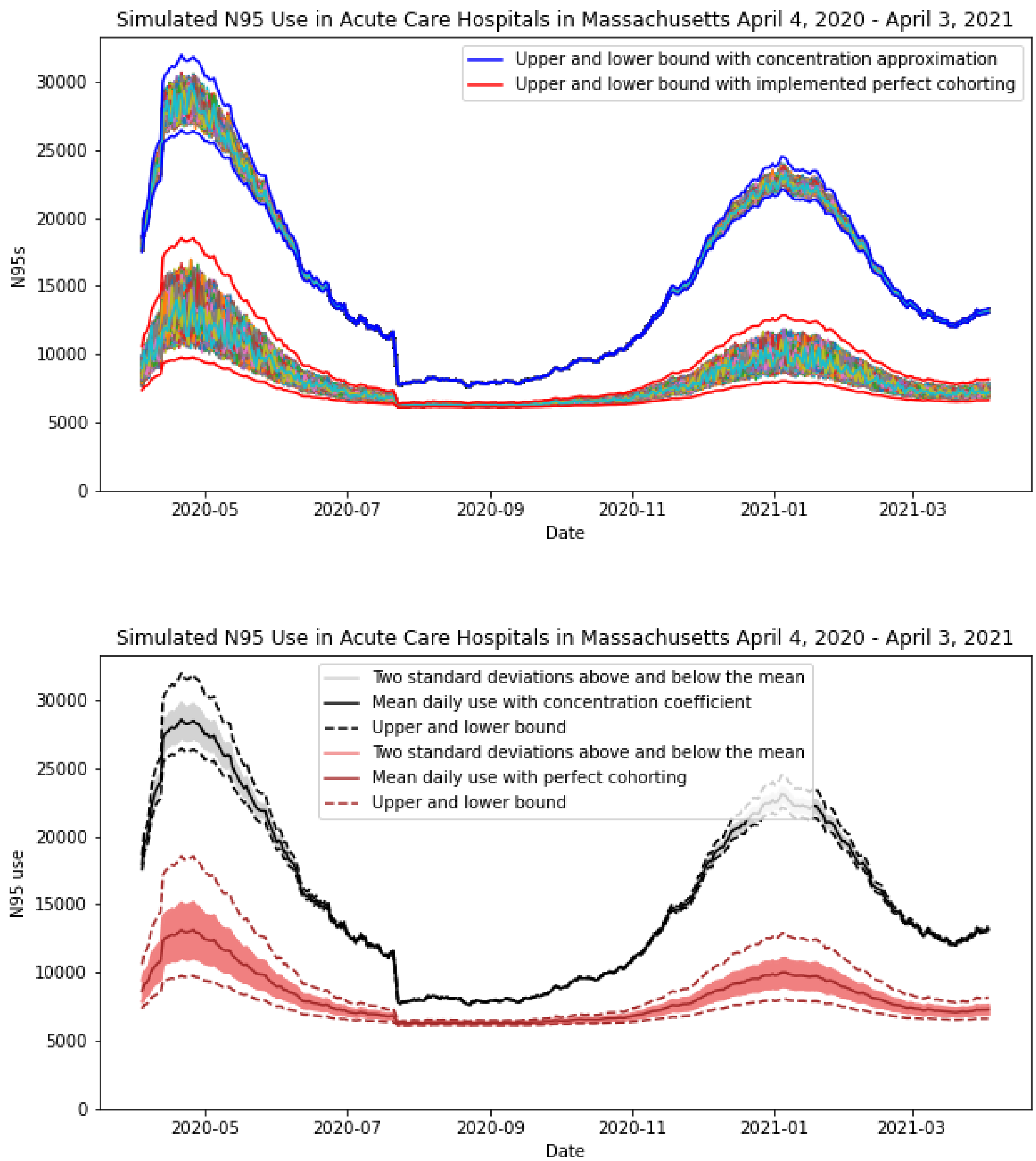
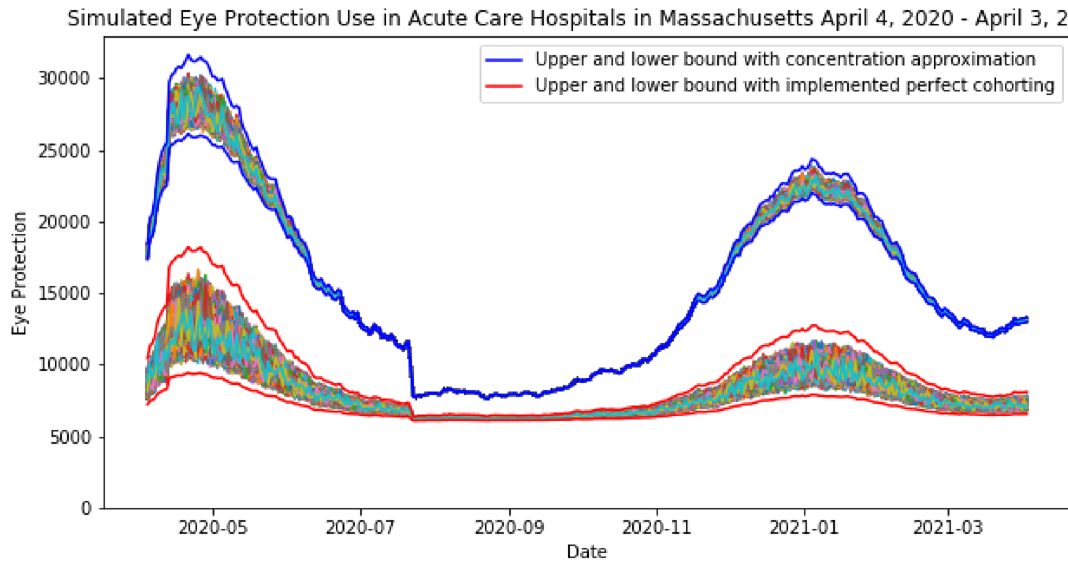
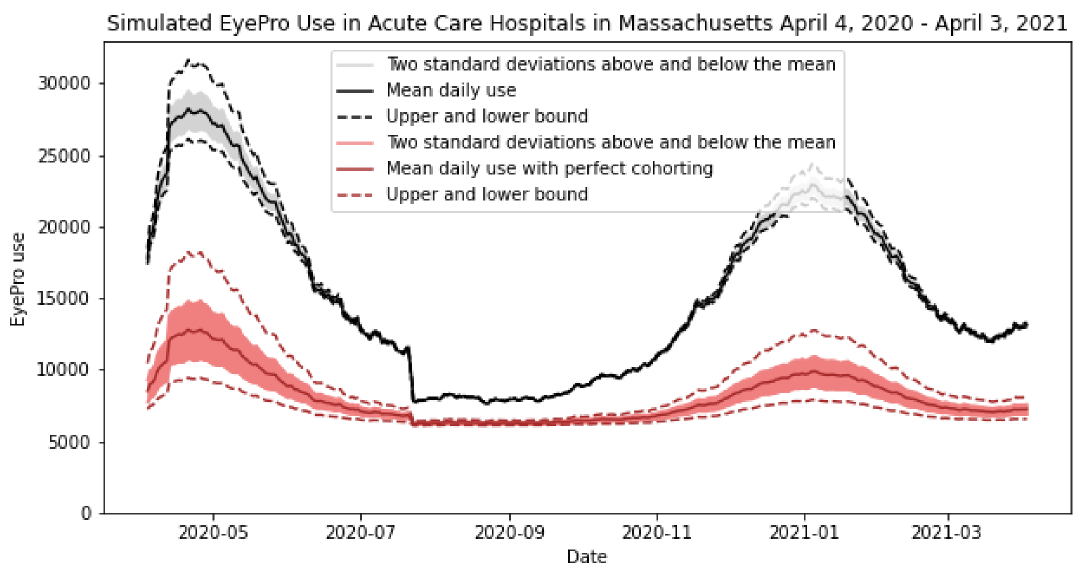


Figure 4.3.2.6: Eye protection daily use Monte Carlo simulation results with and without perfect cohorting





The Monte Carlo simulation run with perfect cohorting shows more variability along with lower overall use. When COVID-19 patients are cohorted, changes to staff to patient ratios have a stronger effect on N95 and eye protection use. This is clear when looking at the coefficient of variation for both the standard Monte Carlo simulation and the Monte Carlo simulation with perfect cohorting. See Figure 4.3.2.7 and 4.3.2.8 below.

Figure 4.3.2.7: Coefficient of variation for N95 daily use in Monte Carlo simulation with and without perfect cohorting

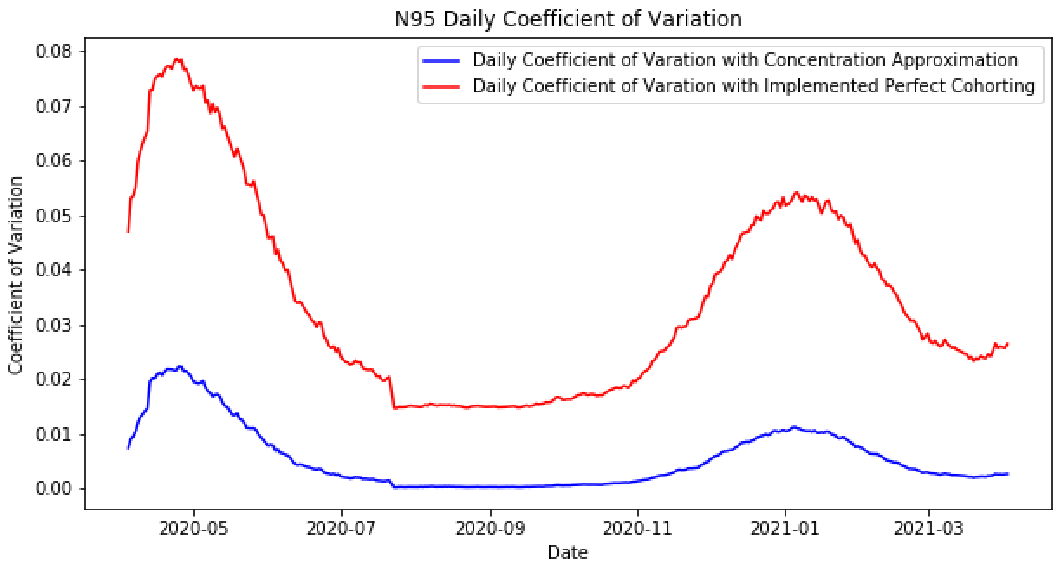
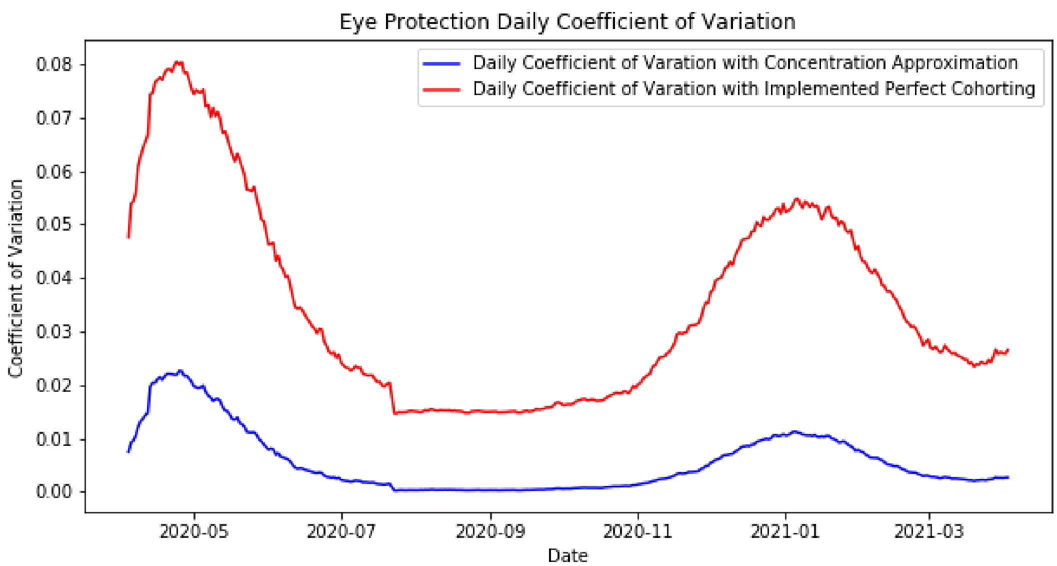


Figure 4.3.2.8: Coefficient of variation for eye protection daily use in Monte Carlo simulation with and without perfect cohorting



Even with perfect cohorting, the coefficient of variation for N95s and eye protection remains lower than one would expect given the range in the triangle distributions for staff per patient ratios. This is due to the baseline N95 and eye protection use caused by emergency room staff, specialists, and non-clinical staff. The simulation assumes that all emergency room staff and specialists will use eye protection and an N95 every shift regardless of daily COVID-19 patients. The total number of emergency room staff and specialists are deterministic in the Monte Carlo simulation, resulting in a baseline N95 and eye protection use across all simulation runs. Non-clinical staff is calculated using a staff to patient ratio, but that ratio is held as deterministic in the simulation, adding to the baseline rate. This baseline use keeps the daily mean N95 and eye protection use high, therefore resulting in lower than expected coefficients of variation. Figure 4.3.2.9 and Figure 4.3.2.10 show the baseline N95 use from emergency department, specialist, and non-clinical staff.

Figure 4.3.2.9: N95 baseline use by emergency room, specialist, and non-clinical staff in Monte Carlo simulation

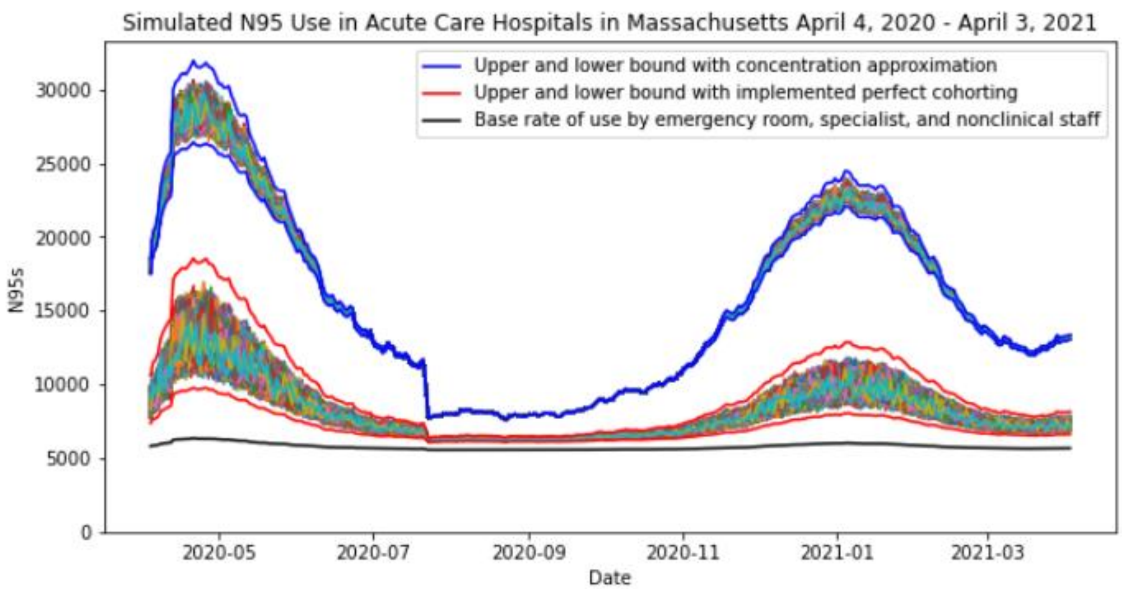
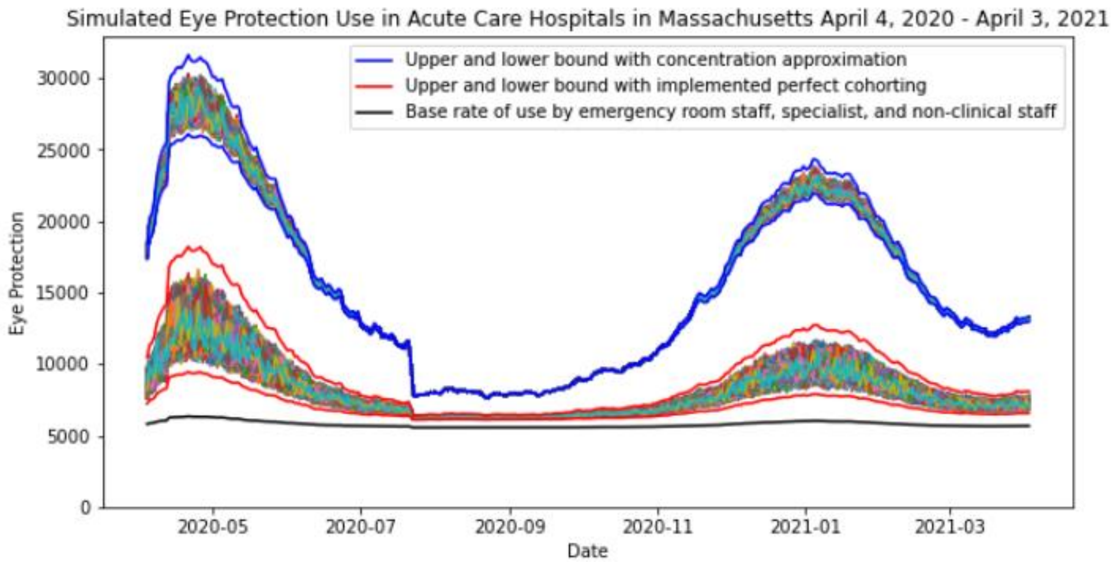
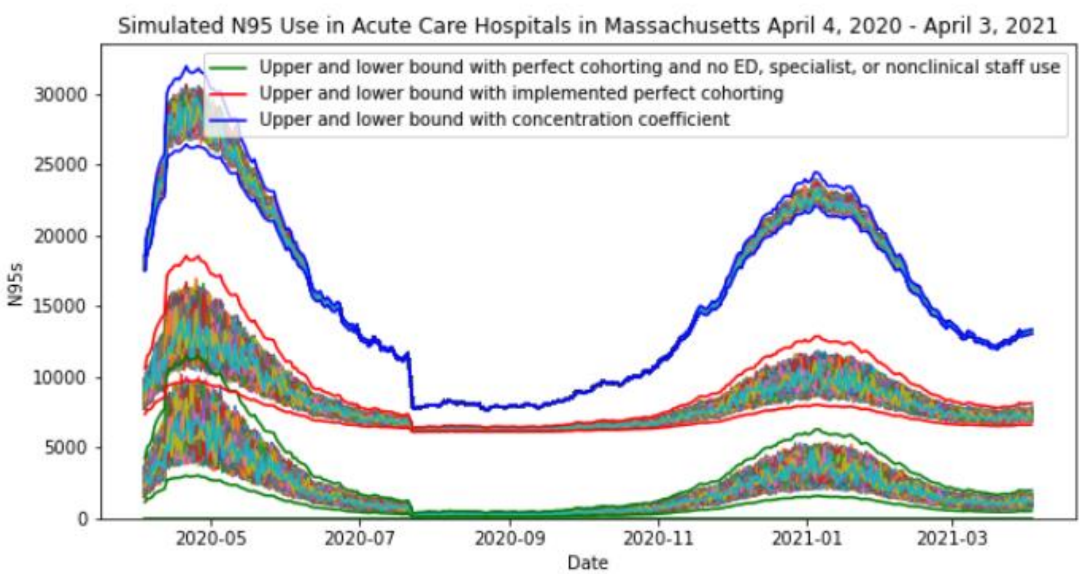


Figure 4.3.2.10: Eye protection baseline use by emergency room, specialist, and non-clinical staff in Monte Carlo simulation



When this baseline use is removed, the lower means allow for a higher coefficient of variation. Figure 4.3.2.11 and 4.3.2.12 show the addition of a Monte Carlo simulation run with all emergency department, specialist, and non-clinical staff removed.

Figure 4.3.2.11: N95 daily use with emergency room, specialist, and non-clinical staff removed from Monte Carlo simulation



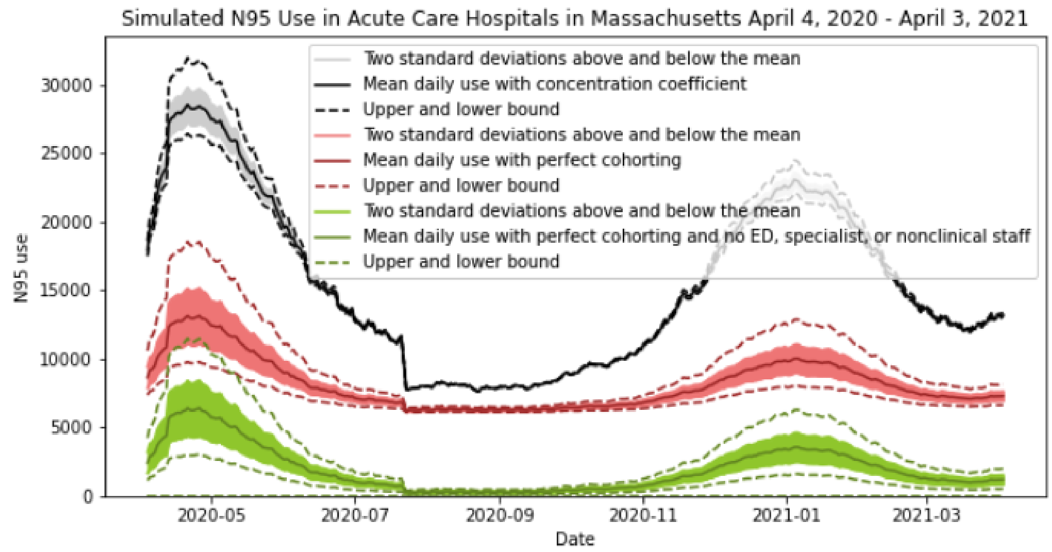
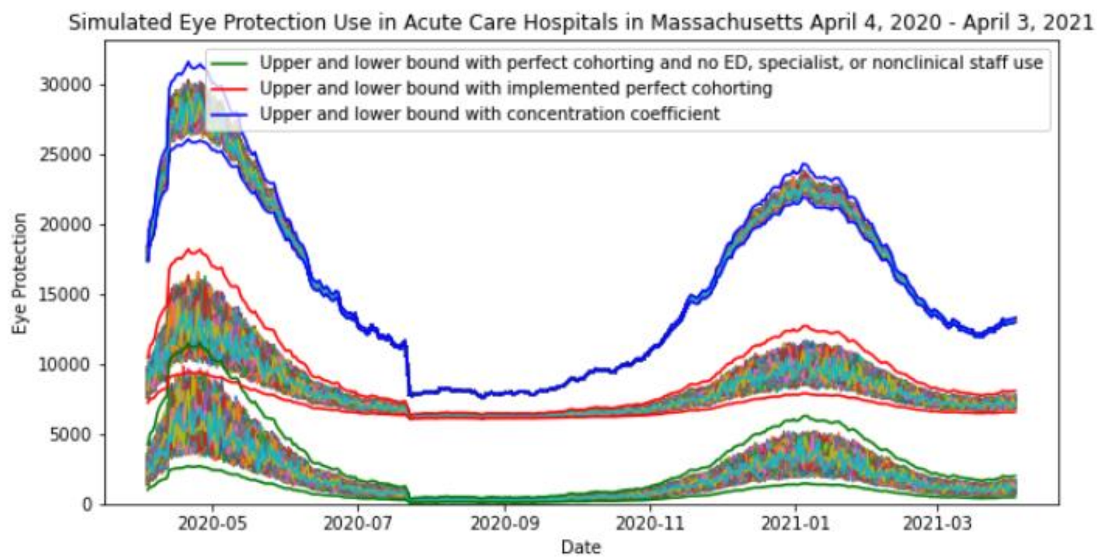
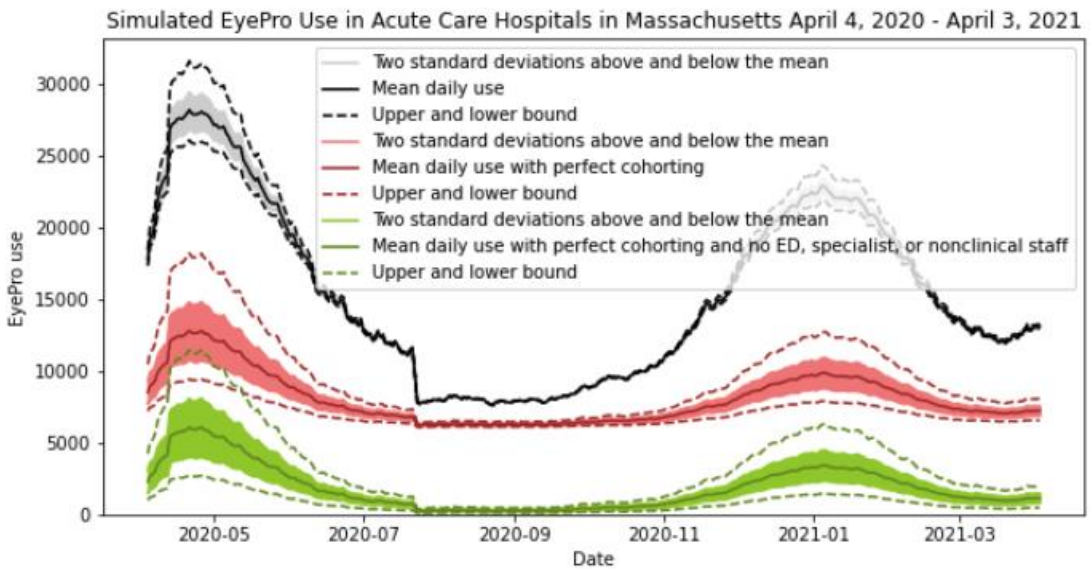


Figure 4.3.2.12: Eye protection daily use with emergency room, specialist, and nonclinical staff removed from Monte Carlo simulation





The lower daily means from the run with no emergency room, specialist, and nonclinical staff use results in a higher coefficient of variation, as shown in Figure 4.3.2.13 and 4.3.2.14:

Figure 4.3.2.13: Coefficient of variation for daily N95 use with and without emergency room, specialist, and non-clinical staff

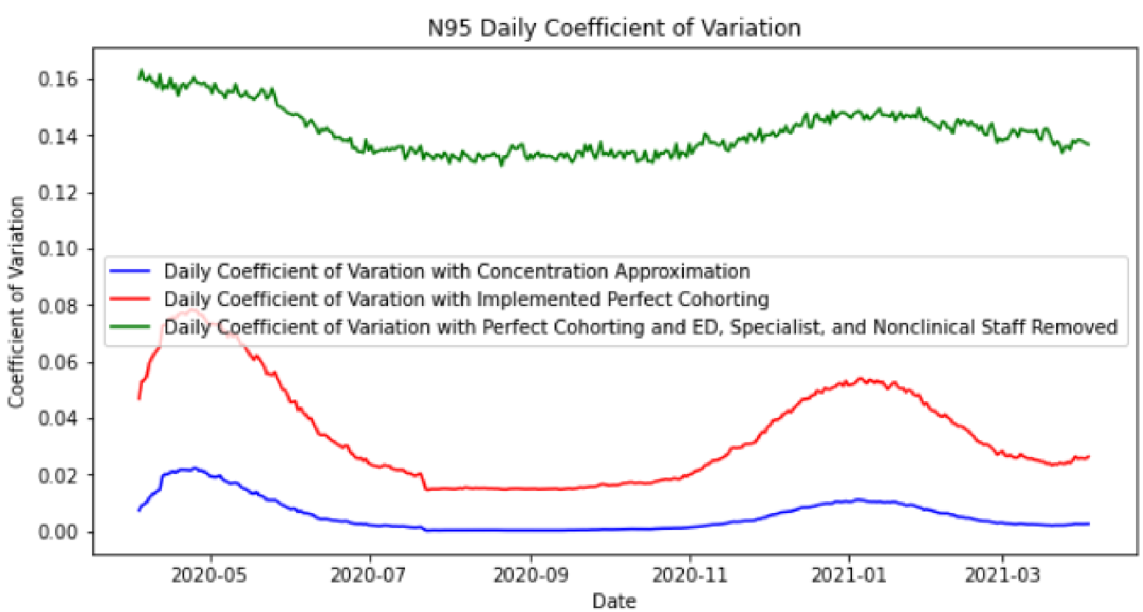
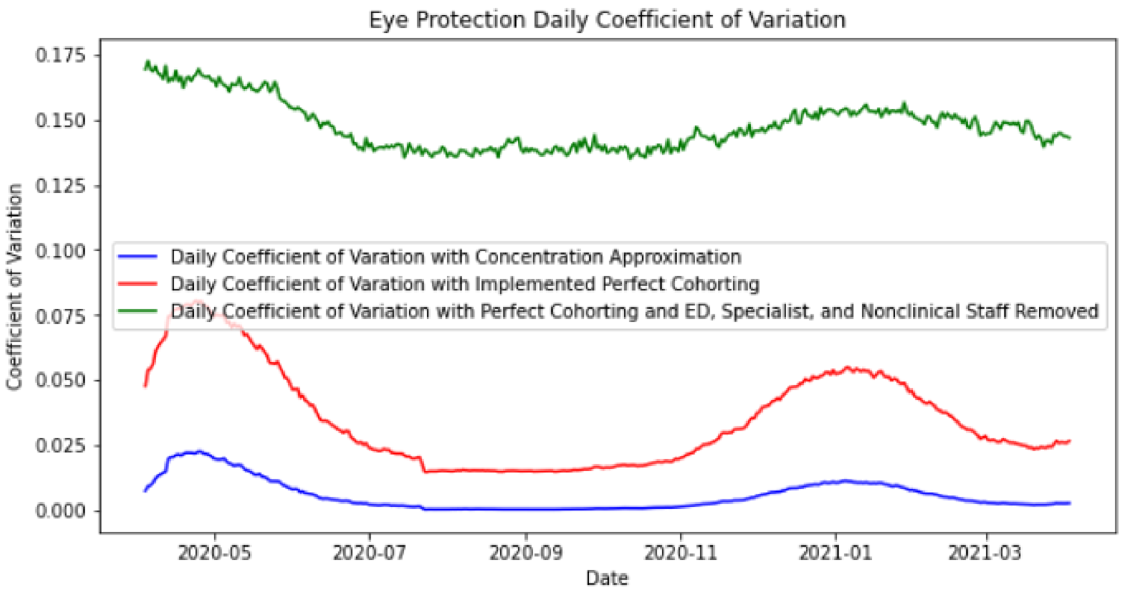


Figure 4.3.2.14: Coefficient of variation for daily eye protection use with and without emergency room, specialist, and non-clinical staff



Across all PPE types with the exception of surgical/procedural masks, the coefficient of variation is correlated with COVID-19 hospitalizations. See Figure 4.3.2.15 through Figure 4.3.2.18. The correlation between COVID-19 cases and coefficient of variation is due to the conditional triangle distributions used for the stochastic variables. As used hospital capacity increases with COVID-19 hospitalizations, the means of the stochastic variable distributions decrease. The decreased means result in higher coefficients of variation for those stochastic variables, resulting in higher coefficients of variation for the PPE use that depends on them. See Figure 4.3.2.19.

Figure 4.3.2.15: Coefficient of variation for gowns presented with COVID-19 cases

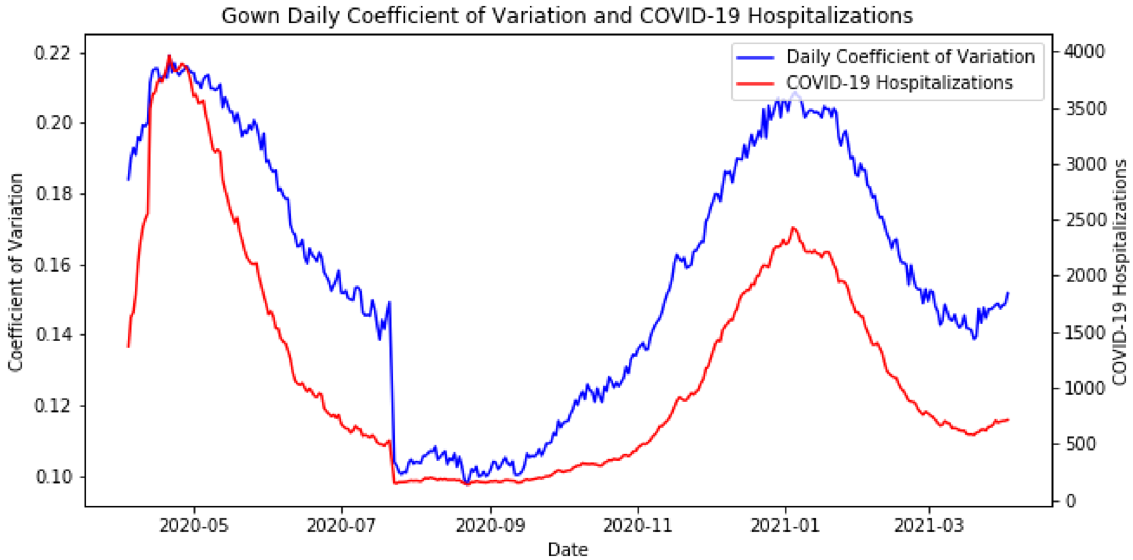


Figure 4.3.2.16: Coefficient of variation for gloves presented with COVID-19 cases

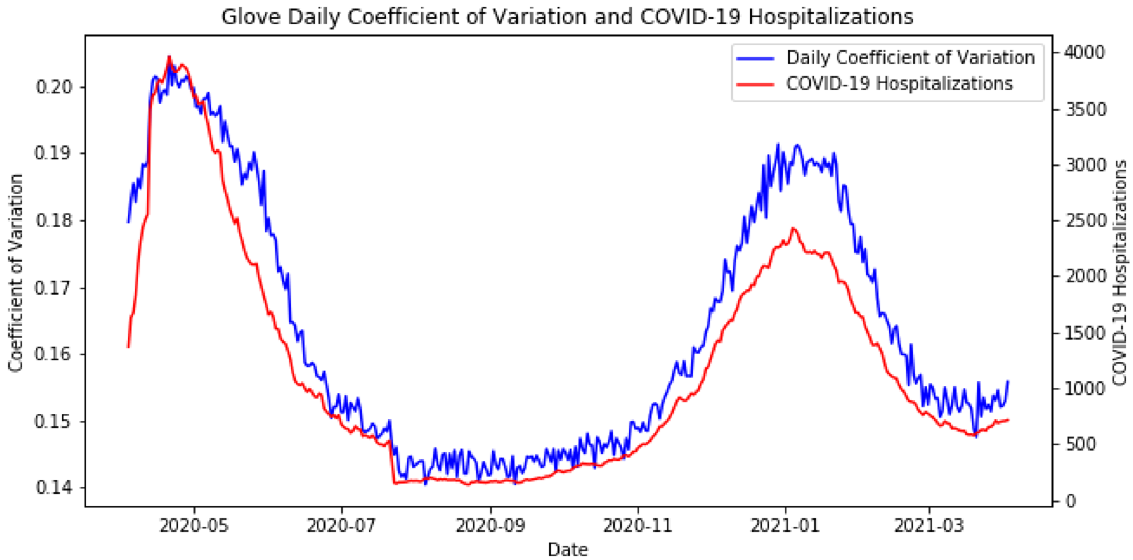


Figure 4.3.2.17: Coefficient of variation for N95s presented with COVID-19 cases

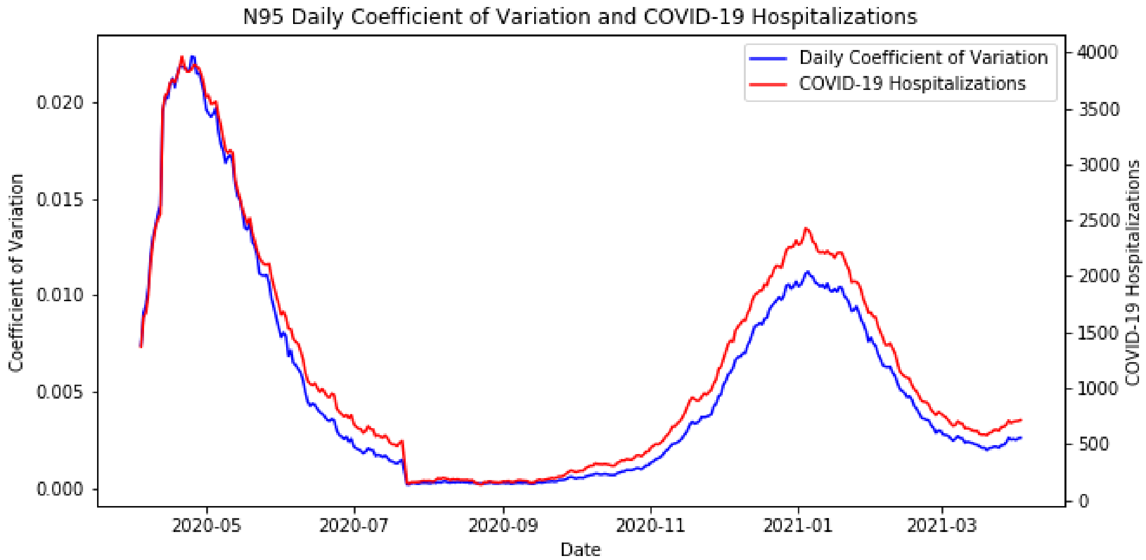


Figure 4.3.2.18: Coefficient of variation for eye protection presented with COVID-19 cases

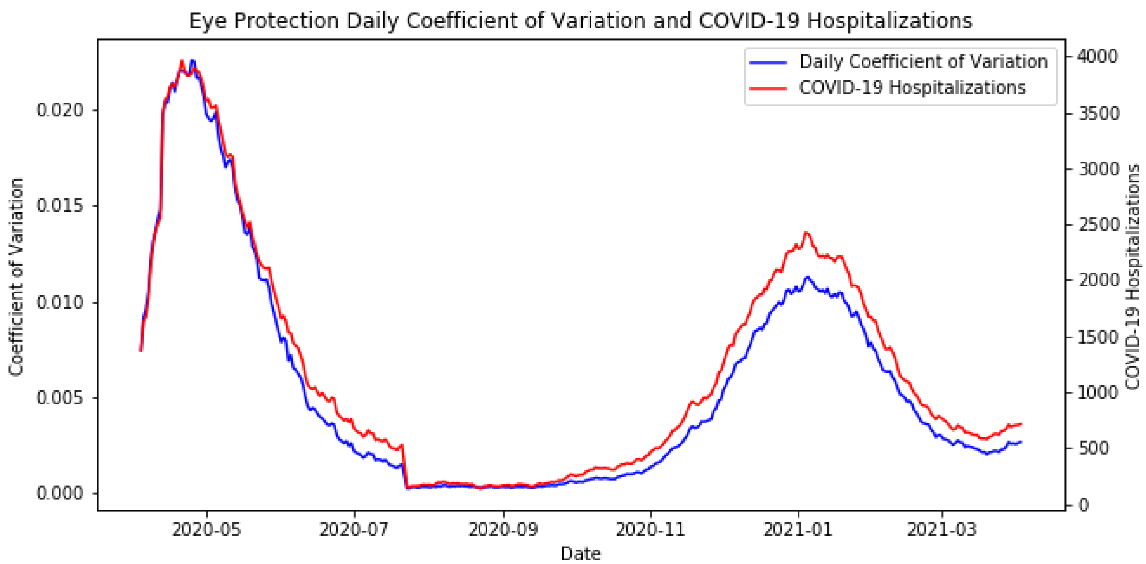
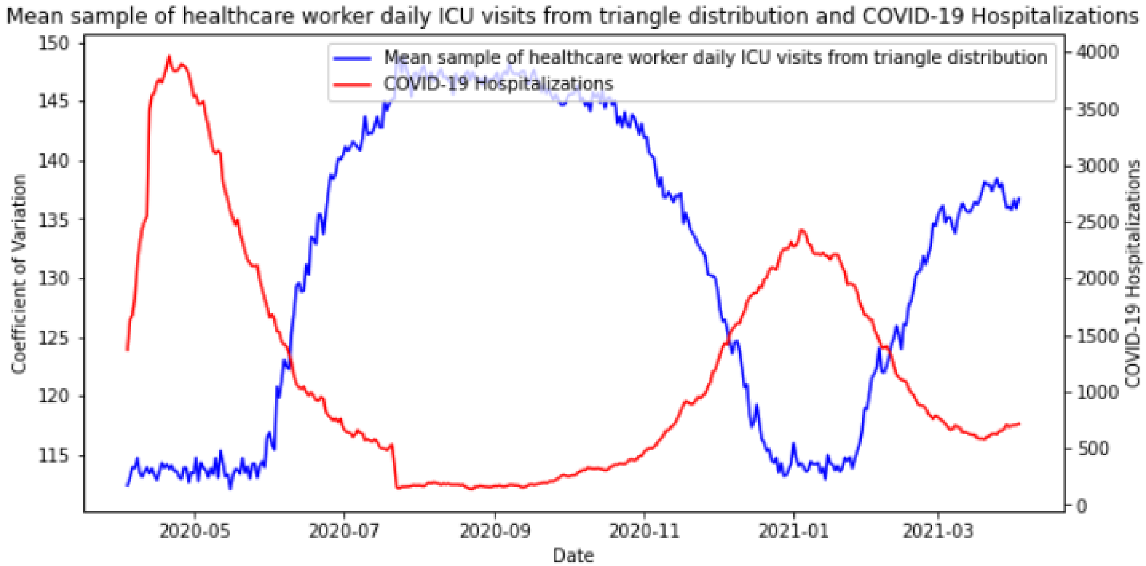
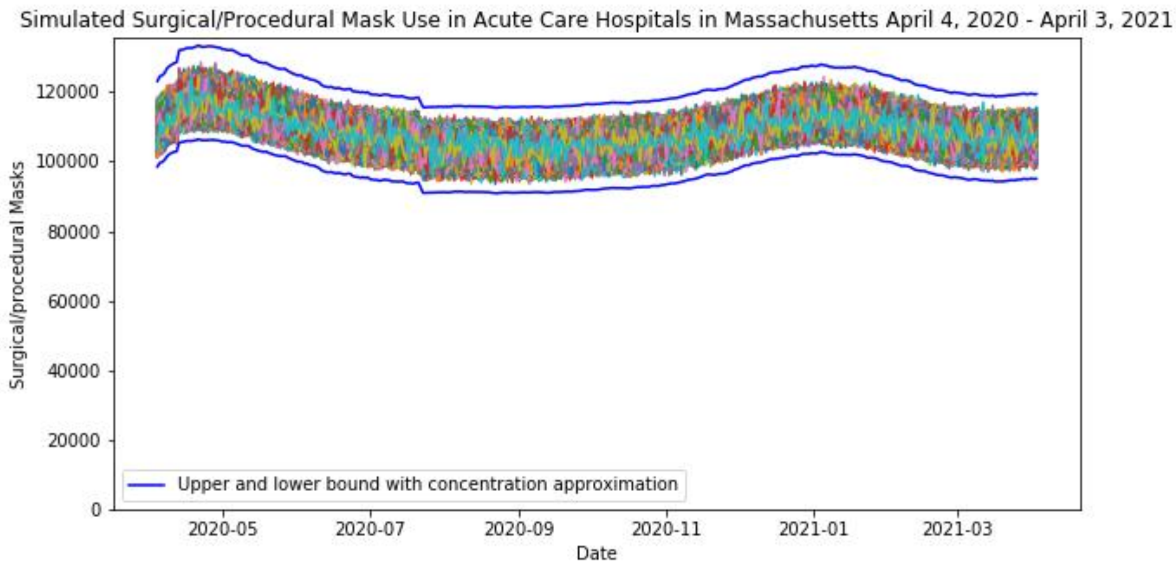


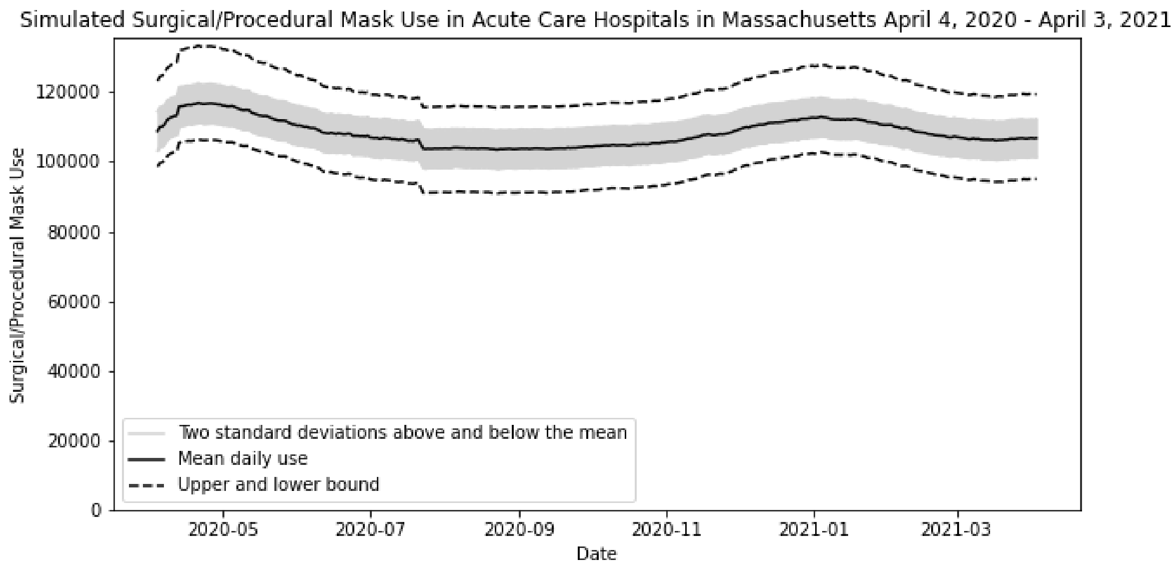
Figure 4.3.2.19: Example sampling of healthcare worker daily ICU visits from triangle distribution



Surgical/procedural masks have very low coefficients of variation because they have a high baseline use rate that does not depend on COVID-19 cases. Surgical/procedural masks are issued to each staff member and patient every day, with the only other use coming from healthcare worker patient visits with contact/droplet precaution patients. Compared to the high base rate, the addition of uncertainty in daily healthcare worker visits to contact/droplet patients has relatively little effect. This can be seen in Figure 4.3.2.21.

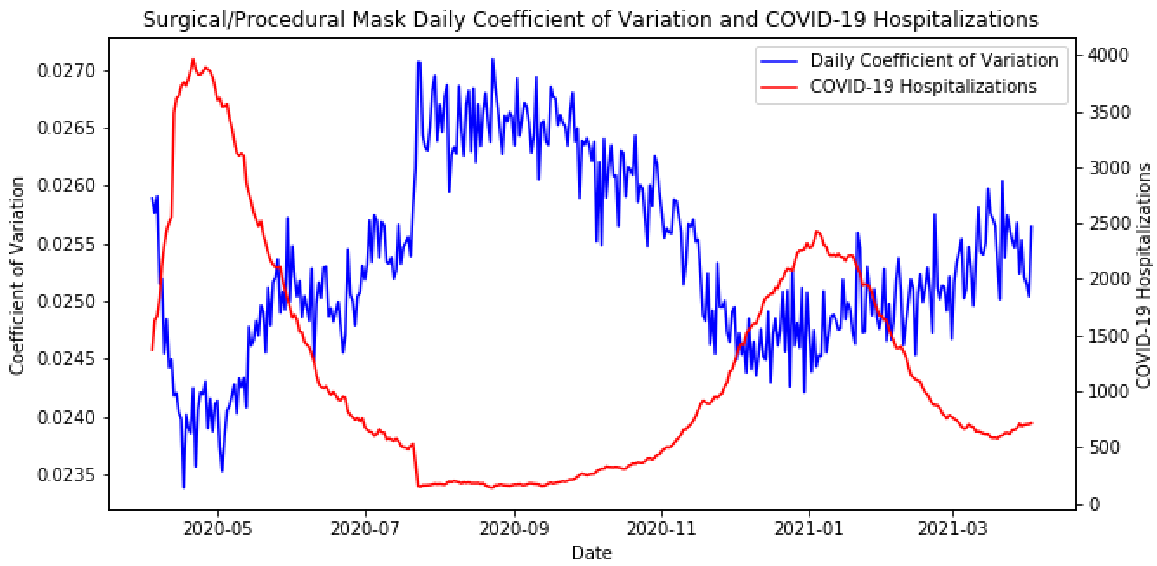
Figure 4.3.2.20: Surgical/procedural mask daily use Monte Carlo simulation results





Counterintuitively, there is an inverse relationship between COVID-19 hospitalizations and surgical/procedural mask variance. This is because as COVID-19 cases rise, there are more contact/droplet patients who become PUIs and are treated with an N95, making surgical/procedural masks slightly less affected by uncertainty in daily healthcare worker patient contacts.

Figure 4.3.2.21: Coefficient of variation for surgical/procedural masks presented with COVID-19 cases



In summary, gowns and glove PPE use predictions showed high variability when uncertainty was added to the healthcare worker daily patient visits input variables, especially during periods with high COVID-19 hospitalizations. N95s and eye protection were more robust to the addition of uncertainty in clinical staff to patient ratios due to the effects of the concentration coefficient and the base rate of use by emergency room, specialist, and nonclinical staff. Surgical/procedural masks were also robust to the addition of uncertainty due to the very high base rate of use from issuing surgical/procedural masks to all staff and patients.

5. Discussion

This section will discuss the applications, limitations, and key findings from the simulation and case study. It will then offer next steps for policy makers to create a robust PPE preparedness plan given the simulation and case study findings. Finally, it will address areas where future research is needed to expand upon the findings in this thesis.

5.1 Simulation applications

The simulation presented in this thesis is a novel approach to forecasting PPE demand in acute care hospitals for a COVID-19 type pandemic because it outputs daily PPE use as opposed to aggregate PPE use, includes hospital policy variables including staff per patient ratios, PPE reuse and healthcare worker daily visits to patients, and incorporates a concentration coefficient which accounts for the natural grouping of COVID-19 patients as their numbers increase. Although the case study applied the simulation to forecasting PPE use at the state level, the simulation can be used at the local or national level when provided the correct inputs. The simulation was initially presented with entirely deterministic inputs, however multiple epidemiological inputs can be run through the model to provide a range of possible outputs when future hospitalizations are uncertain, as shown in the example outputs from December 15, 2020 – January 11, 2021. Similarly, uncertain variables can be accounted for by modifying certain inputs from deterministic to stochastic, as shown in the Monte Carlo simulation portion of the case study.

As local, state, and federal planners prepare to invest in PPE preparedness for the next pandemic, this simulation can be used to inform those efforts by running multiple epidemiological inputs through the simulation. Similar to the deterministic case study in the previous section, states can run actual COVID-19 hospitalization data to determine the estimated PPE used in acute care hospitals during the COVID-19 pandemic. To explore what would be needed for a COVID-19 type pandemic that was of much worse severity, those inputs can be multiplied, the shape of the epi-curve can be made steeper of flatter, additional waves can be added, and the time period can be extended.

Through running multiple iterations of the simulation, planners can explore how different disease trajectories affect daily use. Understanding daily use, as opposed to total aggregate use, allows supply chain planners to make informed decisions on required days of supply on hand given the lead times they expect before resupply. Disease trajectories that result in enormous PPE use very quickly may require investment in stockpiles to meet demand until manufacturing can increase output. A slow-moving pandemic allows for more time to increase manufacturing capacity and may lend itself to investments in adaptive manufacturing practices. It is likely a combination of both will be required. The simulation presented in this thesis can serve as an important part of prioritizing those investments given different possible demand scenarios. It can also be used with epidemiological forecasts to serve as an early warning sign that current stockpiles may be insufficient to meet expected upcoming demand.

5.2 Simulation limitations

This simulation is useful in forecasting PPE use for a COVID-19-type event and understanding what factors influence daily PPE use, but it does have some limitations. The simulation was set up according to the precautions used when treating COVID-19 patients, so the simulation can only be used in its current form to predict PPE use in acute care hospitals for a COVID-19 similar event that requires the same PPE precautions. In order to use this simulation for other disease events, such as Ebola, the simulation would need to be modified to account for the different infection prevention and control requirements.

The simulation only calculates PPE use in the acute care hospital setting. In future pandemics there will also be significant PPE demand from other medical sources, including long term care facilities and emergency medical services (EMS), along with non-medical services such as police, prisons, and essential utility workers. Acute care hospitals are large drivers of PPE demand in a pandemic, and the healthcare workers in those systems are put at serious risk without PPE, but a full PPE preparedness plan will need to include PPE demand from all sectors.

It is assumed within the simulation that staff use PPE in perfect adherence to the infection control standards and reuse policy. Fear, peer pressure, or lack of knowledge of the standard could result in vastly longer or shorter reuse policies by staff than what is published in hospital guidance. As with all simulations of human behavior, there is reason to be skeptical that people will act like machines. Further research is needed to explore the extent of PPE conservation policy adoption during COVID-19 to better understand the relationship between published policy and actual use.

Currently the simulation is created to take in a constant level of typical sick patients, meaning all routine patients continue to seek care at typical rates even in the height of the pandemic. It is likely that in actuality, patients who only need routine medical care will defer their care until after a pandemic, therefore cutting down on the typical sick patients seen daily. During COVID-19, hospitals reported over 20% decreases in non-COVID-19 admissions (Birkmeyer et al., 2020). Due to the conservative assumption that typical sick continue to seek care, it is likely the simulation slightly overestimates PPE use for contact-based use items including gloves, gowns, and surgical masks.

Finally, the simulation only outputs PPE use at acute care hospitals, not the total amount of PPE that will be ordered by acute care hospitals from producers or the amount of PPE that will be requested by acute care hospitals for state or federal support. Raw demand is a crucial building block in the planning process, but raw demand does not translate directly into orders to suppliers. The "bullwhip effect", where small increases in demand can lead to much larger disruptions as it travels up the tiers of suppliers, will likely make this raw demand only a piece of the overall planning needed for a policy response.

5.3 Lessons learned from the case study

The case study section explored multiple applications of the simulation to COVID-19 in Massachusetts. First, the simulation was run with entirely deterministic inputs using data from actual COVID-19 hospitalizations in Massachusetts from April 4, 2020 - April 3, 2021. Sensitivity analysis was then conducted to explore the effect of changes in hospital policy variables on PPE use. Second, to demonstrate the simulation application when faced with multiple epidemiological forecasts, an example case study was run using data from published COVID-19 Massachusetts hospitalization forecasts from December 15, 2020 – January 11, 2021. Finally, to understand the impact of inherent uncertainty in some of the inputs, select inputs were changed from deterministic to stochastic and a Monte Carlo simulation was run with 5,000 iterations. Each of these case study steps produced key lessons for policy makers on PPE use in acute care hospitals during pandemics and the effect of policy changes on daily PPE use.

5.3.1 Key lessons from the deterministic inputs case study

Each PPE type has its own variables that drive total use. In general, PPE can be split up into two types, staff-based use items and contact-based use items.

- **N95s and Eye Protection use are staff-based.** N95s and eye protection are staff-based use items because they are used by a single staff member between multiple patients over the course of his or her shift. New patients do not require the use of additional N95s and eye protection if those patients can be treated by an existing staff member who was already issued an N95 and eye protection for their shift. The key driver of staff-based PPE is the number of staff working with COVID-19 and PUI patients that day. That number depends on the total number of COVID-19 and PUI patients, staff per patient ratios, and the concentration of COVID-19 and PUI patients within the population. Keeping the total number of unique staff members working with COVID-19 patients low will decrease total PPE use.

- **Gloves and gowns are contact-based.** Glove and gown use are contact-based PPE because they are changed after each time a healthcare worker interacts with a patient requiring that PPE precaution. Glove use is driven by the total patient population, as every patient, regardless of precaution level requires gloves use. Gown use is driven by the total number of COVID-19, PUI, and contact/droplet precaution patients. Because both gloves and gowns are contact-based, the less times any staff member interacts with a patient the less is used.
- **Surgical/Procedural masks have a high base rate of use that stays relatively constant.** Surgical/procedural masks do not fall neatly into either category and are mostly determined by the high base rate that comes from issuing surgical masks to all patients and staff members every day. Counter-intuitively, the addition of more COVID-19 patients has a less than one-to-one effect on surgical/procedural mask use, because with more COVID-19 patients and PUIs, more staff are using N95s and opposed to surgical/procedural masks. This effect, however, is small, and is insignificant when compared to the high surgical/procedural mask base rate.
- **The concentration coefficient is crucial to understanding staff-based PPE use.** A significant contribution from this simulation is the inclusion of the concentration coefficient, which approximates the concentration of COVID-19 and PUI patients within the entire patient population. The concentration coefficient is critical to determining staff-based PPE use. A concentration coefficient of 1, meaning COVID-19 and PUI patients are perfectly concentrated in one location, would allow the least possible number of staff members to treat those patients, leading to minimal N95 and eye protection use. A concentration coefficient of 0, meaning COVID-19 and PUI patients are perfectly spread out across facilities or across wards and must each be treated by their own unique staff members, maximizes eye protection and N95 use. Even without any policy intervention to force COVID-19 and PUI cohorting, as COVID-19 and PUI patients increase, they will naturally begin to concentrate and eventually outnumber typical sick. In extreme cases, COVID-19 and PUI outnumber typical sick by so much that the concentration

coefficient approaches 1, such as in the 5X COVID-19 scenario sensitivity analysis. The concentration coefficient is crucial to understanding staff-based PPE use.

5.3.2 Key lessons from sensitivity analysis

Sensitivity analysis was conducted on the deterministic inputs case study to explore the effects of changes in hospital policy, including decreased COVID-19 diagnostic test turnaround times, increased reuse policies, decreased daily patient contacts by healthcare workers, and implemented COVID-19 and PUI cohorting on PPE use. These variables were chosen because they represent possible policy levers that could be pulled by healthcare leaders to influence PPE use in the face of shortages. Each of the policy interventions decrease total PPE use but have different impacts on shaping demand. This section will review the key impact of each of these variables. The policy options associated with this analysis will be addressed in the later section on policy implications.

- **Diagnostic test turnaround time:** Decreasing turn-around times means fewer patients classified as Persons Under Investigation (PUI) and treated with full PPE. In a situation with only one PUI generated for every COVID-19 case, like the one explored in this case study, increasing diagnostic test turn-around time has only a small effect. However, in scenarios where many PUIs are generated for every COVID-19 case, this effect would be more pronounced and may warrant increased investment.
- **Increased reuse policies:** Increasing reuse policies has a linear effect on N95 and eye protection demand. For example, increasing N95 reuse from one use to five uses can decrease N95 demand by up to 80% depending on policy adoption and behavioral factors.
- **Decreased healthcare worker patient contacts:** Decreasing the number of times staff interact with a patient each day limits the number of gown and glove changes required by staff members and has a linear effect on gown and glove use. Decreasing staff to patient contact rate by 50% results in a 50% decrease in gown and glove use.
- **Implemented cohorting of COVID-19 and PUI patients:** Cohorting patients decreases demand for N95s and eye protection because it minimizes the number of unique staff members who are required to wear PPE. Perfect cohorting decreased N95 and eye protection use by 48% in the deterministic case study.

5.3.3 Key lessons from utilizing multiple hospitalization forecasts

In this case study, five published forecasts for Massachusetts COVID-19 hospitalizations from December 15, 2020 – January 11, 2021 were run through the simulation. PPE output varied widely depending on which forecast was used, implying that the model is not robust to incorrect COVID-19 hospitalization inputs. In other words, the simulation is only as good as the epidemiological inputs it uses. Future users of this simulation should consider using an array of forecasts when there is uncertainty in future hospitalizations and use the range of outputs to make a risk-based decision. The simulation is set up to run these multiple forecasts with little computational load, which will facilitate running many scenarios with many forecasts.

5.3.4 Key lessons from the Monte Carlo simulation

In this case study, variables related to healthcare worker daily patient contacts and staff per patient ratios were modified from deterministic to stochastic to represent the natural fluctuation in these practices across different healthcare facilities. The results of the case study identify where variation exists in the output of the simulation and produced some key lessons when considering how and when uncertainty in these inputs affects total PPE use.

- **Output uncertainty depends on COVID-19 severity.** As COVID-19 cases increase, so does the coefficient of variation for all PPE items. Although the coefficient of variation remained low in this Monte Carlo simulation, that would not be the case if alternative epidemiological inputs were used that reflected a COVID-19 type pandemic that was much more severe.
- **Implementing COVID-19 and PUI patient cohorting increases the effect of changes in staff per patient ratios.** When COVID-19 and PUI patients are cohrorted, changing staff to patient ratios has a linear effect on N95 and eye protection use. With imperfect cohorting, however, the dispersed nature of COVID-19 and PUI patients keeps high numbers of unique staff members wearing N95s, even if staff are treating more patients at one time.
- **Identifying accurate healthcare worker patient visit inputs is crucial to accurate output.** This case study used a wide triangle distribution for healthcare worker patient visits, resulting in high variability for contact-based PPE. Gown and glove coefficients of variation were close to 10X higher than those for N95 and eye protection when no

cohorting was implemented. This highly variable output shows the importance of understanding the accurate values for healthcare worker patient contacts.

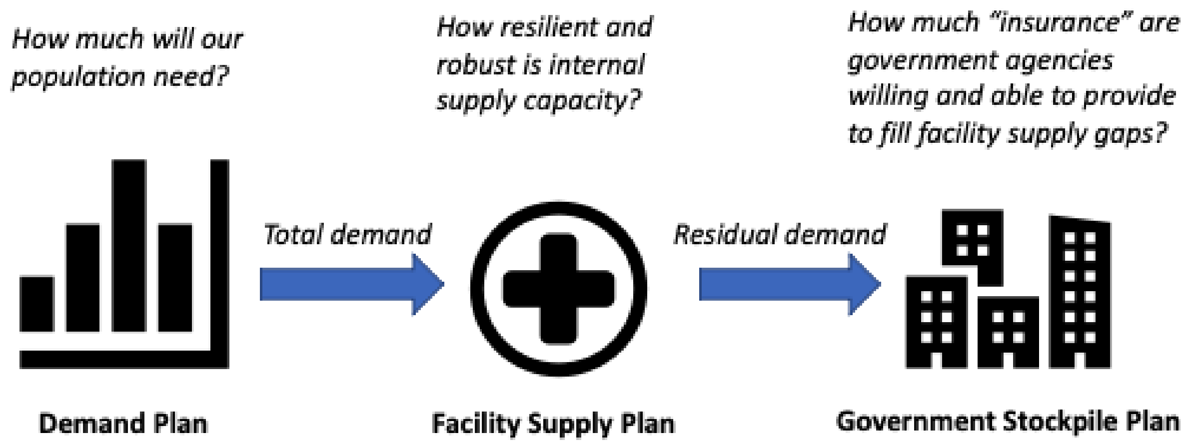
5.4 Policy implications and next steps towards a robust PPE preparedness plan

This section will discuss how policy makers can best use this simulation and the lessons learned in the case study to build a robust PPE preparedness plan given limited resources. This section will first address how policy makers can use the raw demand outputs from the simulation to serve as the first step in a larger process of gaining an understanding of the total PPE support required by healthcare facilities in the next pandemic. It will then discuss how policy makers can hedge against under-preparedness by investing in policy levers that can decrease PPE demand during times of scarcity.

5.4.1 Next steps to determine government investment in PPE preparedness

The simulation presented in this thesis provides a tool planners can use to determine PPE demand at the acute care hospital level. In order to determine the level of government response that will be required for PPE assistance, there are additional steps planners must take to determine the residual demand. Residual demand is the gap between PPE demand and the PPE supply that healthcare facilities are able to supply for themselves through their own internal emergency stockpiles and resupply orders from the market. Residual demand is what will ultimately need to be met by external assistance from government relief. Determining PPE use in the simulation is the first step in this process, but in order to determine residual demand, planners must understand the internal supply capacity of acute care hospitals. To do this, planners must maintain awareness of the size of internal emergency stockpiles and understand the capacity of the PPE market to meet demand. Once facility supply capabilities are understood, policy makers can determine the amount of investment they are willing and able to make to cover the potential residual demand under different pandemic scenarios. This three-step process is outlined in Figure 5.4.1.1 below.

Figure 5.4.1.1: Steps to determine government investment in PPE preparedness



Although a full investigation of current facility supply plans and potential government stockpile plans is out of the scope of this thesis, it is important to position the simulation in its proper place as the first step in a multi-step process towards crafting a PPE emergency response plan. COVID-19 has created urgency around PPE preparedness at all levels, including encouraging increased investment in preparedness at the hospital and hospital system level. Market forces have changed as well, with increased investment in PPE infrastructure that has increased PPE market capacity. In order to properly invest its resources, planners must not only understand potential PPE demand under difference disease scenarios, but also keep tabs on facility and market preparedness and adjust its investment accordingly. This will be especially important when distance from the COVID-19 pandemic decreases attention to PPE preparedness and leads to the inevitable dwindling of facility stockpiles and PPE manufacturing.

5.4.2 Investing in policies that can decrease PPE demand in times of scarcity

Given limited resources, the government will never be able to prepare for every possible pandemic scenario. Policy makers can hedge against under-preparedness by investing in levers that can be pulled to decrease PPE demand at the hospital level in times of scarcity. Many of these methods were deployed during COVID-19, but as discussed in section 2.4, guidance was often vague and conservation policies were unevenly applied across hospital systems. A disciplined approach to investing in smooth transitions to safe PPE conservation policies across all hospital systems could significantly decrease strain on the PPE market and decrease the need for government assistance. This section will discuss the conservation policies that were identified in the simulation as having significant effect on decreasing PPE use and how those conservation policies can be invested in to improve adoption and ease of use.

5.4.2.1 Identify sites and create standard operating procedures to cohort infected patients

Cohorting infected and suspected patients so they can be treated by the minimum number of staff possible has a significant effect on decreasing N95 and eye protection use. The case study showed that implementing a perfect system of cohorting can decrease N95 and eye protection use by 48%. Although perfect cohorting is unlikely, any improvement in cohorting patients will decrease the number of unique staff members wearing an N95 and eye protection each day. Cohorting can be conducted at the hospital, local, or state level and is already a part of existing infection control guidelines to prevent disease transmission to non-infected patients (CDC, 2021).

Efforts to cohort emerged during COVID-19, including the creation of dedicated facilities for treating only COVID-19 patients (Joseph, 2020). Creating predetermined cohorting plans can lead to wider adoption of cohorting and allow for the transition of regular facilities to dedicated facilities more quickly. This has already been explored for Ebola epidemics, where 69 healthcare facilities across states have been identified as Ebola treatment centers and will be prioritized to receive Ebola patients in a future outbreak (HHS, 2018).

In areas that lack dedicated treatment centers, patients can still be cohorted within hospitals by designating specific disease floors or wards. If cohorting is logistically infeasible due to hospital infrastructure, the same decrease in N95 and eye protection use can be achieved by designating specific staff that treat all infected patients in the hospital across floors and wards.

In order to decrease N95 and eye protection use, policy makers should invest in creating cohorting plans and infrastructure before the onset of the next pandemic. These cohorting policies can then be activated during pandemic scenarios to decrease N95 and eye protection demand before it strains the market and facility/government response capacity.

5.4.2.2 Invest in sterilization technology that facilitates N95 reuse

Reusing N95s has a linear effect on N95 use, meaning reusing N95s for five shifts instead of one shift will decrease use by 80%. Reuse policies were widely adopted during COVID-19 in response to severe shortages of N95s. In May 2020, a National Nurses United survey reported 87% of nurses had reused a single use disposable mask or N95 respirator (Cohen & Rogers, 2020). At the onset of COVID-19, there were no published clinical studies on the safety of N95 reuse and limited evaluation of N95 reuse safety in the laboratory (ECRI, 2020). Laboratory studies conducted during the COVID-19 pandemic showed that moist mask heating and vaporous hydrogen peroxide treatment provided reliable viral decontamination of N95 masks (Steinberg et al., 2020). These findings led the Food and Drug Administration (FDA) to approve 15 emergency use authorizations (EUA) for N95 decontamination systems between March 2020 and January 2021. Those EUAs have since been revoked due to the higher availability of N95 masks on the market (FDA, 2021). During the approved period of the EUAs, N95 decontamination allowed hospitals to collect N95s at the end of each shift and send them for sterilization before use on the next shift. If granted full FDA approval and purchased across hospital systems, these decontamination systems have the potential to make N95 reuse safe and uniform. These systems could also be developed for other PPE at high risk of shortage, such as isolation gowns or disposable hazmat suits.

5.4.2.3 Invest in telemedicine solutions

Decreasing healthcare worker daily visits to patients has a linear effect on gown and glove use, meaning decreasing daily healthcare worker patient visits from 40 to 20 cuts gown and glove use in half. Decreasing the number of times healthcare workers physically interact with patients does not have to decrease care standards when coupled with the appropriate use of telemedicine practices. The COVID-19 pandemic spurred a wave of investment in telehealth both inside and outside of hospitals. McKinsey & Company found that telehealth has increased 38X from pre-COVID-19 levels and that both consumer and provider attitudes towards telehealth have improved. The widespread adoption of telehealth solutions resulted in a doubling of telehealth venture capital investment from 2019 to 2020, resulting in systems that were easier to use and more secure entering the market (Bestsennyy et al., 2021). The FDA granted approval for six EUAs related to telehealth technology from April- May 2020, demonstrating the FDA's agreement that telehealth was crucial for infection control and PPE conservation (FDA, 2021).

These telehealth solutions, including video conferencing with hospital inpatients and remote patient vital sign monitoring, deserve continued attention even as COVID-19 eventually fades. Continued investment in these technologies and further research into how they affect patient outcomes will allow for improved telehealth usage in the next pandemic that may further decrease healthcare worker patient visits and decrease PPE use. Even if telehealth solutions are considered unnecessary for non-emergency use, a systematic plan on when and how to implement telehealth is crucial to quickly transitioning to telehealth solutions during future PPE shortages.

5.4.2.4 Invest in diagnostic testing capability

Lower diagnostic test turnaround times reduce PPE use of all types because it decreases the number of PUIs that need to be treated with full PPE precautions. Diagnostic testing faced serious delays during the onset of COVID-19 in March 2020, with backlogs and lack of testing supplies leaving patients without test results for up to a week (Ryan & Lazar, 2020). Although testing availability and turnaround time improved later in the pandemic, it did not come in time to decrease PPE use during the peak of PPE shortages in April 2020. Criticism of the COVID-19 diagnostic testing rollout in the United States has been widespread and has been blamed for the failure to contain COVID-19 in the United States (Shear et al., 2020). Decreasing PPE use by decreasing PUIs is only a small portion of the benefit that can come from increased diagnostic testing infrastructure, which has the potential to significantly lower spread and decrease hospitalizations when coupled with contact tracing.

Although it is impossible to know the genetic makeup of the next pandemic, policy makers can invest in infrastructure and standard operating procedures that will improve diagnostic test availability early in the next pandemic. Examples of these investments include safeguarding the supply chain of crucial testing supplies including medical swabs, streamlining the process to submit diagnostic test technology and protocols to the FDA for emergency approval, and pre-designating locations for local testing centers.

5.5 Future research needs

The simulation presented in this thesis can assist policymakers in forecasting PPE use in the next pandemic and help to inform a robust PPE preparedness plan. It is, however, only one piece of what is needed to prepare the United States to meet the PPE needs of an unknown future pandemic. Although there is much needed research in this area, including research into market capacity, adaptive manufacturing, and stockpile management, this section will focus on further research specifically to improve understanding of acute care hospital PPE demand in pandemics.

5.5.1 Understanding PPE conservation policy adherence

As discussed in section 5.2, even if clear PPE conservation policies are mandated by acute care hospitals, it is not clear this will result in perfect adherence. Future research is needed to understand the effect of conservation policies on PPE consumption at hospitals and other facilities. This empirical research would improve the assumptions in the simulation and lead to more accurate PPE use forecasts. Additionally, behavioral research regarding factors that influence policy adoption can improve the crafting and strategy of PPE conservation policies. Simulating human behavior will always have limitations without an understanding of the nuances that cause people to act unpredictably and counterintuitively.

5.5.1.1 Modifying the simulation for diseases requiring different PPE precaution levels

COVID-19 requires treatment with an N95, eye protection, a level II or above isolation gown, and nitrile gloves. The simulation presented in this thesis was built to model PPE use given that required precaution level. Additional simulations or a modification to the simulation presented in this thesis is required to understand PPE us in a disease requiring a different PPE precaution level, such as Ebola. To create a full picture of potential PPE use in a future pandemic, multiple disease types should be explored.

5.5.2 Understanding how PPE use translates to PPE orders

This simulation calculates the actual PPE use on the floor in acute care hospitals. It does not predict how this use will be translated by supply chain professionals and hospital operations leaders into PPE orders in the private market. It is human nature to stockpile when there are fears of future shortages. This was seen clearly in the United States retail market for dry goods during March 2020 (Benveniste, 2020). Hospital systems are not immune to this practice. A cursory review of N95 orders placed by a major United States hospital system showed a significant attempt to stockpile at the onset of the COVID-19 pandemic along with a second bulk order in preparation for an expected second wave of COVID-19 (Anonymous Hospital Supply Chain Data, 2020). This anecdotal evidence suggests that PPE ordering behavior likely does not align with COVID-19 hospitalizations, despite the simulation showing a correlation between COVID-19 hospitalizations and N95 use.

An initial surge in orders at the onset of a pandemic is not new to COVID-19. Healthcare facilities ordered much more PPE than was needed in preparation for the 2009 H1N1 influenza. United States healthcare facilities demonstrated the same behavior during the 2014 Ebola epidemic in West Africa, ordering massive quantities of full PPE before a single Unites States case was identified (Patel et al., 2017). This behavior is understandable. Hospital planners are attempting to ensure their hospital is ready for an unknown future caseload. It does, however, make it very difficult to understand true demand when typical demand signals are inflated due to excess order placement.

The simulation presented in this thesis attempts to illuminate actual PPE use, but it is likely the strain on PPE supplies in the market will be much higher than is predicted by the use shown in the simulation due to the tendency to overorder during times of uncertainty and fear. Future research is needed to understand how use will transform into orders placed so planners can better prepare for the inevitable bullwhip effect that large initial orders will cause in the PPE supply chain.

5.5.3 Extending the simulation method to other healthcare facility types

Acute care hospitals were chosen as the focus for this work due to their comparatively large volume of PPE use. Long-term care facilities, however, also suffered devastating PPE shortages during COVID-19 and require further research into their pandemic PPE demand. Long-term care facilities are especially vulnerable to supply shortages because unlike acute care hospitals, their day-to-day non-pandemic medical supply needs are predictable and non-complex. The limited nature of long-term care non-pandemic medical supply needs mean many long-term care facilities do not employ full-time medical logistics professionals or have cultivated relationships with medical supply distributors (Milesky, 2020). This lack of logistics infrastructure makes it difficult for long-term care facilities to secure supply allocations during demand surges, making them more likely to need external support.

An initial investigation into long-term care PPE demand shows that many of the same PPE conservation techniques presented in section 5.4.2 would be equally or more affective in the long-term care context. As part of this investigation, a skilled nursing facility and assisted living facility simulation were created by altering the acute care PPE use simulation. These simulations were then run with case inputs for the state of Massachusetts from April 4, 2020 – April 3,2021. As expected, the linear effect of PPE reuse policies and HCW patient visits in both long-term care facility types equaled that seen in the acute care hospital simulation. The effect of implemented cohorting, however, was much more pronounced than the effect seen in acute care hospitals. Implementing perfect cohorting resulted in a 95.2% decrease in N95 use in skilled nursing facilities and a 93% decrease in N95 use in assisted living facilities. This was a significantly larger decrease than the 52% decrease in N95 use seen in the acute care hospital simulation run under the same COVID-19 scenario. The larger effect of cohorting is due to long-term care facilities having few staff members caring for many residents and the expected dispersion of sick patients among many non-sick residents. The effect of COVID-19 test turnaround times was also more pronounced in the long-term care setting compared to the acute hospital setting. Increasing COVID-19 test turnaround time from one to two days in skilled nursing facilities resulted in a 28.2% increase in N95 use and a 29% increase in gown use compared to the 2-3% seen in acute care hospitals. This is because routine interactions between residents in long-term care facilities ensure each positive case results in many PUIs that must be tested, as opposed to acute care hospitals were PUIs are only entering the system if they need unrelated medical care.

These preliminary results suggest that the dynamics of use in long-term care are likely different than acute hospitals and require further exploration. Long-term care may also face unique challenges implementing conservation policies due to the nature of their operation. Cohorting, for example, may be especially difficult for long-term care due to difficulties re-locating older patients to new facilities without causing additional harm. The simulation provides evidence regarding the PPE impact that can inform decisions with such difficult tradeoffs.

6. Conclusion

In response to the severe PPE shortages experienced during the COVID-19 pandemic, the United States is currently investing significant resources into PPE stockpiles and supply chains. In order to appropriately prioritize those investments, policy makers need to understand the potential demand for PPE in the next pandemic. This thesis presented a novel simulation approach to forecast PPE use in acute care hospitals for a COVID-19-type pandemic given hospitalization forecasts. A case study was then presented using data from reported COVID-19 hospitalizations in Massachusetts from April 4, 2020 – April 3, 2021 to demonstrate the potential applications of this simulation and explore the key drivers of PPE use from both case-driven and policy-driven variables.

The glass box nature of the simulation with its daily output will allow policy makers to forecast PPE use for multiple COVID-19-type disease trajectories and create understandable PPE use scenarios that can be used to inform preparedness for the next pandemic. The low computational load allows for multiple simulation runs, including potential for thousands of runs in a Monte Carlo simulation when variables are changed from deterministic to stochastic. This simulation serves as a crucial starting point in the multi-step process of determining how government agencies should invest in PPE preparedness. Too often in humanitarian supply chain literature the focus on efficient inventory management and delivery is emphasized at the expense of understanding the root demand those inventories are meant to be serving. The purpose of this simulation is to provide a reliable method to understand acute care hospital PPE demand at its source, so future analysis can build from a reliable base.

Even if policy makers understand PPE demand, they will not be able to prepare for every pandemic scenario. In order to build a robust preparedness plan, policy makers need to invest now in the PPE conservation policies that will need to be implemented in the face of future PPE shortages. The PPE shortages experienced in COVID-19 led to innovative efforts in diagnostic testing, telemedicine, N95 sterilization, and patient cohorting, but the lack of clear guidance and established best practices in these conservation efforts resulted in inconsistent use across hospital systems. The simulation case study shows that these PPE conservation policies can significantly decrease PPE use. Increased investments in key conservation strategies can improve their adoption in the next pandemic and help hedge against under-preparedness.

There is more work to be done to fully understand PPE demand at acute care hospitals. Although PPE conservation policies decrease PPE use when fully adopted, future research is needed to understand the rate of policy adherence. Additional simulations or a modification to the simulation presented in this thesis is needed to model PPE use for diseases requiring different PPE precautions, such as Ebola. Finally, PPE use does not directly translate into orders. The tendency to stockpile in the face of potential shortages results in supply chain disruptions that outsize actual PPE use. To prepare for these effects, policy makers need to know the extent of this magnification and when it is likely to occur.

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8. Appendix A: Static inputs for Massachusetts case study

Variable	Variable_name	Variable_description	Value	Units	Source
k	Percent_typical_sick_requiring_airborne_precautions	Percent of non-covid sick patients who require staff treating them to wear airborne precautions	0.0023	Percent/100	Hospital system data analyst, e-mail communication, Novermber 24, 2020
K	Percent_typical_sick_requiring_contact_droplet_precautions	Percent of non-covid sick patients who require staff treating them to wear droplet precautions	0.05	Percent/100	Hospital system data analyst, MS, e-mail communication, December 14, 2020
t	COVID_test_turnaround_time	Time from COVID test administration in the hospital to receiving a test result.	1	day	Hospital system data analyst, MS, e-mail communication, December 14, 2020
g	Specialists	Specialists likely to consult on COVID cases including Nephrologists, Pulmonologists, Cardiologists, Infectious Disease Specialists, and Rheumatologists.	3958	Specialists	Commonwealth of Massachusetts Board of Registration in Medicine. Massachusetts state website. Accessed January 29, 2021. http://profiles.ehs.state.ma.us/ProfilesV3/FullSearch?LicenseStatus=1&AMASpecialties=206
y	ED_Staff_per_day	Sum of all RNs, MDs and technicians working in Massachusetts Emergency Departments each day	5358	HCWs	2019 Reports. PatientCareLink website. Accessed December 3, 2020. https://patientcarelink.org/2019-plans/
z	HCWs_per_AGP	Number of healthcare workers who take part in an aerosol generating procedure	2	HCWs	Disaster Medicine Specialist, PhD, oral communication, December 8, 2020
U	Shifts_per_day_clinical	How many shifts per day for clinical staff. Two shifts per day implies 12 hour shifts	2	shifts	Disaster Medicine Specialist, PhD, oral communication, December 8, 2020
u	Shifts_per_day_non_clinical	How many shifts per day for non clinical staff. Three shifts per day implies 8 hour shifts	3	shifts	Disaster Medicine Specialist, PhD, oral communication, December 8, 2020
E	Daily_patients_presenting_to_ED	Number of patients presenting to emergency departments daily	7996	patients	National Hospital Ambulatory Medical Care Survey: 2017 Emergency Department Summary Tables. Center for Disease Prevention and Control website. Accessed November 20, 2020. https://www.cdc.gov/nchs/data/nhamcs/web_tables/2017_ed_web_tables-508.pdf
b	Shifts_per_eye_protection	Number of shifts a healthcare worker wears eye protection before disposing it	1	shifts	Disaster Medicine Specialist, PhD, oral communication, December 8, 2020
τ	Shifts_per_N95	Number of shifts a healthcare worker wears an N95 mask before disposing it	1	shifts	Comprehensive Personal Protective Equipment (PPE) Guidance (2021). Commonwealth of Massachusetts Department of Public Health. January 6, 2021.
ρ	Shifts_per_surgical_mask	Number of shifts a healthcare worker wears a surgical mask before disposing it	1	shifts	Disaster Medicine Specialist, PhD, oral communication, December 8, 2020
ω	Misc_non_clinical_entering_hospital	Total non clinical staff that work in a hospital daily	66701	Staff	Number of hospitals and hospital employment in each state in 2019. U.S. Bureau of Labor Statistics website. April 6, 2020. Accessed December 5, 2020. https://www.bls.gov/opub/ted/2020/number-of-hospitals-and-hospital-employment-in-each-state-in-2019.htm
d_{ICU}	Typical_sick_ICU_occupancy	Number of non-COVID patients in ICUs daily	1023	patients	Wunsch H, Wagner J, Herlim M, Chong DH, Kramer AA, Halpern SD. ICU occupancy and mechanical ventilator use in the United States. Crit Care Med. 2013;41(12):2712-2719. doi:10.1097/CCM.0b013e318298a139
$d_{Inpatient}$	Typical_sick_Inpatient_occupancy	Number of inpatients in the hospital during non pandemic conditions (daily)	2017	patients	Table 82. Hospital admission, average length of stay, outpatient visits, and outpatient surgery, by type of ownership and size of hospital: United States, selected years 1975–2015. Center for Disease Prevention and Control Website. Accessed November 17, 2020. https://www.cdc.gov/nchs/data/hus/2017/082.pdf
x	Non_Clinical_per_patient	Number of non clinical employees with patient contact per patient. For example, .5 would mean a non clinical worker interacts with 2 patients.	0.0625	non-clinical staff	AHA Staffing Methodologies and Standards for Heathcare Environmental Services Departments. Association for the Healthcare Environment. 2015.
μ	HCW_visits_per_patient_ED	How many times a healthcare worker sees an ED patient per visit (requiring a PPE change)	10	visits	Disaster Medicine Specialist, PhD, oral communication, December 8, 2020
θ	HCW_daily_visits_ICU	How many times a healthcare worker sees an ICU patient per day (requiring a PPE change)	170	visits	PPE Assumptions. Johns Hopkins Bloomberg School of Public Health Center for Health Security website. Updated April 18, 2020. Accessed December 15, 2020. https://www.centerforhealthsecurity.org/resources/COVID-19/PPE/PPE-assumptions
λ	HCW_daily_visits_Inpatient	How many times a healthcare worker sees an inpatient per day (requiring a PPE change)	80	visits	PPE Assumptions. Johns Hopkins Bloomberg School of Public Health Center for Health Security website. Updated April 18, 2020. Accessed December 15, 2020. https://www.centerforhealthsecurity.org/resources/COVID-19/PPE/PPE-assumptions
$V_{RN, ICU}$	RNs_per_ICU_patient	Number of RNs who would be assigned to treat an ICU patient. For example, .5 would mean 1 RN treats 2 ICU patients	0.73	RNs	2019 Reports. PatientCareLink website. Accessed December 3, 2020. https://patientcarelink.org/2019-plans/
$V_{MD,ICU}$	MDs_per_ICU_patient	Number of MDs who would be assigned to treat an ICU patient. For example, .5 would mean 1 MD treats 2 ICU patients	0.125	MDs	Disease and Research Policy, University of Minnesota webiste. Updated September 2007, Accessed November 17, 2020. https://www.cidrap.umn.edu/sites/default/files/public/php/340/340_guidance.pdf
$V_{PCA,ICU}$	PCA_per_ICU_patient	patient. For example, .5 would mean 1 PCA treats 2 ICU patients	0.14	PCAs	2019 Reports. PatientCareLink website. Accessed December 3, 2020. https://patientcarelink.org/2019-plans/
$V_{Student,ICU}$	Student_per_ICU_patient	patient. For example, .5 would mean 1 student treats 2 ICU patients	0.15	student	Disaster Medicine Specialist, PhD, oral communication, December 8, 2020
$V_{RN, Inpatient}$	RNs_per_Inpatient	Number of RNs who would be assigned to treat an inpatient. For example, .5 would mean 1 RN treats 2 ICU patients	0.27	RNs	2019 Reports. PatientCareLink website. Accessed December 3, 2020. https://patientcarelink.org/2019-plans/
$V_{MD, Inpatient}$	MDs_per_Inpatient	Number of MDs who would be assigned to treat an inpatient. For example, .5 would mean 1 MD treats 2 ICU patients	0.04	MDs	Disease and Research Policy, University of Minnesota webiste. Updated September 2007, Accessed November 17, 2020. https://www.cidrap.umn.edu/sites/default/files/public/php/340/340_guidance.pdf
$V_{PCA, Inpatient}$	PCA_per_Inpatient	Number of PCAs who would be assigned to treat an inpatient. For example, .5 would mean 1 PCA treats 2 ICU patients	0.12	PCAs	2019 Reports. PatientCareLink website. Accessed December 3, 2020. https://patientcarelink.org/2019-plans/
$V_{Student, Inpatient}$	Student_per_Inpatient	inpatient. For example, .5 would mean 1 student treats 2 ICU patients	0.1	student	Disaster Medicine Specialist, PhD, oral communication, December 8, 2020

9. Appendix B: Dynamic inputs for Massachusetts case study

Date	COVID_in_Inpatient	COVID_in_ICU	New_PUI_in_ICU	New_PUI_in_Inpatient	AGPs_performed	Percent_ED_patient_COVID_risk
4-Apr-20	932	438	34	117	68	31%
5-Apr-20	1106	526	40	138	80	31%
6-Apr-20	1135	542	42	142	84	31%
7-Apr-20	1256	575	44	157	88	31%
8-Apr-20	1460	659	51	183	102	31%
9-Apr-20	1617	685	53	202	106	31%
10-Apr-20	1734	701	54	217	108	31%
11-Apr-20	1762	745	57	220	114	31%
12-Apr-20	1789	765	59	224	118	31%
13-Apr-20	2543	942	72	318	144	31%
14-Apr-20	2651	965	74	331	148	31%
15-Apr-20	2650	987	76	331	152	31%
16-Apr-20	2728	998	77	341	154	31%
17-Apr-20	2753	1003	77	344	154	31%
18-Apr-20	2728	1000	77	341	154	31%
19-Apr-20	2769	1020	78	346	156	31%
20-Apr-20	2827	1040	80	353	160	31%
21-Apr-20	2915	1050	81	364	162	31%
22-Apr-20	2839	1034	80	355	160	31%
23-Apr-20	2782	1048	81	348	162	31%
24-Apr-20	2772	1058	81	347	162	31%
25-Apr-20	2777	1077	83	347	166	31%
26-Apr-20	2803	1089	84	350	168	31%
27-Apr-20	2865	1010	78	358	156	31%
28-Apr-20	2845	1011	78	356	156	31%
29-Apr-20	2802	1001	77	350	154	31%
30-Apr-20	2764	952	73	346	146	31%
1-May-20	2676	925	71	335	142	31%
2-May-20	2710	907	70	339	140	31%
3-May-20	2626	913	70	328	140	31%
4-May-20	2628	914	70	329	140	31%
5-May-20	2640	922	71	330	142	31%
6-May-20	2583	853	66	323	132	31%
7-May-20	2517	832	64	315	128	31%
8-May-20	2415	814	63	302	126	31%
9-May-20	2318	810	62	290	124	31%
10-May-20	2289	813	63	286	126	31%
11-May-20	2309	818	63	289	126	31%
12-May-20	2307	794	61	288	122	31%
13-May-20	2078	781	60	260	120	31%
14-May-20	2018	749	58	252	116	31%
15-May-20	1945	747	57	243	114	31%
16-May-20	1895	702	54	237	108	31%
17-May-20	1859	674	52	232	104	31%
18-May-20	1800	672	52	225	104	31%
19-May-20	1843	675	52	230	104	31%
20-May-20	1749	647	50	219	100	31%

21-May-20	1695	628	48	212	96	31%
22-May-20	1627	610	47	203	94	31%
23-May-20	1611	558	43	201	86	31%
24-May-20	1576	556	43	197	86	31%
25-May-20	1548	560	43	194	86	31%
26-May-20	1550	556	43	194	86	31%
27-May-20	1579	533	41	197	82	31%
28-May-20	1506	485	37	188	74	31%
29-May-20	1451	453	35	181	70	31%
30-May-20	1388	436	34	174	68	31%
31-May-20	1343	404	31	168	62	31%
1-Jun-20	1263	394	30	158	60	31%
2-Jun-20	1291	393	30	161	60	31%
3-Jun-20	1236	401	31	155	62	31%
4-Jun-20	1183	350	27	148	54	31%
5-Jun-20	1172	359	28	147	56	31%
6-Jun-20	1109	335	26	139	52	31%
7-Jun-20	1093	322	25	137	50	31%
8-Jun-20	1082	315	24	135	48	31%
9-Jun-20	1016	319	25	127	50	31%
10-Jun-20	964	296	23	121	46	31%
11-Jun-20	867	276	21	108	42	31%
12-Jun-20	820	249	19	103	38	31%
13-Jun-20	795	244	19	99	38	31%
14-Jun-20	773	253	19	97	38	31%
15-Jun-20	801	244	19	100	38	31%
16-Jun-20	771	227	17	96	34	31%
17-Jun-20	741	227	17	93	34	31%
18-Jun-20	795	199	15	99	30	31%
19-Jun-20	764	200	15	96	30	31%
20-Jun-20	733	194	15	92	30	31%
21-Jun-20	740	180	14	93	28	31%
22-Jun-20	772	181	14	97	28	31%
23-Jun-20	758	181	14	95	28	31%
24-Jun-20	648	174	13	81	26	31%
25-Jun-20	635	156	12	79	24	31%
26-Jun-20	626	143	11	78	22	31%
27-Jun-20	614	134	10	77	20	31%
28-Jun-20	624	138	11	78	22	31%
29-Jun-20	613	120	9	77	18	31%
30-Jun-20	637	123	9	80	18	31%
1-Jul-20	568	113	9	71	18	31%
2-Jul-20	550	106	8	69	16	31%
3-Jul-20	533	107	8	67	16	31%
4-Jul-20	536	100	8	67	16	31%
5-Jul-20	504	99	8	63	16	31%
6-Jul-20	517	104	8	65	16	31%
7-Jul-20	560	102	8	70	16	31%
8-Jul-20	532	103	8	67	16	31%
9-Jul-20	534	98	8	67	16	31%
10-Jul-20	485	87	7	61	14	31%
11-Jul-20	490	93	7	61	14	31%
12-Jul-20	481	89	7	60	14	31%
13-Jul-20	467	93	7	58	14	31%
14-Jul-20	500	80	6	63	12	31%

15-Jul-20	480	77	6	60	12	31%
16-Jul-20	439	76	6	55	12	31%
17-Jul-20	413	86	7	52	14	31%
18-Jul-20	434	64	5	54	10	31%
19-Jul-20	416	67	5	52	10	31%
20-Jul-20	450	63	5	56	10	31%
21-Jul-20	469	63	5	59	10	31%
22-Jul-20	292	59	5	37	10	31%
23-Jul-20	135	20	2	17	4	31%
24-Jul-20	126	22	2	16	4	31%
25-Jul-20	129	32	2	16	4	31%
26-Jul-20	130	30	2	16	4	31%
27-Jul-20	131	31	2	16	4	31%
28-Jul-20	133	31	2	17	4	31%
29-Jul-20	135	35	3	17	6	31%
30-Jul-20	138	37	3	17	6	31%
31-Jul-20	137	34	3	17	6	31%
1-Aug-20	141	33	3	18	6	31%
2-Aug-20	140	31	2	18	4	31%
3-Aug-20	139	28	2	17	4	31%
4-Aug-20	149	32	2	19	4	31%
5-Aug-20	163	35	3	20	6	31%
6-Aug-20	161	30	2	20	4	31%
7-Aug-20	162	40	3	20	6	31%
8-Aug-20	156	39	3	20	6	31%
9-Aug-20	155	35	3	19	6	31%
10-Aug-20	144	34	3	18	6	31%
11-Aug-20	153	37	3	19	6	31%
12-Aug-20	145	38	3	18	6	31%
13-Aug-20	150	39	3	19	6	31%
14-Aug-20	141	39	3	18	6	31%
15-Aug-20	140	41	3	18	6	31%
16-Aug-20	143	37	3	18	6	31%
17-Aug-20	143	39	3	18	6	31%
18-Aug-20	138	36	3	17	6	31%
19-Aug-20	145	35	3	18	6	31%
20-Aug-20	124	38	3	16	6	31%
21-Aug-20	118	33	3	15	6	31%
22-Aug-20	109	33	3	14	6	31%
23-Aug-20	105	35	3	13	6	31%
24-Aug-20	122	40	3	15	6	31%
25-Aug-20	118	42	3	15	6	31%
26-Aug-20	129	41	3	16	6	31%
27-Aug-20	123	43	3	15	6	31%
28-Aug-20	120	41	3	15	6	31%
29-Aug-20	120	40	3	15	6	31%
30-Aug-20	119	38	3	15	6	31%
31-Aug-20	127	35	3	16	6	31%
1-Sep-20	134	35	3	17	6	31%
2-Sep-20	132	35	3	17	6	31%
3-Sep-20	137	36	3	17	6	31%
4-Sep-20	132	32	2	17	4	31%
5-Sep-20	130	33	3	16	6	31%
6-Sep-20	138	31	2	17	4	31%
7-Sep-20	151	27	2	19	4	31%

8-Sep-20	148	31	2	19	4	31%
9-Sep-20	141	33	3	18	6	31%
10-Sep-20	135	38	3	17	6	31%
11-Sep-20	131	39	3	16	6	31%
12-Sep-20	121	35	3	15	6	31%
13-Sep-20	122	35	3	15	6	31%
14-Sep-20	130	35	3	16	6	31%
15-Sep-20	139	40	3	17	6	31%
16-Sep-20	146	39	3	18	6	31%
17-Sep-20	144	34	3	18	6	31%
18-Sep-20	145	38	3	18	6	31%
19-Sep-20	148	40	3	19	6	31%
20-Sep-20	143	50	4	18	8	31%
21-Sep-20	160	40	3	20	6	31%
22-Sep-20	150	45	3	19	6	31%
23-Sep-20	159	45	3	20	6	31%
24-Sep-20	159	52	4	20	8	31%
25-Sep-20	162	49	4	20	8	31%
26-Sep-20	173	49	4	22	8	31%
27-Sep-20	179	57	4	22	8	31%
28-Sep-20	189	65	5	24	10	31%
29-Sep-20	203	63	5	25	10	31%
30-Sep-20	198	61	5	25	10	31%
1-Oct-20	197	53	4	25	8	31%
2-Oct-20	202	56	4	25	8	31%
3-Oct-20	209	55	4	26	8	31%
4-Oct-20	213	50	4	27	8	31%
5-Oct-20	239	49	4	30	8	31%
6-Oct-20	244	55	4	31	8	31%
7-Oct-20	251	60	5	31	10	31%
8-Oct-20	246	63	5	31	10	31%
9-Oct-20	266	64	5	33	10	31%
10-Oct-20	259	65	5	32	10	31%
11-Oct-20	264	58	4	33	8	31%
12-Oct-20	263	58	4	33	8	31%
13-Oct-20	265	60	5	33	10	31%
14-Oct-20	261	59	5	33	10	31%
15-Oct-20	263	53	4	33	8	31%
16-Oct-20	247	61	5	31	10	31%
17-Oct-20	251	60	5	31	10	31%
18-Oct-20	273	61	5	34	10	31%
19-Oct-20	275	67	5	34	10	31%
20-Oct-20	292	66	5	37	10	31%
21-Oct-20	279	75	6	35	12	31%
22-Oct-20	289	79	6	36	12	31%
23-Oct-20	282	82	6	35	12	31%
24-Oct-20	280	82	6	35	12	31%
25-Oct-20	298	79	6	37	12	31%
26-Oct-20	318	82	6	40	12	31%
27-Oct-20	326	77	6	41	12	31%
28-Oct-20	320	73	6	40	12	31%
29-Oct-20	327	80	6	41	12	31%
30-Oct-20	345	89	7	43	14	31%
31-Oct-20	350	86	7	44	14	31%
1-Nov-20	373	96	7	47	14	31%

2-Nov-20	389	96	7	49	14	31%
3-Nov-20	393	109	8	49	16	31%
4-Nov-20	383	115	9	48	18	31%
5-Nov-20	395	118	9	49	18	31%
6-Nov-20	408	127	10	51	20	31%
7-Nov-20	424	144	11	53	22	31%
8-Nov-20	445	143	11	56	22	31%
9-Nov-20	468	150	12	59	24	31%
10-Nov-20	507	152	12	63	24	31%
11-Nov-20	510	151	12	64	24	31%
12-Nov-20	534	153	12	67	24	31%
13-Nov-20	554	151	12	69	24	31%
14-Nov-20	578	159	12	72	24	31%
15-Nov-20	622	159	12	78	24	31%
16-Nov-20	676	159	12	85	24	31%
17-Nov-20	712	173	13	89	26	31%
18-Nov-20	736	181	14	92	28	31%
19-Nov-20	725	179	14	91	28	31%
20-Nov-20	704	187	14	88	28	31%
21-Nov-20	701	192	15	88	30	31%
22-Nov-20	718	204	16	90	32	31%
23-Nov-20	749	205	16	94	32	31%
24-Nov-20	734	208	16	92	32	31%
25-Nov-20	755	211	16	94	32	31%
26-Nov-20	777	209	16	97	32	31%
27-Nov-20	820	225	17	103	34	31%
28-Nov-20	843	238	18	105	36	31%
29-Nov-20	930	244	19	116	38	31%
30-Nov-20	952	239	18	119	36	31%
1-Dec-20	995	264	20	124	40	31%
2-Dec-20	1063	261	20	133	40	31%
3-Dec-20	1116	278	21	140	42	31%
4-Dec-20	1145	283	22	143	44	31%
5-Dec-20	1118	298	23	140	46	31%
6-Dec-20	1214	302	23	152	46	31%
7-Dec-20	1242	310	24	155	48	31%
8-Dec-20	1268	308	24	159	48	31%
9-Dec-20	1300	307	24	163	48	31%
10-Dec-20	1296	309	24	162	48	31%
11-Dec-20	1336	334	26	167	52	31%
12-Dec-20	1365	342	26	171	52	31%
13-Dec-20	1434	354	27	179	54	31%
14-Dec-20	1463	371	29	183	58	31%
15-Dec-20	1469	382	29	184	58	31%
16-Dec-20	1488	383	29	186	58	31%
17-Dec-20	1504	370	28	188	56	31%
18-Dec-20	1544	383	29	193	58	31%
19-Dec-20	1532	387	30	192	60	31%
20-Dec-20	1581	410	32	198	64	31%
21-Dec-20	1592	412	32	199	64	31%
22-Dec-20	1657	409	31	207	62	31%
23-Dec-20	1686	409	31	211	62	31%
24-Dec-20	1682	409	31	210	62	31%
25-Dec-20	1661	416	32	208	64	31%
26-Dec-20	1740	416	32	218	64	31%
27-Dec-20	1800	430	33	225	66	31%
28-Dec-20	1828	431	33	229	66	31%
29-Dec-20	1824	433	33	228	66	31%

30-Dec-20	1854	417	32	232	64	31%
31-Dec-20	1894	429	33	237	66	31%
1-Jan-21	1868	412	32	234	64	31%
2-Jan-21	1875	416	32	234	64	31%
3-Jan-21	1916	423	33	240	66	31%
4-Jan-21	2003	425	33	250	66	31%
5-Jan-21	1974	442	34	247	68	31%
6-Jan-21	1931	455	35	241	70	31%
7-Jan-21	1871	440	34	234	68	31%
8-Jan-21	1846	445	34	231	68	31%
9-Jan-21	1766	459	35	221	70	31%
10-Jan-21	1760	451	35	220	70	31%
11-Jan-21	1768	451	35	221	70	31%
12-Jan-21	1744	461	35	218	70	31%
13-Jan-21	1772	454	35	222	70	31%
14-Jan-21	1750	451	35	219	70	31%
15-Jan-21	1764	433	33	221	66	31%
16-Jan-21	1732	433	33	217	66	31%
17-Jan-21	1779	427	33	222	66	31%
18-Jan-21	1781	432	33	223	66	31%
19-Jan-21	1765	444	34	221	68	31%
20-Jan-21	1722	430	33	215	66	31%
21-Jan-21	1672	426	33	209	66	31%
22-Jan-21	1637	418	32	205	64	31%
23-Jan-21	1537	409	31	192	62	31%
24-Jan-21	1537	418	32	192	64	31%
25-Jan-21	1520	431	33	190	66	31%
26-Jan-21	1512	418	32	189	64	31%
27-Jan-21	1473	405	31	184	62	31%
28-Jan-21	1377	412	32	172	64	31%
29-Jan-21	1346	393	30	168	60	31%
30-Jan-21	1305	371	29	163	58	31%
31-Jan-21	1303	373	29	163	58	31%
1-Feb-21	1287	353	27	161	54	31%
2-Feb-21	1300	335	26	163	52	31%
3-Feb-21	1219	335	26	152	52	31%
4-Feb-21	1181	322	25	148	50	31%
5-Feb-21	1141	310	24	143	48	31%
6-Feb-21	1071	318	24	134	48	31%
7-Feb-21	1058	329	25	132	50	31%
8-Feb-21	1077	324	25	135	50	31%
9-Feb-21	1049	309	24	131	48	31%
10-Feb-21	1009	304	23	126	46	31%
11-Feb-21	923	300	23	115	46	31%
12-Feb-21	858	291	22	107	44	31%
13-Feb-21	835	290	22	104	44	31%
14-Feb-21	821	286	22	103	44	31%
15-Feb-21	821	275	21	103	42	31%
16-Feb-21	815	273	21	102	42	31%
17-Feb-21	758	271	21	95	42	31%
18-Feb-21	732	258	20	92	40	31%
19-Feb-21	724	246	19	91	38	31%
20-Feb-21	693	234	18	87	36	31%
21-Feb-21	659	229	18	82	36	31%
22-Feb-21	654	225	17	82	34	31%
23-Feb-21	656	219	17	82	34	31%
24-Feb-21	632	221	17	79	34	31%
25-Feb-21	596	211	16	75	32	31%

26-Feb-21	581	204	16	73	32	31%
27-Feb-21	577	183	14	72	28	31%
28-Feb-21	604	184	14	76	28	31%
1-Mar-21	588	187	14	74	28	31%
2-Mar-21	582	173	13	73	26	31%
3-Mar-21	573	168	13	72	26	31%
4-Mar-21	536	180	14	67	28	31%
5-Mar-21	511	176	14	64	28	31%
6-Mar-21	491	174	13	61	26	31%
7-Mar-21	492	180	14	62	28	31%
8-Mar-21	519	185	14	65	28	31%
9-Mar-21	506	183	14	63	28	31%
10-Mar-21	504	176	14	63	28	31%
11-Mar-21	471	170	13	59	26	31%
12-Mar-21	467	176	14	58	28	31%
13-Mar-21	467	169	13	58	26	31%
14-Mar-21	455	169	13	57	26	31%
15-Mar-21	455	164	13	57	26	31%
16-Mar-21	462	158	12	58	24	31%
17-Mar-21	428	163	13	54	26	31%
18-Mar-21	429	157	12	54	24	31%
19-Mar-21	436	152	12	55	24	31%
20-Mar-21	436	144	11	55	22	31%
21-Mar-21	458	145	11	57	22	31%
22-Mar-21	460	148	11	58	22	31%
23-Mar-21	481	147	11	60	22	31%
24-Mar-21	494	137	11	62	22	31%
25-Mar-21	483	139	11	60	22	31%
26-Mar-21	511	143	11	64	22	31%
27-Mar-21	516	141	11	65	22	31%
28-Mar-21	516	159	12	65	24	31%
29-Mar-21	539	172	13	67	26	31%
30-Mar-21	521	169	13	65	26	31%
31-Mar-21	534	166	13	67	26	31%
1-Apr-21	545	160	12	68	24	31%
2-Apr-21	543	164	13	68	26	31%
3-Apr-21	548	167	13	69	26	31%