COVID's Dynamic Impact on Consumer Behavior in the US:

A System Dynamics Approach to Understanding People's Perception, Cognition, and Reaction to COVID-19

Thesis submitted in partial fulfillment of the requirements for
Master of Philosophy in System Dynamics from the University of Bergen.

Will Noyes (285294)

Supervised by: Christina Gkini,
PhD Candidate, Center for the Science of Learning and Technology (SLATE), Faculty of Psychology and System Dynamics Group, Department of Geography, Faculty of Social Sciences, University of Bergen

Co-supervised by: Pål Davidsen,
Professor, System Dynamics Group, Department of Geography, Faculty Social Sciences, University of Bergen

UNIVERSITY OF BERGEN
Faculty of Social Sciences

Table of Figures

Table of Tables

Table of Contents

Acknowledgements:

First, I would like to thank my supervisor Christina Gkini, who provided invaluable direction, advise, and feedback throughout the writing of this thesis. Even more, her passion, patience, honesty, and intense desire to help people learn and grow has inspired me and countless others these past two years. Additionally, I would like to thank my co-supervisor Pål Davidsen who helped substantially on the front end of this work and helped me to take a very vague idea and turn it into a solid thesis project. In general, I would like the thank the entire System Dynamics Group here at the University of Bergen for their contribution to and investment in my education as a system dynamics modeler. There is a generous spirit and a strong community in this department.

Next, I want to thank my fellow students and friends who have been by my side on a daily basis throughout this entire program. The days I have spent working on this thesis alongside Besir Suleyman Oz, Noedine Isaacs-Mpulo, Min Xiang, Richard Sarfo, Abu-Bakr (Ovi) Siddique, and Faith Kiprono in room 713 will be some of my most cherished memories of my time here in Bergen. Doing this work alongside them has turned the drudgery of writing a thesis into thoroughly enjoyable experience. I have been truly blessed by them and the friendship, encouragement, input and camaraderie of many others here in Bergen.

I also want to thank my family back in the States, for their generous support, prayers, and encouragement of my studies here in Bergen over the past several years. My parents have invested immensely in my education over the years and have inspired in me a love of learning that has taken me here today.

I must thank my coworkers at Baruch Senior Ministries, for extending the flexibility for me to join this program and for generously providing the opportunity to continue working remotely from Norway. Additionally, they have given me the opportunity to immediately put to use what I am learning here by assigning projects where I can use the system dynamics methodology. After all, this thesis was born from a project taken up as part of my work at Baruch.

I must finally thank my friends back in the States, for their encouragement, support, and prayers as I decided to move to Norway to take part in this program. Without the encouragement and

immense help from many of my friends, and especially from Phil Beezhold, over the past two years in, it would not have been feasible for me to undertake this master's program.

It is truly humbling to reflect on all the incredible people in my life who have directly and indirectly contributed to this work and to me personally these past few years, and for that I am incredibly grateful. I am pleased to present to you all the final product of my education here in Bergen.

Preface

Inspiration for this research project came out of a very practical assignment that I received in June 2020 as part of my position as a financial analyst at a mid-size senior housing operator in Michigan. I was tasked with conducting some analysis to assess how COVID was impacting elderly people's decision to move into a senior housing facility. The senior housing industry has suffered immensely under this pandemic, and among one of the many major problems facing the industry was a steep decline in new residents moving into the facilities. I had plenty of operational data specific to that organization available to me as well as general public data about COVID, so I wanted to see if I could build a model that could reasonably explain the patterns we were seeing in new move-ins given how the COVID situation had developed. After a few weeks of playing around with some basic system dynamics model structures, I managed to create a simple model that was able to nicely replicate the historical move in patterns our organization witnessed during the initial months of the pandemic. I have to admit that I mostly stumbled into the model structure and while I was happy to see that the model could reproduce the historical data, I had no basis whatsoever for claiming that the model was producing the right behavior for the right reasons. After all, there were only a few months of data available at that point and any number of possible model formulations could have probably managed to reproduce such a short period of behavior. The project struck my curiosity though and I began to consider how I could go about testing if this model had any structural validity to it. As time went on and I continued to update the model with new COVID data, it continued to produce the trends we saw in the real number of move-ins, so I began investigating the model assumptions further.

Around that time, I was also in the midst of trying to select a topic for my master thesis and being that I was already in the middle of investigating this model, it seemed like a natural choice to continue investigating it in a formal academic manner. However, I was hesitant to adopt this as a formal research project since the starting point would just be a model for which I had little reason to believe had any validity other than the fact it seemed like it worked pretty well for the very specific problem I was analyzing. The typical process for building system dynamics models starts by defining a problem, then investigating the structure of the system that produces that problem, and then building a model of the system (Luna-Reyes & Anderson, 2004). This project has undergone an inverted process by essentially starting with a model that seems to work for a very specific problem, then investigating the structure of the model compared to the real-world system, and then finally determining how the model can be broadly applied and what kinds of questions it can actually answer. Given this inversion of the process, there was a significant risk that I would end up with a project for which all I could conclude from it was that I took a model with no theoretical foundation and found that it was invalid: hardly a valuable academic contribution. It felt like a gamble to conduct research that might only expose the model as insufficient, invalid, or lacking any sort of general applicability. However, the results I continued to get from the initial model were difficult to ignore, and the potential insights that could be gained from a model like this made it worth that risk, and I believe it has so far shown to pay off.

However, the greater risk in this project has been and remains that of falling for the confirmation bias, whereby I set out only to prove what I suspect already to be true. After all, I had a structure that has worked well since the beginning, so I have only needed to find information that confirms the [unfounded] assumptions within my original model. While I do believe that this research process has led to a substantially more robust model, both from a theoretical and mathematical standpoint, and that it certainly makes a compelling case for explaining how certain cognitive processes shape people's behavior in response to changes in COVID, ultimately much more empirical and experimental research will need to be undertaken to validate this model. The boundary for this model is also very tight and certainly ignores several other important factors. Additionally, I may have misconstrued what phenomena are truly responsible for the trends we observe and falsely attributed the effects we have observed to ultimately irrelevant causes. The model also runs a risk of being far too simple, and in being so fail to provide an accurate structural explanation of the trends we observe in people's behavior. Therefore, the conclusions drawn in this research should be considered in light of the significant additional research that must be conducted. In fact, the best I hope to accomplish by this project is merely to propose a plausibly valid model with a good theoretical and mathematical foundation which may inspire further research and experimentation from other researchers in other fields who are more qualified for studying this kind of problem; I have after all just a layperson's knowledge of the cognitive and psychological processes that underly the theory for this model. In the meantime, I hope it could at least be of some use to other modelers as they also grapple with how COVID is influencing people's behavior in the problems that they are researching.

Abstract

COVID-19 has instigated sweeping and universal changes in how people carry on their day to day lives as they are forced to adjust to a constantly evolving pandemic. This research project investigates how general behavior patterns in many different industries have emerged from the evolving COVID pandemic. This project specifically considers theories from psychology and behavioral and cognitive science that are most likely to explain how people perceive, understand, and react to news about COVID (including anchoring and perception biases, Weber-Fechner's laws of psychophysics, and the log-normal distribution of risk assessment for the population). These theories and cognitive mechanisms are then represented in a simulation model as a means of testing to what extent they are capable of explaining the time-series behavior data taken from a variety of industries and domains. The results have shown that a simple and general model of these cognitive mechanisms is able to substantially explain observed behavior patterns in many industries, including airline travel, dining at restaurants, workplace mobility, senior housing, and others. The result of this research provides a general model structure that, given reasonable parameterizations, offers a causal explanation as to how a population behaves at the aggregate level in a wide variety of domain just by accounting for some basic cognitive biases and heuristics. The insights provided by this model are both theoretical and practical. First, it offers a causal explanation of how COVID causes changes in behavior by means of the cognitive processes people undergo to perceive, understand, and react to COVID. Second, it offers a quantified explanation as to why behavior differs in different industries and domains by estimating a response distribution of the population for each particular domain. Third, it provides insights to policy makers and business managers as to how people may respond under different hypothetical COVID scenarios. Finally, it provides a general cognitive model structure that can be used in other COVID modeling projects or potentially other crisis situations beyond the COVID pandemic.

Problem Introduction:

Problem Background:

On March 11, 2020, the World Health Organization declared COVID-19 to be a world pandemic (World Health Organization, 2020). The COVID pandemic quickly plunged the world into turmoil as economies shut down, governments enforced lockdowns and social-distancing restrictions, and fear swept the globe as to how this pandemic would impact the future of our increasingly global society. Needless to say, this pandemic has left almost no area of our economy, society, or culture unchanged. Furthermore, COVID remains an extremely unpredictable situation as new variants continually pop up and regions are battered with wave after wave of infections, lockdowns, hospital overloads, and social unrest due to the pandemic. Businesses and governments have continuously grappled with understanding how people respond to the ever-changing pandemic situation. For businesses it is critical understand how consumer behavior is impacted by the virus. Many industries, such as hospitality and travel, have suffered an especially debilitating loss of business due to fear of the virus as well as government-imposed restrictions; and such industries are not anticipated to fully recover for many years (Constantin, Saxon, & Yu, 2020). Industries need to know how much business they are likely to lose or recover as the pandemic continues to evolve. Additionally, governments need to understand how people react to the pandemic so that they can design effective economic, social, and health-related policies to combat the pandemic and its effects. Proper behavior forecasting is an essential component to designing effective short and mid-term strategies, whether in the private or public sphere.

As the pandemic is only a little over a year old as of the time of this research paper, little research has been completed that offers a structural and well-quantified explanation as to how COVID is affecting a population's behavior in domains not directly related to COVID. For instance, while much initial research has been done to show how changes in the pandemic are affecting health behaviors, such as hygiene habits, social distancing, mask wearing, vaccine sentiment, etc. (see for example, (Volker, Weiss-Cohen, Filkukova, & Ayton, 2021; Gkini, 2020; Anaki & Sergey)), there has been little that provides a causal or structural explanation for how COVID impacts behavior in other domains (such as mobility or consumption); and while loads of behavior data are readily available, most research so far has been limited to merely drawing correlational inferences from the data. This is certainly helpful and can point to interesting further research opportunities to gain a deeper understanding as to what really drives people's behavior. Along this line, many theories have been proposed (but not formally modeled) that could offer a structural explanation for the trends that have been observed, such as the effect of pandemic fatigue diminishing people's vigilance in the fight against COVID (Crabtree, 2020), or our own perceptive inability to understand the enormous numbers involved in the COVID statistics that are constantly reported (O'hara, 2020). Explicitly modeling some of these theories in light of the ample data available could offer new and valuable insights into how a population responds on an aggregate level to changes in the pandemic. Furthermore, the insights that could be drawn from a model like this would ideally extend beyond just the category of 'health behavior' and encompass many other types of behaviors that are certainly being impacted by COVID.

Research Objectives

The primary objective of this paper is to develop and test a generally applicable model structure that represents the cognitive processes that shape peoples' behavior patterns in response to news about COVID. At this point, it would be helpful to define what is meant by the terms, 'domain' and 'behavior', since these are general terms and will be used often throughout this paper. 'Domain' will refer typically to a specific industry, but could more generally refer to any economic, social, or cultural sector of society in which people participate, make decisions, and take actions. 'Behavior' is also a general term to refer to the relative level of activity within a particular domain. When the domain represents an industry, the behavior would mostly represent consumer behavior— or people's demand or propensity to purchase what that industry has to offer. This research will be particularly interested in looking at domains where people's behavior has been greatly impacted by COVID.

As an example of the kinds of questions this research will explore, consider how the pandemic has affected airline travel in the US. Figure 1 shows the number of new daily reported COVID cases for the US from the beginning of the pandemic until May 14, 2020:

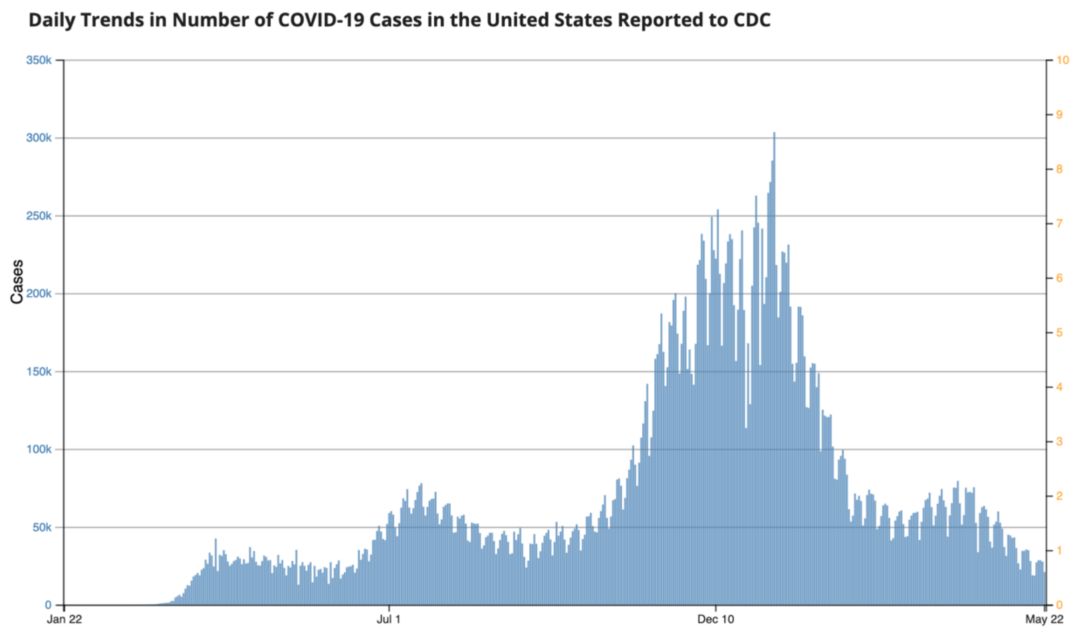


Figure 1: Daily reported cases in the US since the beginning of the pandemic. (CDC, 2021)

As seen above, the pandemic hit the US in three progressively more severe waves; and based on this development, the impact on air travel (as measured in number of passengers) is shown by the blue line as compared to the pre-pandemic level of air travel as shown by the red line in Figure 2 below.

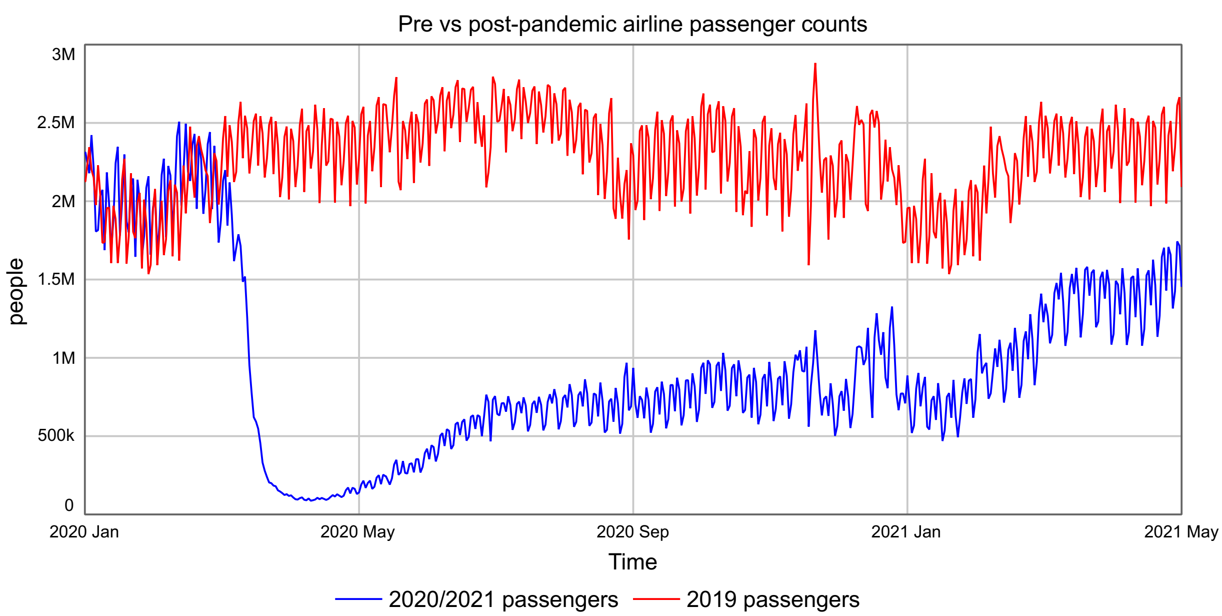


Figure 2: Passenger volumes through US airports before and after the start of the pandemic. (TSA, 2021)

The airline industry has been impacted severely, yet the effect of COVID on air travel has lessened substantially since the inception of the pandemic, in spite of the fact that the pandemic became significantly worse with each progressive wave. Trends like this indicate that people are do not necessarily adapt their behavior in a consistent or rational manner that might be expected as the pandemic continues to worsen. As such this project hopes to investigate the causal relationships that exist between news of COVID and changes in behavior to offer a general explanation of how COVID is impacting behavior. The research questions set forth by this project are as follows:

Research Questions

1. How does a population's behavior change on the aggregate level in response to changes in the pandemic?
    a. Can a generic simulation model be developed and utilized that approximates for a variety of domains how these behavior patterns result from changes in COVID?
    b. Can such a model provide a better understanding of how the level of behavior could develop under different, hypothetical COVID scenarios?
    c. What are the implications of this analysis for policy-makers or industry leaders as they create short and mid-term strategies to combat the effects of COVID?
2. Are there specific cognitive mechanisms or heuristics that can be used to offer a causal explanation of how people's behavior changes in response to the COVID pandemic?
    a. Can such cognitive mechanisms be adequately represented in a simulation model?
    b. Can a populations behavioral response be sufficiently explained by only considering the cognitive mechanisms that shape a response given the current information about the pandemic?
3. Are there meaningful differences in a population's behavioral response in different domains?
    a. Can such differences be quantified in a meaningful way?
    b. Can such a quantification also be used to offer insights regarding people's cognitive mechanisms under different situation?
    c. Could such a model be utilized in crisis situations beyond the covid pandemic?

Hypothesis

The primary hypothesis of this research project is that a general model can be developed to sufficiently explain the historically observed behavior patterns at an aggregate population level in a variety of different domains and geographies merely by accounting for some relevant fundamental cognitive mechanisms governing how people perceive, understand, and respond to information about COVID.

Literature Review:

This section will review what research has already been conducted concerning behavioral responses to COVID as well as a review of some common cognitive processes that may be at work in shaping people's responses to the pandemic. Immense research has gone into studying the behavioral response to the pandemic, with the area of greatest interest being that of the pandemic's impact on health-related behavior, such as hand hygiene, social distancing, vaccine sentiment, or wearing masks (see (Volker, Weiss-Cohen, Filkukova, & Ayton, 2021; Anaki & Sergey)). Such research often seeks to understand correlations between different variables and construct a statistical model that identifies the strongest determinants of the desired health behavior (Volker, Weiss-Cohen, Filkukova, & Ayton, 2021). The studies by Anaki & Sergey and Volker, et al. conduct mass surveys and establish certain demographic factors, cognitive measures, and other potentially influencing factors that contribute to how people adapt their health behaviors. Using regression analysis, they identify the attributes that best predict the desired health behavior outcomes. This kind of analysis offers valuable insight into understanding what factors lead to the most and least compliant health behaviors. See Figure 3 on the following page for some interesting statistics discovered in Anaki & Sergey's study.

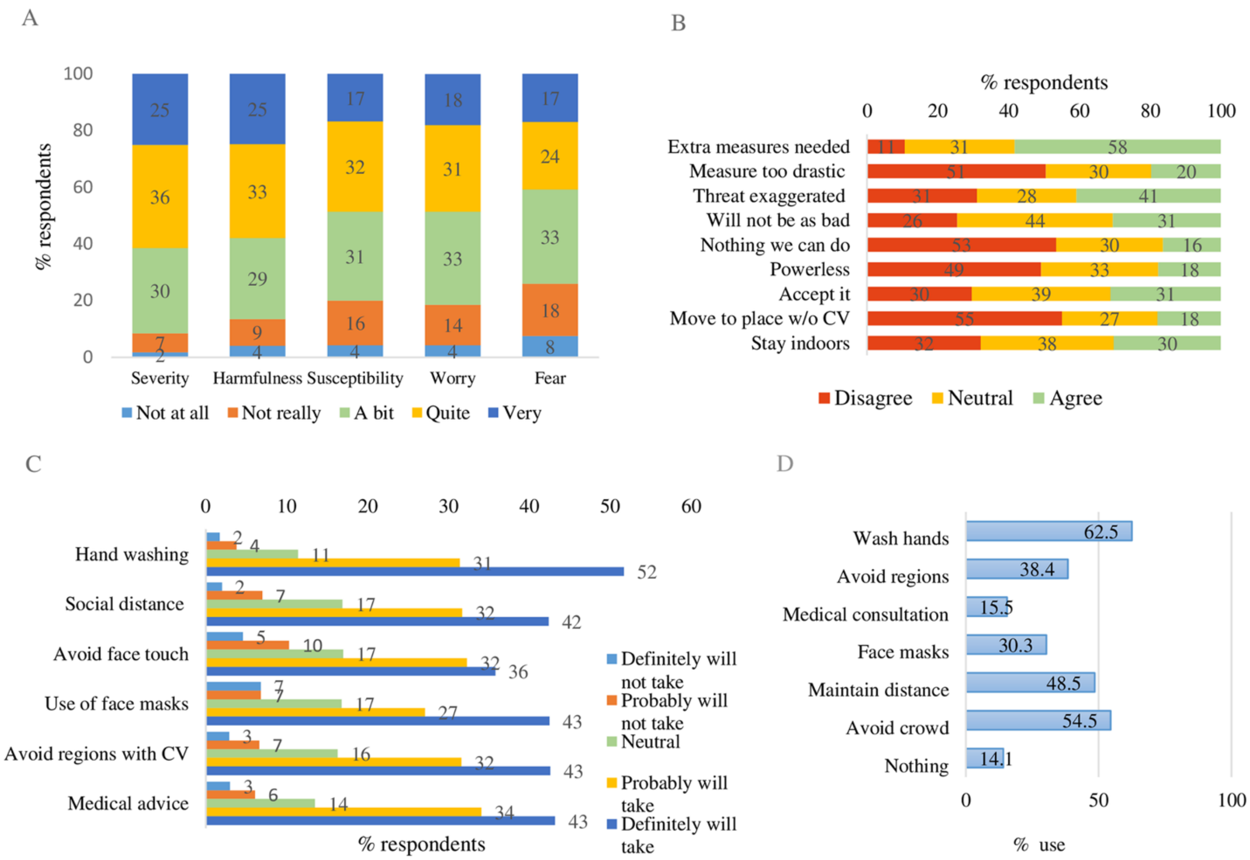


Figure 3: Results from a study about precautionary health behavior during COVID (Anaki & Sergey)

Such research can also help identify possible chains of causality, such as the result of Anaki and Sergey's research that linked together various theoretical determinants of health behavior, illustrated in Figure 4 below. This can help point toward more of a structural understanding of what drives health behaviors. Additionally, many researchers have published models looking into the feedback processes of how the COVID situation impacts health behavior, and then how health behavior in turn changes the course of the pandemic. (see (Homer, 2020; Gkini, 2020)) These models attempt to establish even more of a structural understanding of what drives health behavior over simply just measuring correlations between variables. This has been incredibly effective research that helps policy makers understand the potential progression of the virus

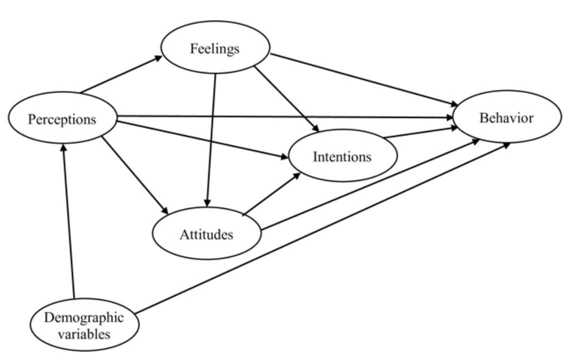


Figure 4: Theoretical model linking the primary determinants to health behavior (Anaki & Sergey).

considering the likely impact of different restrictions and infection control measures implemented for a country.

Being that the fundamental claim made by this research is that a few basic cognitive processes can explain most of the variation in aggregate behavior that is observed over time in response to changes in the COVID situation, it is necessary to review the leading theories that can help to construct a basic cognitive framework upon which the model will be built. According to the theory of bounded rationality, rational decision making in humans is ultimately limited by information and computational capacity (Simon, 1990), so any realistic theory of behavior should consider the biases and heuristics people use to filter and understand the information informing their decisions. Here we can turn to cognitive psychology for a process structure which can be used as the framework for this model. The diagram in Figure 5 below illustrates a typical process for how people go from perception of a situation to an action (Davis, 2008). This framework also matches quite closely with the results from Anaki & Sergey's empirical study discussed above.

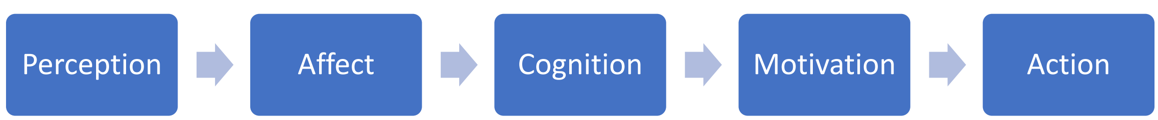


Figure 5: The cognitive process by which action emerges from perception. Adapted from (Davis, 2008).

However, this is merely a high level, theoretical framework and specific cognitive mechanisms must be identified and quantified if a useful model is to be built. As a starting point, a list of the 188 most influential cognitive biases that have been identified in the fields of psychology and behavior science are summarized in the image on the next page (Figure 6 (Manoogian III & Benson, 2017)). Each bias listed here has been considered as to whether it might play a role in shaping the way that people respond to COVID. After investigating these and cross-referencing with the existing literature, a handful of likely candidates have emerged and are categorized in the following sections according to the theoretical framework shown above in Figure 5.

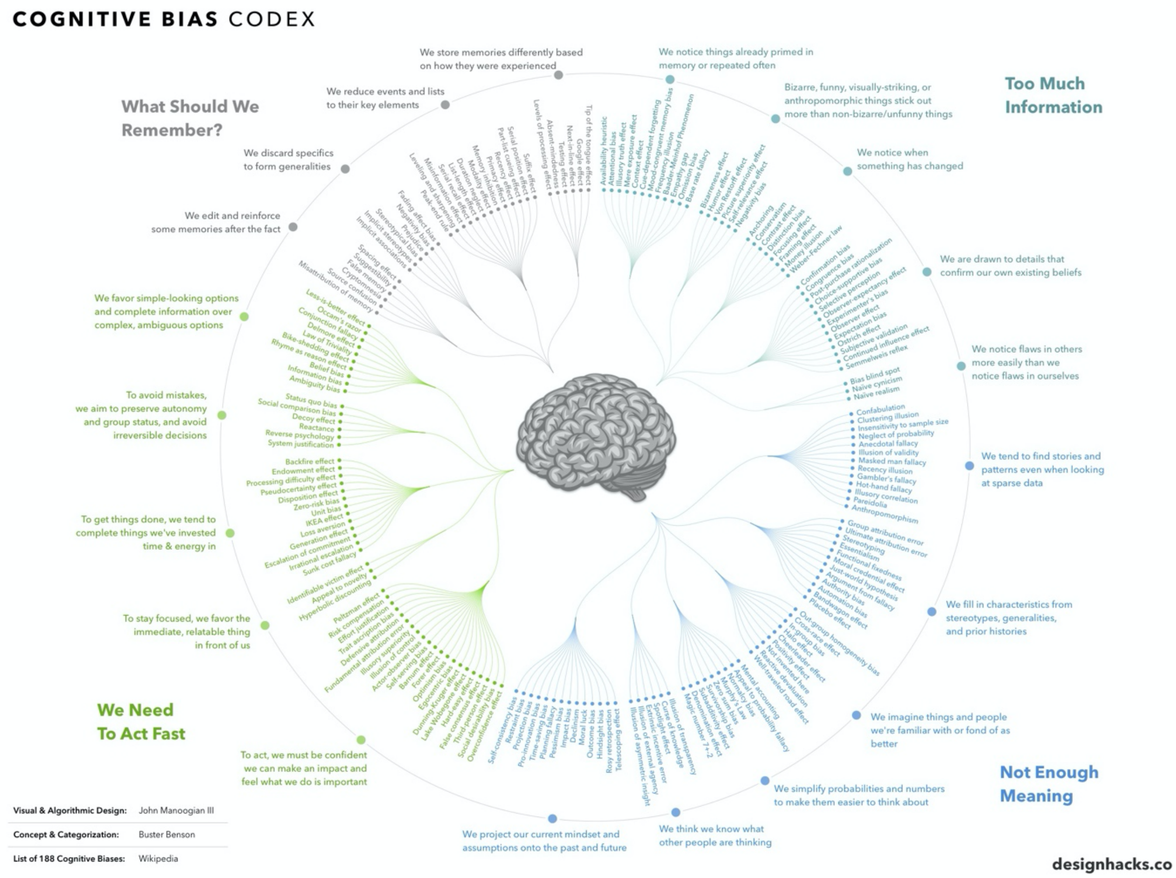


Figure 6: Diagram that categorizes 188 different cognitive biases and heuristics (Manoogian III & Benson, 2017)

Perception

Perception of the prevalence of COVID is the very first step in the process of reacting to COVID. According to Funk, et al., behavior in the midst of the pandemic is assumed to be "prevalence elastic" meaning the behavior is ultimately assumed to be a function of the prevalence of the disease (Funk, Salathé, & Jansen, 2010), so it must be understood how people perceive the current pandemic. First and foremost, one must have a basic understanding of the situation as it is perceived to be. According to Sydhaugen, the goal of our perceptive capacities is to present the world to us the way it actually is. Our own ability to perceive represents an "openness to, or awareness of, the external world." (Sydhagen, 2017). Unfortunately, in the case of COVID, perception is complicated by the reality that it is entirely intangible- not perceptible by any of our physical senses unless perhaps we happen to become infected ourselves. Many have referred to COVID as ‘the invisible enemy’ (Patki, Banasal, & Basavaraja, 2020) and therefore our perception of the information has depended entirely upon the news and statistics that are reported about the situation. Typically, the daily cases, daily deaths, and hospitalizations are reported on a daily basis in most areas of the world and represent our most basic understanding of the current situation (Lehman, 2020). In fact, broadly speaking, there is no other way to understand the current severity of the pandemic other than to rely on the statistics produced by testing and data collected from hospitals. It is widely agreed that any effective public strategy against COVID demands timely, thorough, and accurate statistics about the virus (Pearce, Vandenbroucke, VanderWeele, & Greenland, 2020). Given the universal dependence on COVID data for properly understanding the current situation, in a behavior model, it is safe to assume that statistics reported about COVID are likely the key input to determining a populations perception of the pandemic.

Affect

Next, the perception will come amidst a perceptual/emotional backdrop, referred to as “affect”. According to the American Psychology Association, affect is “any experience of feeling or emotion” and “represents one of the three traditionally identified components of the mind.” (American Psychological Association, n.d.). As it pertains to COVID, the most prominent affective responses that have been identified include worry, fear, boredom, and annoyance (Selka, et al., 2020). The general affective state of a population will influence how the perception of the current situation is cognitively processed and can provide an emotional or mental context by which the perceived information will be evaluated. A variety of possible cognitive biases may come into play to shape our affective state in regard to COVID.

For instance, there is a growing recognition that ‘pandemic fatigue’ is causing less and less adherence to social distancing restrictions. According to a Gallup poll conducted over the first 6 months of the pandemic, there was a steadily decreasing trend of social distancing as time went on (Crabtree, 2020). This could show that new cases will be perceived against a backdrop of exhaustion, apathy, or strong desire for things just to go back to normal. People and governments alike may fall prey to the present bias or status-quo bias, whereby the present, status-quo situation comes to be accepted and preferred over any alternative options. This is not to say that people don’t want to go back to normal, but if they have grown accustomed to the current pandemic and sufficiently adapted their lifestyle accordingly, it may seem better just to concede to the situation instead of make a concerted and costly effort to continue the fight against COVID (Soofi, Najafi, & Karami-Matin, 2020).

Cognition

Cognition involves the mental processes of understanding, evaluating, and judging information; it represents the process we go through to describe what we think about the current COVID situation (Sydhagen, 2017). People need to take the perception of the current state of the pandemic and assess it in the context of their current understanding and affective state toward the situation in order to make a judgment about the situation. First of all, there is likely an effect of anchoring bias at play, whereby the present condition is viewed in the context of the historical development of the pandemic. When historically there were zero cases of COVID, even a few numbers of COVID cases are unacceptable; however, after a year or more of wave after wave of COVID, the mental anchor by which one judges how many cases of COVID is to be expected inevitably increases over time (see: (Sterman J. , Expectation Formation in Behavioral Simulation Models, 1986). Therefore, the historical development of COVID provides the best context by which to understand the current situation. After this context has been determined, people need to evaluate the current condition.

At this point a very important and powerful bias likely comes into play, which is described by Weber and Fechner's Laws of Psychophysics. This law simply states that the magnitude by which we sense a stimulus is a power function of the actual magnitude of the stimulus (Stevens, 1986). It is widely speculated that this same law is at work in our ability to sense and understand the true magnitude of the COVID pandemic (O'hara, 2020); (Djulbegovic B, 2020 Oct). We have a fundamental limitation on our ability to accurately understand the scale of problems as they grow bigger; as such we are prone to dramatically discount the severity of the pandemic the worse it gets. Paul Slovic has observed the same dynamic at work when we judge the severity of other mass-tragedies such as genocides (Slovic, 2007). Figure 7 to the on the following page, taken from Slovic's 2007 paper, illustrates the power law relationship he has

Figure 7: A psychophysical model describing how the saving of human lives may actually be valued. Taken from Slovic, 2007

observed in the public assessment of genocides, whereby the value of saving a life increases only logarithmically as the number of lives potentially saved increases. This represents a very dangerous bias that could cause a massive underestimation of the true magnitude of the pandemic. This distorted understanding will certainly have an impact on the decisions and behavior that ultimately emerge from this process.

Motivation

Motivation represents the factors at play which a person uses to form the actions they take. In this case, people need to balance living as normal of a life as possible while sufficiently reducing the risk of being infected or inadvertently infecting others with the virus. Game theoretical approaches suggest that the primary motivation for a particular behavior is maximizing the cost/benefit outcomes of any situation (von Neumann & Morgenstern, 1944). The benefits in the case of this research project are not limited to any particular area. The benefits may be social, economic, health-related, etc.: generally speaking, any benefit that engaging in 'normal' behavior patterns would otherwise produce. The complicating factor in this case is the risk cost that COVID adds to any of these cost-benefit appraisals. The appraised cost of the risk includes two components: the susceptibility to infection and the severity of infection (the probability and the impact if one were to get COVID) (Gkini, 2020). The greatest perceived risk, and presumably the greatest impact on behavior, will emerge if both the susceptibility and severity of infection is assessed as high. However, the motivation for changed behavior in light of COVID is not necessarily only limited to personal risk assessment, but also can include pro-social choices to limit one's impact on

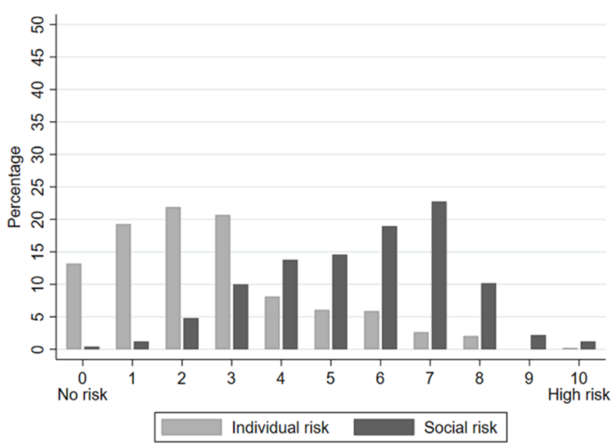


Figure 8: Distribution of individual vs. social risk perceptions in Switzerland, according to a study conducted by Franzen & Wöhner, 2021.

others (Campos-Mercade, Meier, Schneider, & Wengström, 2021). Figure 8 on the previous page shows the results of a survey conducted in Switzerland that measured people's individual and social assessments of the risks posed by COVID. Individual risk represents the perceived risk of COVID to their own health and social risk represents the perceived risk of COVID to society as a whole (Franzen & Wöhner, 2021).

Motivation for behavior in light of COVID thus represents a complicated assessment of the personal and social costs and benefits of engaging in a particular behavior in light of the current pandemic situation. Such an assessment surely varies based on the state of the pandemic, the type/domain of behavior under consideration, as well as fundamental characteristics of the people making the decisions (as observed in the studies by Anaki & Sergey and Volker, et al.).

Action

Finally, after going through this multi-stage process of perception, affect, cognition and motivation, a response can then be estimated. At this point only general data and processes have been described, yet the level of action that will be observed is the aggregation of many individuals making their own decision under the given circumstances. While this process starts with a general input, applies general theories, and returns a general estimate of behavior levels, the distribution of how each individual in a population is expected to respond cannot be ignored. At any point during the pandemic there will be people who decide to act 'normally' and those who abstain from 'normal' behavior-- no matter how good or bad the current situation is. This implies that at any given level of severity, there is a distribution of possible behavioral outcomes that reflects individual differences in risk tolerance, personality, demographics, etc. The results of the Swiss survey in

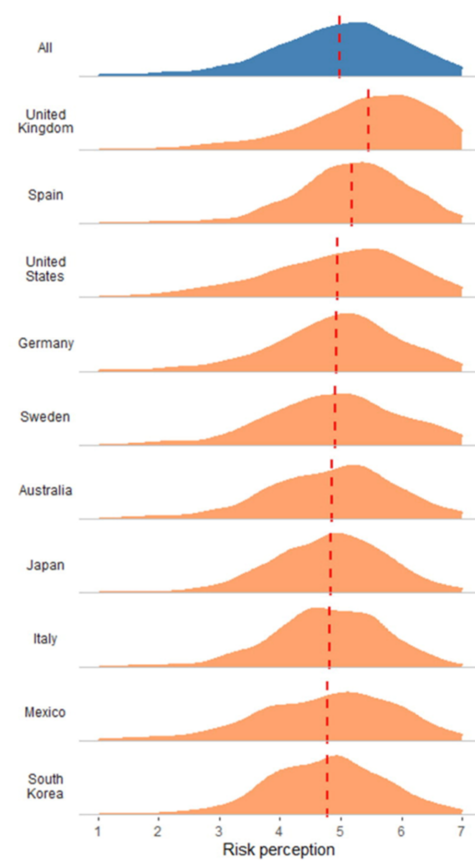


Figure 9: Risk perception density plots by country, figure taken from (Dryhurst, et al., 2020)

Figure 9 illustrate this distribution of assessments of the situation. A more in-depth study, conducted by Dryhurst, et al. surveyed people in 10 different countries to construct risk perception distributions for each country (Dryhurst, et al., 2020).

This concludes the brief review of the theoretical framework upon which this model will be built. The cognitive biases and heuristics described above, along with the rapidly changing nature of the COVID pandemic, contributes to a dynamic behavior pattern in many domains of private and public life. This research project will attempt to unify the most relevant of these cognitive heuristics into a simple model that can be used to explain how decision making and behavior patterns emerge at the aggregate level in response to the pandemic as it continues to unfold.

Methodology:

The methodology used for this research is simulation modeling. The general system dynamics modelling methodology is described below a specific description of how it will be applied for this research project follows afterwards.

System Dynamics

The system dynamics methodology is the ideal analysis methodology for this kind of research due to its capability to model dynamic complexity. The model in this research is not ultimately looking correlations among variables, but rather a causal explanation for the behavior of a complex phenomenon (people's behavior in response to COVID) over time. Understanding this problem necessitates the inclusion of variables and processes from many different fields, including epidemiology, behavioral psychology, economics, and others. Simulation modeling allows one to construct a simplified model of the real-world processes that make up a complex, dynamic system to gain insight and understanding for the how the behavior emerges from that system. According to John Sterman, some of the attributes of complex dynamic systems are:

- **Dynamic**- components of a system are constantly changing over different time scales and interacting with each other as each change.
- **Governed by Feedback**- the chain of causality can, over time, come back to change the initial conditions, thereby creating feedback loops within a system.
- **Nonlinear**- Effects are not proportional to their causes
- **History Dependent**- the behavior of the system is governed by long time delays or results from an accumulation over time.

- **Counterintuitive**- due to the complex relationship between cause and effect, the behavior of dynamic systems often defies intuitive expectations. (Sterman J. , 2000)

These characteristics describe the problem set forth in this research project. In fact, many researchers have employed such simulation modeling in explaining cognitive processes, as this model will attempt to do (See (Sterman J. , 1986) for a model describing how people cognitively form expectations of future trends given)

Specific considerations for this project

System dynamics modeling necessitates an explicit representation of the assumptions used in the model, thus the methodology contrasts with *black box* modeling (as described by Townsend, Wenger, & Houpt, 2018, which simply tries to produce an algorithm that can properly predict output given a certain input, without emphasizing the structural set of real world processes and relationships that form the true chain of causality between the input and output. In other words, proper system dynamics models seek not just to produce the right behavior but also demonstrate with a level of confidence that the model produces the right *behavior for the right reasons* (Oliva, 2001).

The specific modeling strategy employed for this particular project is what is referred to as *phenomenon driven explanation* (de Gooyert, 2018). Under this strategy, the starting point is the observation that current theories are not capable of explaining the observed empirical data. Then a new theory (or in this case a combination of existing cognitive and behavioral theories) is presented and a model is built to represent the new theory. If it can reproduce the observed behavior with a plausible model structure, then confidence is built in the theory. The end result offers, according to de Gooyert, "a potential explanation of the phenomenon by proposing the structure, in terms of causal relations, that drives the behavior." (de Gooyert, 2018)

It is worth noting here that the model is quite small compared to other system dynamics models that have been developed. The model does not contain any major feedback loops that are typically found in system dynamics models. The reason for this is that this model serves to explain one basic phenomenon, which the causal effects of how COVID influences a population's behavior. Larger models might include many such phenomena interacting with each other, but the end product of this research will be a relatively small system dynamics model component. The term 'model component' is used to emphasize that this project consists of a very simple piece of model structure, not a full system dynamics model in and of itself. The purpose of this project is to develop a new model structure (or component) that can capture, explain, and replicate the chain of causal relationships between COVID and changed behavior. Given the size and potential utility of such a model in larger projects, this research aims to thoroughly validate every single variable, equation, relationship, and theory inherent in this model and fully explore the applicability and explanatory power of the model in several different domains and areas.

Data

This research project benefits from an abundance of reliable, high-frequency, time-series data that has been made publicly available since the inception of the pandemic. COVID data has been downloaded from the CDC's API, Socrata, and other data has been downloaded or scraped from various websites that continue to publish daily data that reflect behavior in different domains. The data has been cleaned and processed into a format that Stella Architect can read as input into the system dynamics model. Table 1 below shows a summary of the primary data sources used:

Table 1: Summary of primary data sources used in this research project, with reference to how they were included in the model.

worksheet	import to variable:	description	citation	source URL
arrays	N/A	sets the state array	N/A	N/A
population	**.state population (top-level)**	population of each state in the US as of 2019	(United States Census Bureau, 2019)	https://www.census.gov/data/tables/time-series/demo/popest/2010s-state-total.html
elderly population	**brookdale.% senior**	percentage of 65+ population in each state	(PRB, 2018)	https://www.prb.org/which-us-states-are-the-oldest/
brookdale	**brookdale.brookdale bed capacity**	number of senior housing beds operated by Brookdale as of 2020	(Brookdale Senior Living INC, 2021)	https://www.sec.gov/ix?doc=/Archives/edgar/data/1332349/000133234921000045/bkd-20201231.htm
brookdale occupancy	**Senior Housing.brookdale historical**	Brookdale consolidate occupancy numbers by month since March 2020	(Brookdale Senior Living, 2021)	https://s26.q4cdn.com/858530099/files/doc_news/2021/04/Brookdale-Reports-Mar-2021-Occupancy.pdf
covid_cases	**.new daily cases (top-level)**	new daily reported COVID cases in each US state	(United States Center for Disease Control, 2021)	https://dev.socrata.com/foundry/data.cdc.gov/9mfq-cb36
covid_deaths	**.new daily deaths (top-level)**	new daily reported COVID deaths in each US state	(United States Center for Disease Control, 2021)	https://dev.socrata.com/foundry/data.cdc.gov/9mfq-cb36
tsa_data	**Airlines.2019 passengers** **Airlines.2020 passengers**	number of passengers registered each day at all US airports	(United States Transportation Security Administration, 2021)	https://www.tsa.gov/coronavirus/passenger-throughput
restaurants_data	**Restaurants.dineinrevenue**	daily dine in restaurant revenue as % of pre-pandemic levels	(OpenTable, 2021)	https://www.opentable.com/state-of-industry
us_mobility	**Mobility.us workplacese** **Mobility.us retail and recreation** **Mobility.us transit stations** **Mobility.us grocery and pharmacy**	Google mobility data by sector for all US, scaled to pre-pandemic levels	(Google LLC, n.d.)	https://www.google.com/covid19/mobility/
grocery_and_pharmacy	**Mobility.grocery and pharmacy**	Google mobility data by state for grocery and pharmacy locations, scaled to pre-pandemic levels	(Google LLC, n.d.)	https://www.google.com/covid19/mobility/
retail_and_recreation	**Mobility.retail and recreation**	Google mobility data by state for retail and recreation locations, scaled to pre-pandemic levels	(Google LLC, n.d.)	https://www.google.com/covid19/mobility/
transit_stations	**Mobility.transit stations**	Google mobility data by state for transit station locations, scaled to pre-pandemic levels	(Google LLC, n.d.)	https://www.google.com/covid19/mobility/
workplaces	**Mobility.workplaces**	Google mobility data by state for workplaces locations, scaled to pre-pandemic levels	(Google LLC, n.d.)	https://www.google.com/covid19/mobility/

Research Ethics:

As no primary data were collected during this research process, a statement of ethics regarding the collection, protection, use, and publication of such data is not applicable for this research. All data used in this project are from publicly available sources.

Model Overview:

Model Description

Understanding how COVID effects people's decision making requires a thorough look at the whole cognitive process one goes through from being confronted with the facts, to perceiving the facts, to making contextual judgements about the facts that lead to changed decision making behavior. This section will provide a detailed description of the model component that forms the core of this research project and attempts to model explicitly the cognitive processes people go through. The term 'model component' is used to emphasize that this project consists of a very simple piece of model structure, not a full system dynamics model in and of itself. This component is then applied, tested, and validated in a variety of different domains as you will find in the analysis section. What will be described in this section is the generic structure of this component outside of any domain specific context. Refer to Figure 10 below for the Stock and Flow Diagram of this model component.

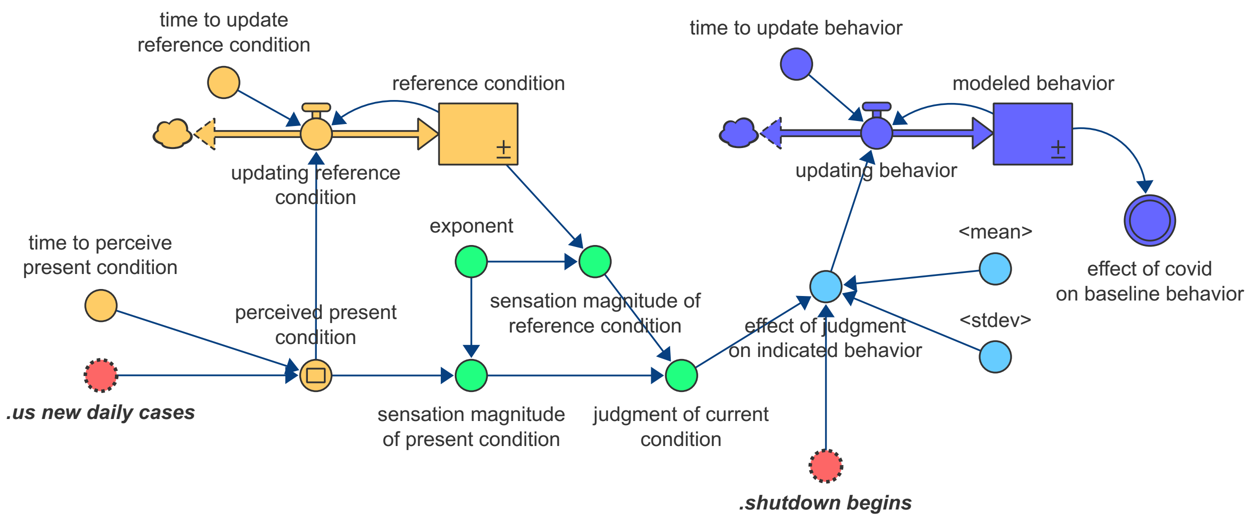


Figure 10: Overview of the structure of the model component developed for this research project. Each step in the cognitive process is colored differently and explained in detail below.

The model operates in 5 sequential steps that begins with information about the COVID situation and ends in a changed level of behavior that is observed over the population. The steps are listed below and color-coded to match the stock and flow diagram above:

1. **INPUT- INFORMATION ABOUT THE COVID SITUATION:** Determine the relevant information that a population in a particular geographic area would use to guide their decisions in light of the pandemic. In this model the relevant information is always assumed to be the new daily reported COVID cases for that area.
2. **PERCEPTION OF THE SITUATION:** The population then uses this information to form a present perception of the COVID situation and also to update their assessment of the average historical COVID situation.
3. **COGNITION AND JUDGMENT OF THE SITUATION:** The number of cases is then distorted according to Stevens' Power Law into the sensation produced by the observed condition. This sensation is what is used to evaluate the severity of the current situation.
4. **REACTION TO THE SITUATION:** That evaluation is then considered in the context of how a population's behavior is distributed within a particular domain. This is used to indicate the percentage of the population that would engage in the 'normal' behavior expected in that domain.
5. **OUTPUT- MODIFIED BEHAVIOR:** This indicated level of behavior is finally materialized into an estimated level of the proportion of the population that will engage in normal behavior and decision making in light of the pandemic.

Input- Information about the COVID Situation:

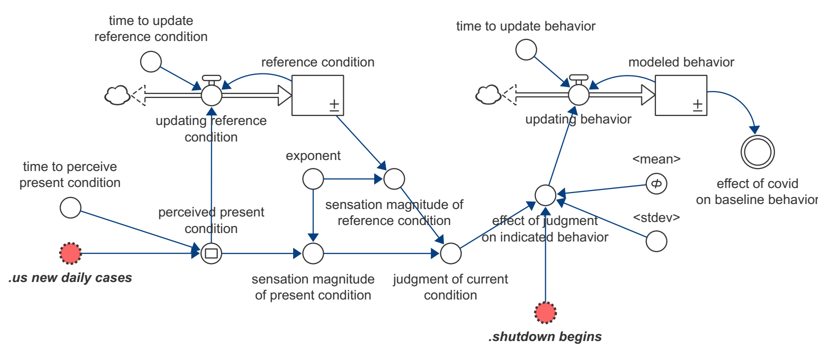


Figure 11: The generic model with the primary inputs highlighted in red

The input to this model will be new daily reported cases as reported by the US Center for Disease Control; this represents the data that was reported throughout the pandemic which the federal, state, and local governments based their policies upon, and which people had available to them as they modified their normal behavior to minimize their own perceived risk of being infected. Number of new daily reported cases has universally been used as a key metric by which the severity of the pandemic is measured. It is a leading indicator to hospitals, deaths, as well as used to estimate the R0 metric which is used to estimate whether the infections are spreading or decreasing in a given area (Lehman, 2020).

The United States Center for Disease Control publishes daily statistics on the number of new reported COVID cases for each state in the US (United States Center for Disease Control, 2021). This data is fed into the model component under the ‘total new daily cases’ variable. The data used here will be whatever COVID data is applicable to the particular geographic area under consideration (which in this case will either individual states or the entire US). FIGURE below shows the number of new daily reported COVID cases for the entire US for the 500-day period from January 1, 2020, to May 14, 2021:

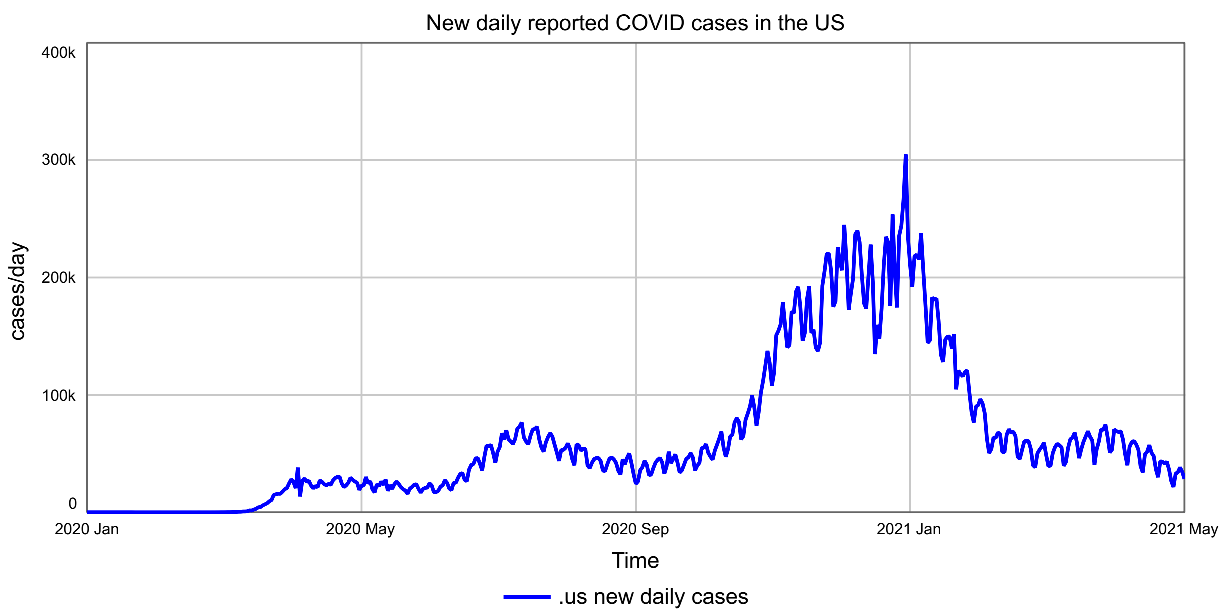


Figure 12: New daily reported COVID cases in the US (United States Center for Disease Control, 2021)

Perception of the Situation:

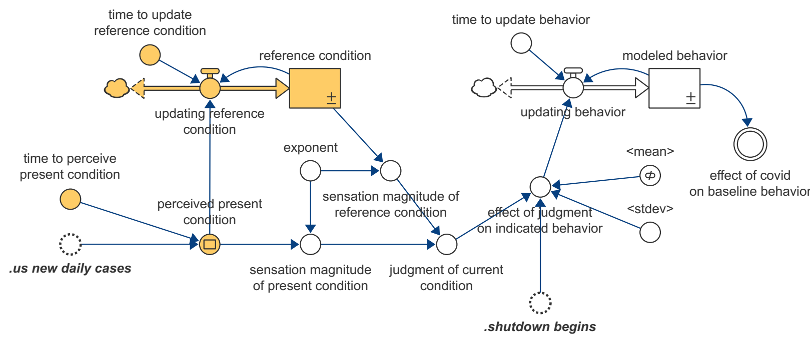


Figure 14: Generic model with perceived and reference cases highlighted in gold.

The first part of the model structure developed in this paper will borrow directly from the structure described in John Sterman's 1986 paper, *"Expectation Formation in Behavioral Simulation Models"* (Sterman, 1986). In this paper, Sterman describes how the TREND function can be used to model how people take in an incoming stream of data and then use that data to form expectations for future trends in the data. While this research project does not look at how people develop future expectations about how COVID will develop, the basic processes of information gathering, and processing should mirror very closely those described in Sterman's paper. As you can see in Figure 14 below, taken from Sterman's original paper, the structure is quite simple. Information must first be gathered, which will happen with some delay due to the data collection and distribution time. Then this information about the present condition must be considered with some context. Because the only information immediately available to us is past information, and because information in the recent past is more easily remembered and considered than information in the distant past, the context we typically use to evaluate the present is some average experience of the past condition, which Sterman refers to as the 'reference condition'. These two information stocks are critical for the purposes of the model developed in this research paper,

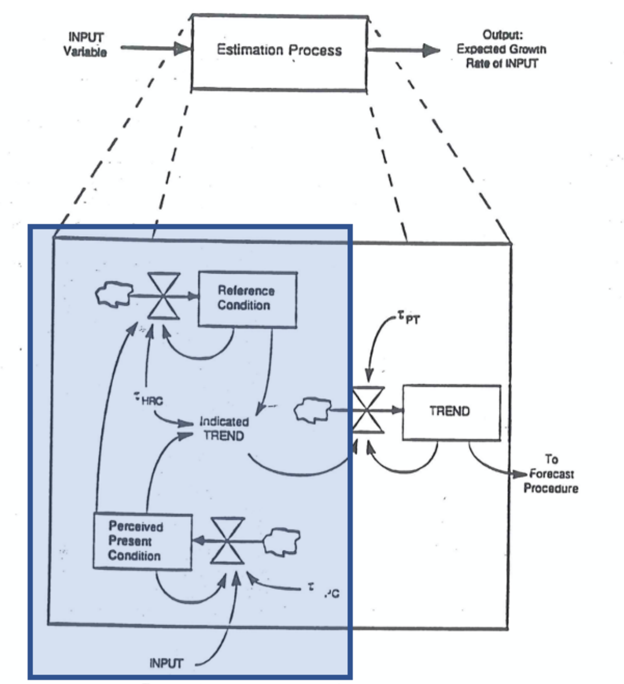


FIG. 1. Causal Structure of the TREND Function.

Figure 13: Stock and flow diagram of the TREND function with the portion that is used in this model indicated in the blue shaded rectangle. Adapted from Sterman, 1986.

though the model presented here will deviate at this point from Sterman's model. This is due to the fact that the present and reference condition must be used in this case to make a judgment of the current condition rather than form an expectation of future development. Thus, the structure in this model will drop the trend stock and related structure and instead of calculating an indicated trend, calculate a judgment of the present condition, using the knowledge of the present condition and the context provided by the reference condition. Figure 14 on the previous page highlights the portion of the structure that will be used in this project.

The structure provided by Sterman applies intuitively to the COVID pandemic. There are a handful of delays in getting from the real current COVID situation to what people perceive the situation to be. For one, it takes some amount of time to collect, aggregate, and publish the data (and then potentially revise and republish as additional data comes in or errors are discovered). After the data has been accurately published, it will take additional time for the population to fully absorb the news of the current condition. Due to the several stages of possible delay in this process, a third order exponential delay of 10 days of the 'total new daily cases' variable is used to compute the 'perceived present condition' in this model.

Then, in order to form a historical context about the COVID pandemic, the perceived current condition is used to compute a 'reference condition'. This is a first order delay of the 'perceived present condition' with generally a much longer delay time. The 'reference condition' represents what people perceive the recent average level of COVID to have been looking back some period of time. In this formulation, the most recent knowledge of the pandemic will carry the greatest weight in forming the reference condition. On average people are assumed to be looking a year back in time and offering increasingly discounted weight to information further in the past. The real-world application here is that this variable could represent the level at which people expect the new daily COVID cases should be. Of course, prior to the pandemic starting, no one expected there should be any COVID cases in their region and this assumption likely held for some period of time; but now a year or more later, most people would likely be incredulous to hear that there were zero new COVID cases in their region and would probably be pleased just to know that there were only a few cases. This simple mental exercise alone demonstrates that there has been an effect of people getting comfortable with a certain level of COVID. At what level we are comfortable is very likely correlated with what level the COVID cases has been in our recent memory. This is why sentiment in the US now is very optimistic and states are quickly opening up despite the fact that cases are currently stable around the level of the peak of the second wave that hit the US late last summer; the reference level has raised substantially to allow people to perceive the current situation of 30,000 to 70,000 cases per day as generally ‘safe’. Refer to Figure 15 below for a demonstration of how the perceived present condition and reference condition change in response to COVID data as it is reported (Note that a delay time of 360 days is used to calculate the reference condition).

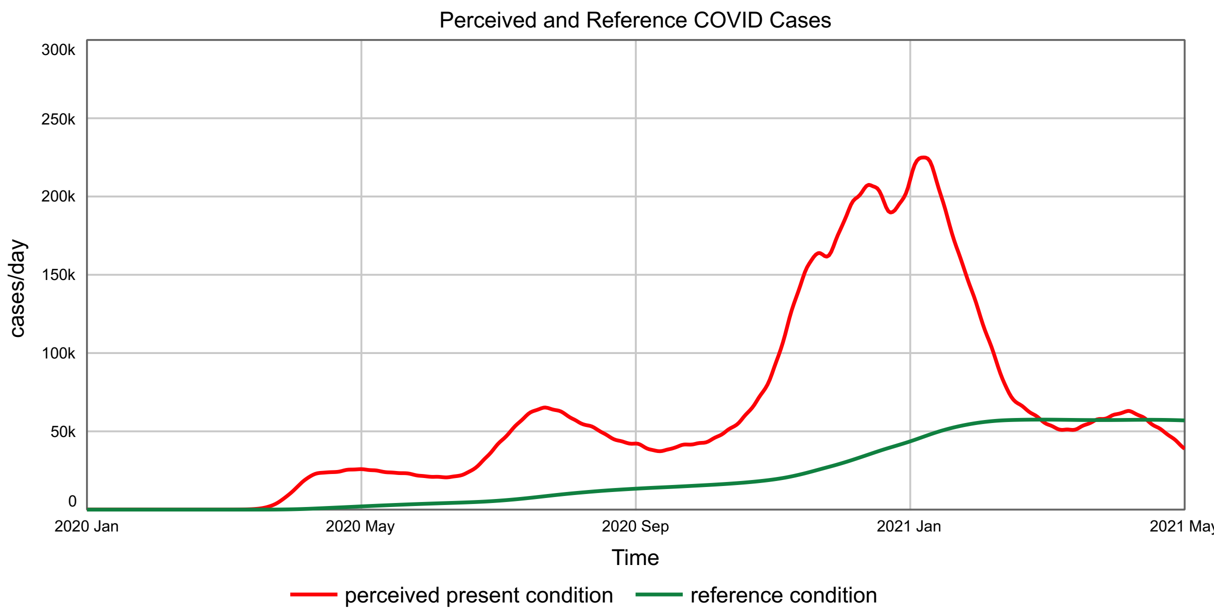


Figure 15: Perceived and reference number of COVID cases in the US, using a 10 day and 360-day delay time respectively.

Cognition and Judgment of the Situation:

Now that the perceived present condition and the reference condition can be plausibly estimated based on the recent development of COVID, it is necessary to transform these values into what people actually sense them to be.

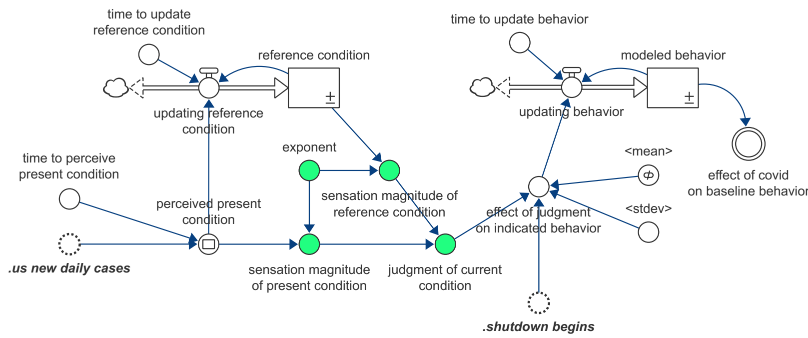


Figure 16: Generic model with the judgment process highlighted in green.

There is a significant distortion that takes place between the objective number of cases and the subjective sensation of the magnitude of those cases. The field of psychophysics has shown that the magnitude of a sensation about a stimulus grows as a power function of the magnitude of the stimulus (Zwizlocki, 2009). Conceptually the stimulus and the sensation are two completely different things. The stimulus can be objectively measured; the sensation or impression produced by that stimulus is the result of cognitive and psychological processes that produce a conscious sensation, impression, or feeling about the stimulus. In this case, the stimulus will be the perceived or reference level of COVID cases. It is assumed that people remember these values at their face value, but it should not be assumed that they sense them at those values; thus, a transformation from the objective to the subjective must take place. The field of Psychophysics began with E. H. Weber and Gustav Fechner in the mid 1800's. They hypothesized and then proved through experimentation that people's ability to sense or perceive changes in a stimulus decreases quickly as the stimulus intensity increases (Slovic, 2007). A common example of how this power law functions is by demonstrating how we perceive changes of brightness. If a room is completely dark and even a match is lit, it will be very noticeable how that small amount of light illuminates the entire room. However, when the room is already bright, lighting a match will not produce any sensation that the room is brighter, even though the same amount of light is still being added to the room. Therefore, our ability to sense changes in the level of light decrease as the room becomes brighter and brighter.

The psychologist, S. S. Steven first proposed that sensation follows a power law from the stimuli that produce it in his 1953 paper and suggested it as a general law applying to how we sense changes in any physical or subjective stimuli. The formula states that:

$$\psi = k\phi^{\theta}$$

> *Where ψ represents the magnitude of the sensation, k represents a dimensional constant, ϕ represents the intensity of the stimulus, and θ represents the power exponent (Zwizlocki, 2009).*

While this theory was born and developed through experiments with physical stimuli, such as light, sound, weight, etc., Stevens devotes an entire chapter in his book to discussing its relevance to a wide variety of social situations and non-physical and even non-quantifiable types of stimuli as well. These include applications in sociology, criminology, and politics (Stevens, 1986). Further research has been done by Paul Slovic, pioneering research of the theory of *psychic numbing* which applies the concept of these same power laws to situations involving people's responses to mass tragedies, namely genocides. His research has shown that our capacity to experience affect, which he describes as "the positive and negative feelings that combine with reasoned analysis to guide our judgments, decisions, and actions," increases only marginally as the magnitued of the situation increases (Slovic, 2007). His paper, entitled *'If I look at the mass I will never act': Psychic numbing and genocide,* offers ample anecdotal theoretical, and experimental evidence to show how people react very strongly to tragedies effecting small numbers of people, yet quickly lose interest as the number effected grows larger.

This demonstrates that Steven's power law could easily be extended to how people sense the scale of the COVID pandemic; and Slovic has even informally made this claim himself (O'hara, 2020). In fact, there has already been research that shows that even the governors of US states have instituted state-wide lockdowns according to Weber and Fechner's laws of psychophysics (Djulbegovic B, 2020 Oct). This means that people and governments alike will react very strongly to reported case numbers when the numbers are low and only marginally more so when the numbers are high. When there have been no cases in a particular region, news that a few cases have been discovered becomes cause for worry and concern, prompting people to stay home and prompting local governments to institute restrictions. However, if there are already several thousand cases in a region, even news that a few hundred more have been discovered likely would not trigger any new meaningful response from people or the government; perhaps it would take thousands of additional cases to prompt the same magnitude of reaction as the first few cases initially did.

This effect must then be included in the model if it is to produce reasonable estimates of how people respond to incoming news about the COVID pandemic. People will become desensitized to growing numbers of cases. For this model, both the 'perceived present condition' and the 'reference condition' have been subjected to Steven's power law by using the equation presented previously. A power exponent of 0.5 is used in all domains to which the model is applied. This value was estimated based on a calibration of each domain that produced values between 0.4 and 0.8. The best estimate was shown to be 0.5. There is little research that would indicate we should expect drastically different power exponents given the same stimulus, so this variable should be fixed for all domains in this model. This exponent would imply the relationship shown in Figure 17 between the objective, real-world value and the sensation magnitude it would induce. An example below is given for how the 'magnitude sensation of the perceived present condition' is impacted by the 'perceived present condition' according to Steven's Power Law. The same relationship will also hold for the effect of 'reference condition' on 'sensation magnitude of reference condition'.

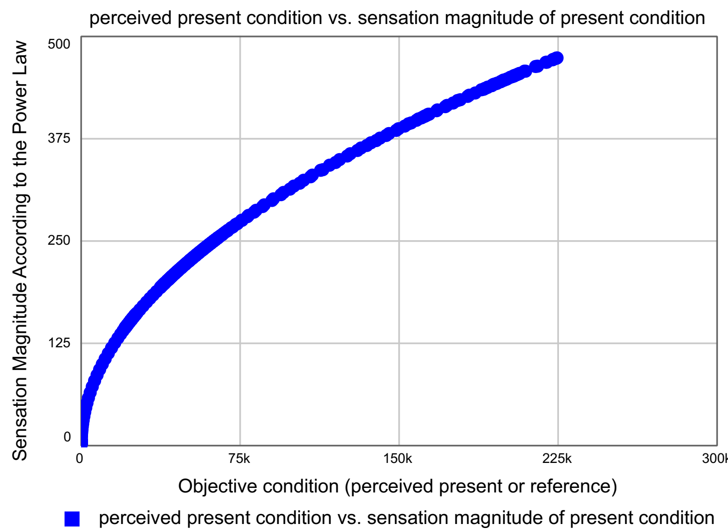


Figure 17: Graph showing the power law relationship between the objective values and the sensation magnitudes produced by those values

The constants are disregarded in this model since the subsequent 'judgment of current condition' variable will divide both sensation magnitudes by each other and would therefore cancel each constant value out. Figure 19 on the next page shows how the sensation magnitudes of the perceived present and reference conditions are estimated to change over time given how the

COVID pandemic has developed in the US (as shown if Figure 18). As you can see, the effect of the power law dramatically reduces the scale of each progressive wave. While the third wave was objectively four times more severe than the second, the power law shows that it was likely perceived to be only twice as bad.

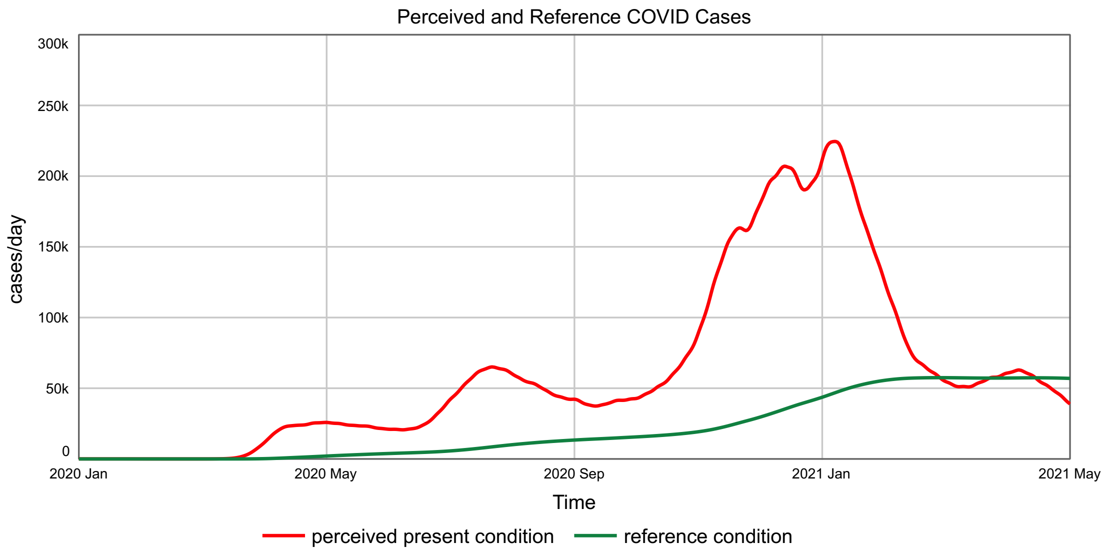


Figure 18: Perceived and reference number of COVID cases in the US, using a 10 day and 360-day delay time respectively (Thes represent the objective stimuli)

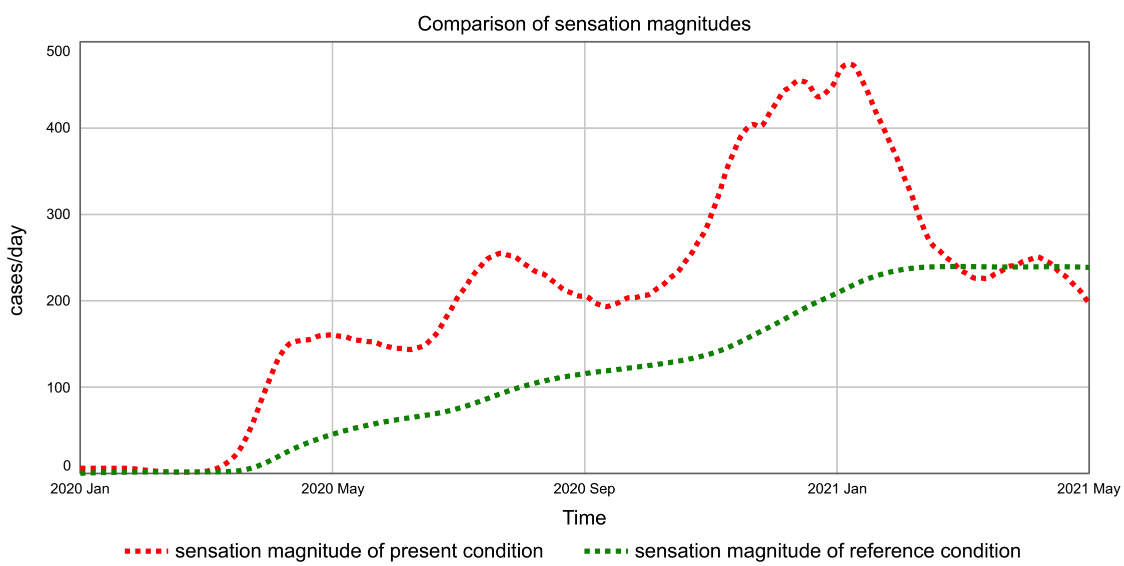


Figure 19: The sensation magnitudes produced by the same graphs in Figure 11. Notice the change in scale and the slight change in shape of the graphs. (These represent the subjective sensations produced by the stimuli)

The next step is to conduct a simple comparison of the ‘sensation magnitude of the present condition’ and the ‘sensation magnitude of the reference condition’. At every point in time, people must evaluate how good or bad the COVID situation is before they can make a decision. This evaluation will involve a judgement as to what the current condition is and compare this to a judgement as to what the normative condition should be for them to evaluate whether the situation is good or bad, and to what extent it is so. This comparison thus represents the evaluation of the current situation by expressing a ratio of the ‘sensation magnitude of the present condition’ over the ‘sensation magnitude of the reference condition’. If the ‘sensation magnitude of the present condition’ is 250 cases per day and the ‘sensation magnitude of the reference condition’ is 50 cases per day, then the situation would be generally viewed to be 5 times worse than it should be. On the other hand, if it were the same 250 cases per day, but after a severe wave of infections, the ‘sensation magnitude of the reference condition’ were 500 cases per day, then the situation would be generally viewed to be only half as bad as it should be and thus the situation would seem relatively good. This ratio can range from 0, which would be the worst possible scenario, to infinity, which would be the best possible scenario. A value of 1 would represent a situation whereby on average the situation is as it is expected to be. The graph below (Figure 20) shows how this judgment (expressed as the sensation magnitude of the reference condition as a % of the sensation magnitude of the present condition) has been estimated to change over the course of the pandemic.

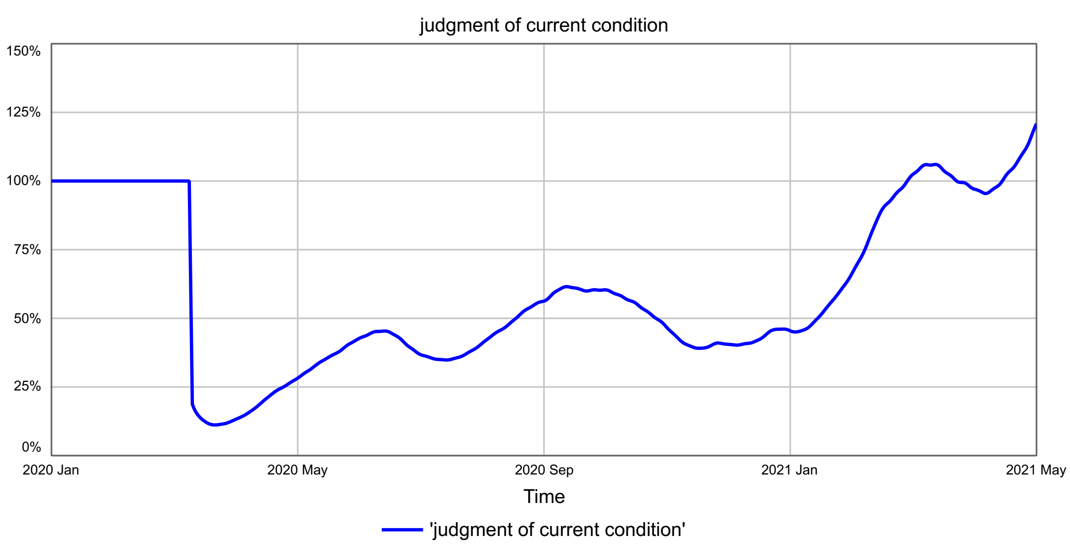


Figure 20: The value over time of the judgment of the current condition.

Reaction to the situation:

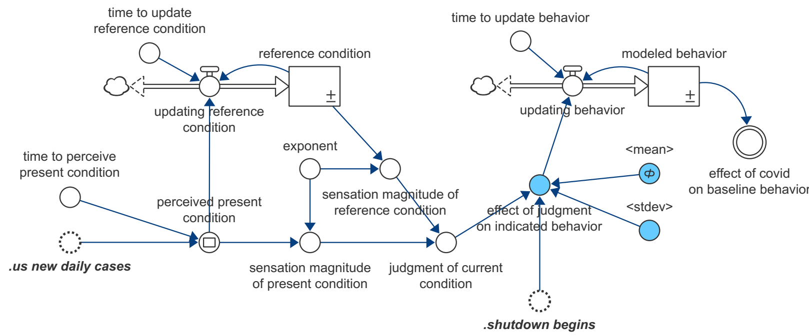


Figure 21: Generic model with reaction mechanism highlighted in blue.

Once a judgment value (the sensation magnitude of reference condition as a percentage of the sensation magnitude of the present condition) can be estimated, that judgment must be converted into a response. Populations, by nature of the inherent variability among its individuals, do not respond as a block to the average expected response. Even though the assumption is made in this model that a judgment value of 1 would indicate that the COVID situation is as expected, it cannot be assumed that the entire population would then *en masse* decide to engage in normal behavior once again. The individuals within a population rather exist on a spectrum whereby a judgment value of much less than one (say 0.5) would be enough for some more risk tolerant people to re-engage in normal behavior and other more risk averse people will require a judgment value much higher than one before they engage in normal behavior.

The log-normal distribution was selected as the most appropriate distribution for this case for a variety of reasons. To start, log-normal distributions appear ubiquitously in all sorts of natural and social phenomena, including the fields of economics, sociology, linguistics, biology, ecology, etc. (Limpert, Stahel, & Abbt, 2001). This fact alone makes it a likely candidate among the different common types of distributions. Additionally, the distribution of a population's behavioral response conforms to the three traditional hallmarks of log-normal distributions, which, according to Limpert, et al. are:

1. Values cannot be negative- the lowest number of people engaging in a certain behavior is 0.
2. Mean values are low- the average person will be comfortable returning to normal behavior if the reference condition equals the present condition, representing a low value of 1.
3. Variances are large- in many cases, there is extreme variation in how people adapt their behavior and decision making to COVID.

Two parameters are needed to define a particular log-normal distribution: the mean and the standard deviation. The mean variable has the general effect of raising or lowering the distribution curve, while the standard deviation variable is responsible for the shape of the skewedness of the curve In nearly all observed instances where data fits a log-normal distributions, the standard deviation variable typically ranges from 1.1 to 3, and while it is possible, and potentially common to find log-normal distributions with values less than 1.1, such a distribution would closely resemble a normal distribution (Limpert, Stahel, & Abbt, 2001). Such a flexibility may be useful in this model where behavior patterns in a particular domain may appear more normally distributed. Figure 22 below shows a sample of four different log-normal distribution curves and their respective cumulative distributions.

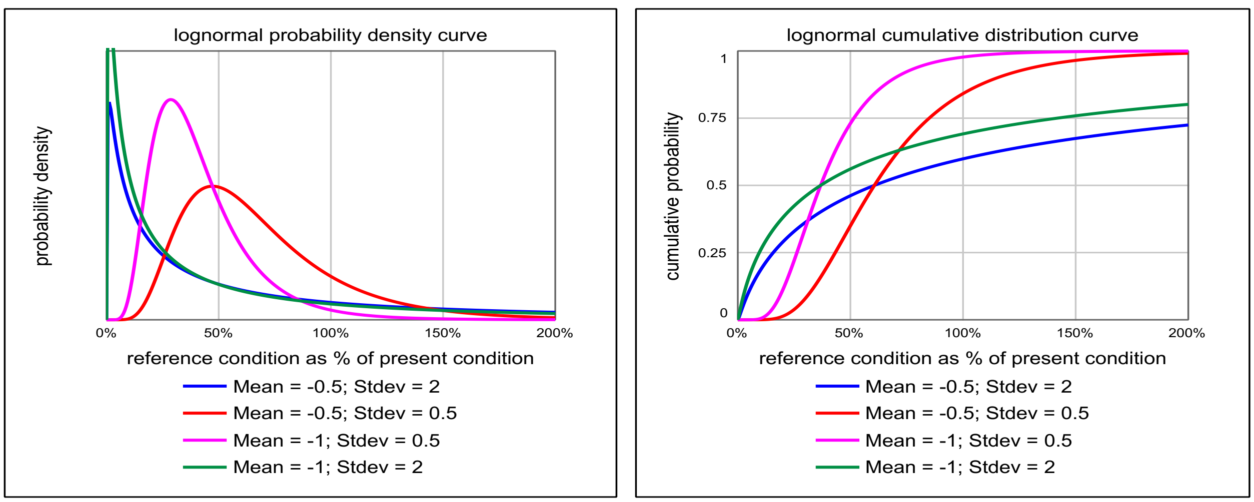


Figure 22: The probability density curves and cumulative distribution curves for a selection of four different log-normal distributions.

This model will select an indicated behavior value based on the cumulative distribution of the population that is estimated to be engaging in normal behavior at the given judgment value. For example, consider the blue curve in Figure 22 above. If a 'judgment of current condition' value (reference condition as % of present condition) of 100% were passed to this function, it would indicate that roughly 60% of the population would be resuming normal behavior. If the judgment value increased to 200%, just shy of 75% of the population is expected to resume normal behavior.

Since each domain is very different in terms of necessity, risk perception, regulatory impact, etc., it is expected that each domain may have very different distribution curves that describe how behavior is affected by different judgment values. Some domains, such as grocery or workplace attendance are relatively unaffected by changes in the COVID situation; while other more discretionary domains that carry a higher risk of infection, such as dining out or air travel, are much more sensitive to changes in the COVID situation. This sensitivity can be described by a properly calibrated log-normal distribution. Since it is assumed that this distribution will have the greatest impact on how the various domains studied in this research are impacted by COVID, the only difference among each domain is the parameterization of the mean and standard distribution variables that characterize this log-normal distribution. The analysis section will discuss in more depth what different parameterizations mean from a practical and theoretical standpoint. Additionally, sensitivity analysis regarding the mean and standard deviation can be found in Appendix B.

Output- Modified Behavior:

The final step is to materialize the indicated behavior into an actual behavior. Due to the natural delays that exist between decision and action, it is assumed that demand updates with a 10-day delay time on average. In many cases, people need to plan their behavior which may be difficult to change, require adjusting habits, or there simply may just be a delay in the entire cognition process which would be captured in this delay. The modeled behavior stock then represents the proportion (on a scale of 0-1) of the population who is engaging in normal behavior for the given domain.

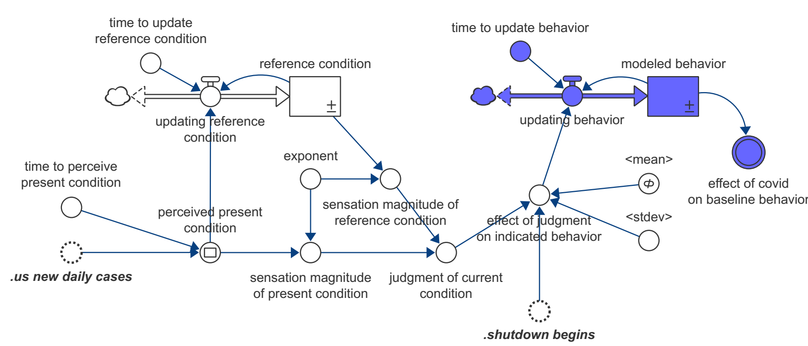


Figure 23: Generic model with the updating behavior component highlighted in purple.

Depending upon the particular domain, additional adjustments may be necessary for the final output. These adjustments may include adjustment of the output to reflect external limitations to certain behaviors (for example government imposed categorical restrictions on certain activities or behaviors), aggregation of state output to a national output, or rescaling of the output to match data. Any such adjustments are thoroughly described in the analysis section of this paper or in Appendix A.

Other modeling decisions

The model logic and structure has now been fully discussed. This section describes other miscellaneous modeling decisions that have been made in the development of this model

Parameterization:

Table 2 below gives a summary of all exogenous parameters used in the generic model.

Table 2: Table of parameter values used in this model.

Parameter	Value	Units	Description	Source
Time to perceive present condition	10	days	Assumption of the time it takes for the real data to be perceived by the population.	Assumption
Time to update reference condition	360	days	Assumption of the time it takes to grow accustomed to a certain level of COVID	Calibrated
exponent	0.5	dmnl	Calibrated, should be between 0 and 1	Calibrated; (Stevens, 1986)
Shutdown begins	71	day	Day that the pandemic begins to substantially effect general behavior patterns.	(U.S. state and local government responses to the COVID-19 pandemic, 2020)
Standard Deviation (<stdev>)	Calibrated per domain	dmnl	Describes the distribution of behavioral responses	Calibrated
Mean (<mean>)	Calibrated per domain	dmnl	Describes the average behavioral response	Calibrated
Time to update behavior	10	days	Assumption of time to update actual behavior given an indicated behavior	Assumption

Calibration:

Many of the parameter values mentioned above were estimated using a calibration routine. Additional information regarding how these parameters were calibrated can be found in the analysis section of this paper.

Time Horizon Choice:

The time horizon for this model is relatively short as the model's purpose is to demonstrate the immediate effects of changes in COVID cases on a population's decision-making behavior. As such the model begins on January 1, 2020, and is run for 500 days until May 15, 2021. This allows for a period of approximately 60 – 70 days of steady state behavior prior to the start of the pandemic and covers substantially all behavior up to the submission deadline of this thesis.

Level of Aggregation:

The model has been built to work at a high level of demographic and geographic aggregation as it considers the entire population within the state level or within the US as a whole. Further research and testing could be undertaken to investigate this model's validity at lower levels of aggregations (such as at the city or county level or looking at the response of particular subgroups of the population). There are a few reasons that it makes sense to test this model on higher levels of aggregation:

1. Public policies regarding lockdowns and restrictions are established primarily at the state or federal level, so the effects of changes in the level of COVID in one state are likely to affect everyone within that state.
2. Statistics are most commonly reported either for the US as a whole or for each state as a whole, so state-wide or country wide COVID information will be most readily accessible to people.
3. The law of averages will smooth out other potential local factors that may influence how people react to COVID (these factors may include climate, general political leaning, demographic make-up, local culture, etc.) As these factors fall outside of the boundary of this model, but might have a strong effect at smaller scales, using a larger scale will average out the effect of these local differences.

Future research can test how the model holds up at more localized scales, but the purpose of this research is to identify the general response mechanisms that would be at play among the entire population.

Model Boundary:

There is a very tight boundary around the model used for this thesis. The only inputs to the model are the relevant number of COVID cases for the region being analyzed as a few other major influencing structural factors that may shape the outcome and which are known to exist in that domain. The output is the average level of behavior that is to be expected in that domain based on the COVID situation

The model only applies to domains where it is expected and observed that the level of behavior reduces from the pre-pandemic baseline. It has not been adapted to domains for which an increase in the level of behavior is expected or observed.

DT and Integration Method:
A DT of 1/16 with Euler's integration method is used to run this model.

Model Validation:

A critical stage of any model's development is its validation. According to J.W. Forrester and Peter Senge,

"Validation is the process of establishing confidence in the soundness and usefulness of a model. Validation begins as the model builder accumulates confidence that a model behaves plausibly and generates the problem symptoms or modes of behavior seen in the real system." (Forrester & Senge, 1980)

Furthermore, Yaman Barlas explains that the assessment of the validity of a model cannot be divorced from a consideration of the purpose of the model. In other words, validating a model is fundamentally assessing "its usefulness with respect to its purpose" Thus validating this model requires assessing both its purpose and its usefulness of achieving that purpose, which is subjective and qualitative to some extent (Barlas, 1996).

An important aspect of validating this particular model is establishing its usefulness across a variety of domains. Given that the model is able to reproduce behavior modes in several domains (given reasonable parameterization of the model as it is applied in

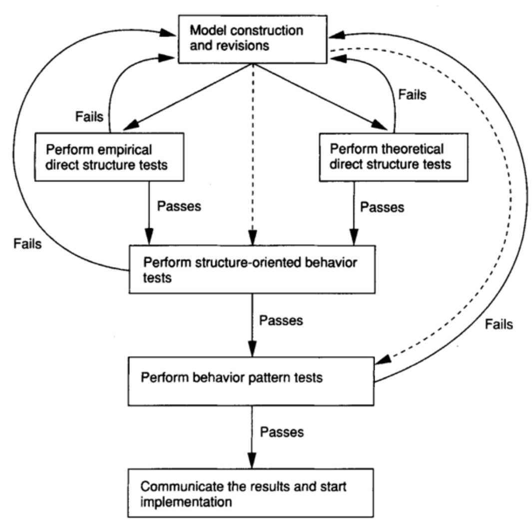


Figure 24: Logical sequence of formal steps of model validation (Barlas, 1996)

each case), this lends good credibility to the usefulness of this model to its purpose—which is to develop a generic model capable of explaining how people change their behavior in response to COVID.

Validation, after all, is built into the entire process of developing, testing, and analysing a model. Figure 24 on the previous page shows how validation comes into play at every stage and largely contributes to the *iterative* nature of simulation model development. The development of this model has undergone the same iterative process of development, testing, validation, then redevelopment, retesting, and revalidation until the end result converges toward a plausible model structure that is useful for its purpose and produces the right behavior for the right reasons.

This being said, Barlas outlines a handful of formal validation tests that should always be carried out prior to presenting a model. They are outlined in Table 3 below:

Table 3: Summary of validity tests according to (Barlas, 1996)

Type of Test	Test	Purpose
Direct Structure Tests	Structure Confirmation	Is the model structure consistent with the knowledge of the real-world system?
	Parameter Confirmation	Are the parameter values used known or reasonable estimates of the real-world values?
	Extreme Conditions	Do the equations in the model return logical outputs even if the input to each equation takes on extreme values?
	Dimensional Consistency	Are the units of measurement consistent without use of *scaling* or *dummy* variables?
Structure-oriented behavior tests	Behavior Sensitivity	Is the behavior of the model appropriately sensitive to changes in its various parameters?
	Boundary Adequacy	Is the boundary (what is included in or excluded from the model) appropriate for the purpose of the model?
	Extreme Conditions	Does the model overall behave logically if it is subject to extreme shocks or policies?
Behavior Pattern Tests	Behavioral validity	Is the model capable of reproducing the behavior patterns observed in the real-world system?

Structural Confirmation

The structural confirmation of this model is supported by the literature that has informed the theoretical framework upon which this model was built. While the structure certainly over-simplifies the real-world processes at play (all models do), the processes that are included have sufficient theoretical backing in the psychology literature to make us confident that the structure plausibly and sufficiently represents the real-world cognitive process.

Parameter Confirmation

Parameter confirmation has been particularly speculative for this project due to the high proportion of variables in this model for which values cannot be corroborated through other research or literature. While the calibration routines discussed in the analysis section of this paper have been conducted in accordance with the best practices of the methodology and the values produces all fall within a logically reasonable range (when considered individually and when evaluated in the context of the values produced in other domains), the weakest basis for confidence in this model lies with the parameter values used.

Extreme Conditions of Equations

All equations produce logical outputs when subjected to extreme inputs.

Dimensional Consistency

All units are dimensionally consistent in this model and no *dummy* variables are introduced as a means of forcing dimensional consistency. It is worth noting, that the model file will indicate 10 unit errors (all in the 'sensation magnitude' variables), yet these do not represent true logical dimensional inconsistencies. The software simply struggles to account for fractional exponents.

Extreme Conditions

The model has been subjected to extreme conditions and continues to produce logical results. For example, if COVID cases are zero, it would be expected that behavior would not be impacted.

Sensitivity Testing

The model has been subjected to sensitivity testing for each of the key parameters used. Additional information regarding the results of sensitivity analysis can be found in Appendix B, however it is worth noting here some observations that arose from the sensitivity tests:

- There is potential overlap between the 'time to update reference condition' and the 'mean' variable in terms of the effect each has on the output of the system. Sensitivity testing revealed that changes in each variable led to similar changes in the behavior level estimated by the model.

A change up in either variable roughly causes the entire behavior curve to shift downwards, though the mean is much more sensitive.

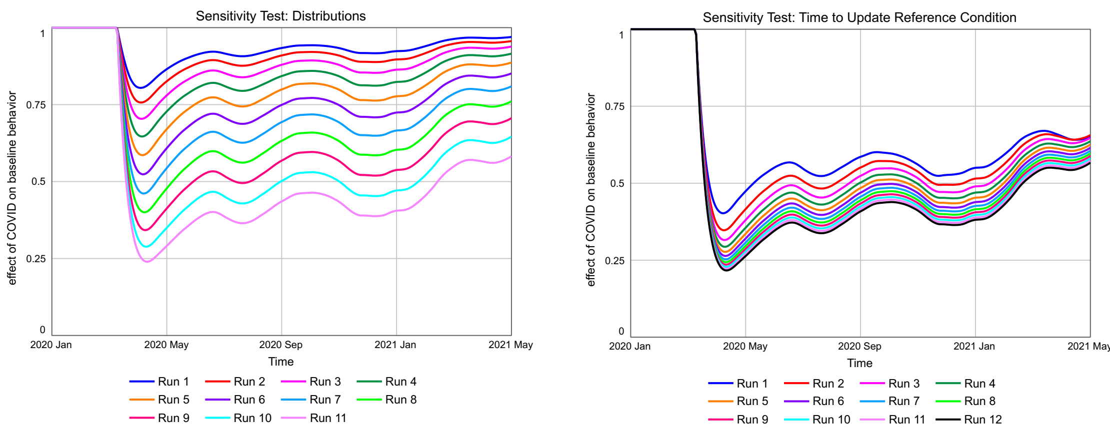


Figure 25: Sensitivity results (Mean to the left; Time to update reference condition to the right)

- There is also potential overlap between the 'exponent' and the 'standard deviation' variable in terms of each's effect on the estimated behavior level. As each variable increases, the behavior pattern is stretched into more extreme patterns. The exponent variable stretches the behavior curve further from a judgment value of 1 and the standard deviation variable stretches the behavior curve further from the mean value. It is worth noting that a low standard deviation value produces more extreme behavior patterns, and a high exponent value produces more extreme behavior patterns.

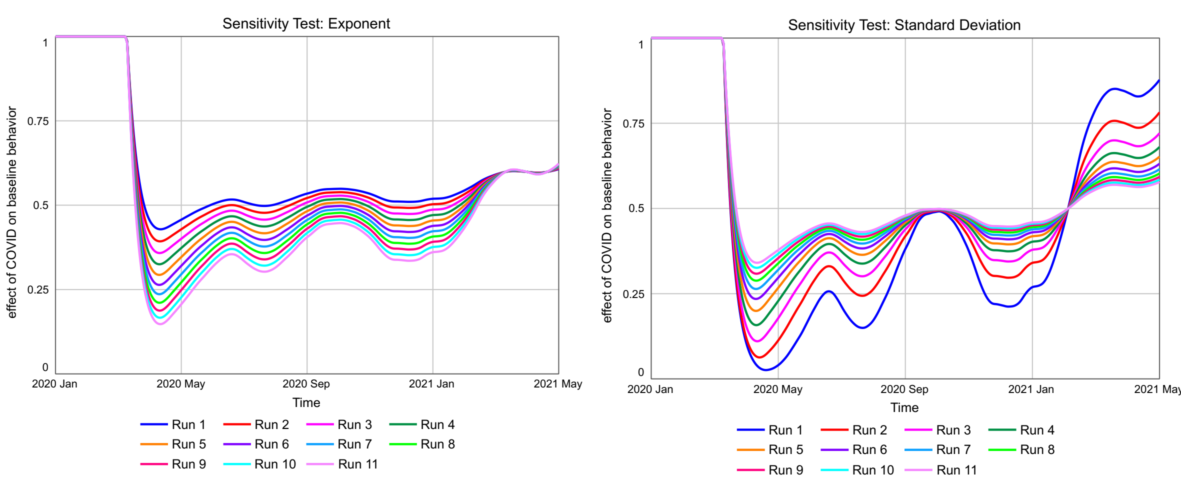


Figure 26: Sensitivity results (Exponent to the left; Standard deviation to the right)

These indicated that further testing and validation will need to be conducted to ensure that each of these variables is not falsely attributed a value that could be compensated for by a false value of the corresponding variable. In this case the calibration process and the reasonableness of the final parameter values for each domain must be thoroughly assessed.

Behavioral Validation

In order to assess the statistical significance of the model output compared to the historical data, the Theil statistics have been calculated and presented the in Table 4 below. The statistics were calculated using the module created by Rogelio Oliva (Oliva, 1995), which was based on John Sterman's 1984 paper, *Appropriate Summary Statistics for Evaluating the Historical Fit of System Dynamics Models* (Sterman J. D., 1984).

Table 4: Theil Statistics and R-squared results of the behavioral fit of the model output to the historical data.

Domain	MSE	U^M	U^S	U^C	R^2
Airlines	0.00471	0.0152	0.0514	0.933	0.836
Restaurants	0.0159	0.864	0.265	0.649	0.771
Senior Housing*	0.000026	0.235	0.112	0.653	0.989
Workplaces**	0.000627	0.00263	0.000593	0.997	0.857
Retail and Recreation**	0.00164	0.00106	0.106	0.893	0.782
Transit Stations**	0.00218	0.00393	0.0169	0.979	0.624
Grocery and Pharmacy**	0.00283	0.0169	0.685	0.298	0.285

*Evaluated from time 0-456 since this is the timeframe of the available data. Additionally, the data was compared with the output of the industry sub-model, which used the output from the generic model as it's input.
**due to the high amount of noise in the historical mobility data, the Theil statistics were calculated based on a 10-day first order exponential smooth of the data and model results.

MSE = Mean Square Error
U^M= Fraction of MSE due to bias
U^S= Fraction of MSE due to unequal variance
U^C= Fraction of MSE due to unequal covariance
R^2= Correlation coefficient between modeled and actual data

Many of the above results indicate a very strong fit of the model results to the historical data. Generally, the model fits better in situations whereby the historical data describes more specific behavior patterns (e.g., in the restaurant, airline, and senior housing domains) and does not fit as well in the mobility domains which capture broader categories of behavior patterns. Given the tight boundary around this model, it can be assumed that taking more factors into consideration (such as the specific effects of government restrictions or other structural variations between each domain) would produce closer results than revealed here. The model limitations section and future research section will discuss further modifications that could be made to improve its output.

Analysis

Domains studied

As a means of testing this model and assessing the broadness of its application, in accordance with the research objectives, this model was tested in seven different domains. The term 'domain' here refers to a certain class of observed behavior. For the sake of this model, it refers specifically to consumption behavior in a particular industry or the decision to go to a certain type of place. Some of the domains used in this model are more specific than others, for instance the example about the restaurant industry refers specifically to demand for dining out (not delivery or take away, which saw increases in demand during the pandemic (Guszkowski, 2020). It is important to make this distinction in this case since dining out was subject to an entirely different decision process than was ordering delivery or take away, and the specificity of the data in this case led to more compelling results as you will see. In other cases, particularly the mobility data, the behavior is much more generally defined, which can lead to some issues in terms of calibration. For instance, the retail and recreation mobility sector clearly includes a diverse variety of behaviors under its umbrella (including that of dining out at restaurants among many other domains that could fall into this category). Because the data is much more general in this case, it will be more difficult to calibrate the model to the data which inevitably includes many different sub-classes of behavior under its umbrella, many of which likely cancel each other out when calculating a change to an overall baseline. Therefore, domains for which very specific types of behavior are measured are preferable to those for which only general types of behavior are measured. In each domain tested, there will be a discussion on the impact of the data upon the results.

Model Calibration

Calibration has been a critical feature of this modeling process due to the number of parameters in this model with generally unknown values. According to Rogelio Oliva, calibration can serve as a valuable means of testing a model and linking its structure to the real-world behavior. Due to the relative importance of calibration to the development of this model, special attention has been paid to what Oliva lists as three critical heuristics to properly leverage calibration as a testing tool (Oliva, 2001):

1. Do not override known or observable structure
2. Tackle small calibration problems
3. Use automated calibration to test the dynamic hypothesis

The model developed in this research project aims to conform as best as possible to these criteria, and for the sake of consistency, the same calibration procedures have been applied to each domain, with the exception of certain well-justified adjustments that will be explained in more detail under each domain's results section.

In order to conform to Oliva's criteria, the model was subject to automated calibration routines built into the Stella Architect software (isee Systems , 2021); the details of which can be found in Appendix C. This is to ensure that the calibration is both replicable and statistically sound. Furthermore, a two-stage calibration process was undertaken for this model: the first step being to use automated calibration to determine likely values for the 'time to update reference condition' and 'exponent' variables, which in this model are treated as constants across all domains; then to determine the 'mean' and 'standard deviation' values for the distribution curves used in each domain. The first calibration step involved running, for each domain, a calibration routine to search for the combination of values for each of the four variables ('time to update reference condition', 'exponent', 'mean', and 'stdev') which produced the greatest fit between the model results and the data. This step is necessary because it is not known what specific values should be used for the 'time to update reference condition' and the 'exponent' variable, though it is assumed in this model that these values should be fixed for all domains. A fundamental [and untested] assumption of this research is that any variation in behavior patterns observed between domains emerges not from the fact that people perceive and evaluate the COVID situation differently in each domain, but rather that the differences emerge due to the fact that people react to the same situation differently from domain to domain. Therefore, all the domains were subject to the initial calibration for the purpose of discovering plausible values for those two variables; and after they were estimated, they were fixed for all domains to reflect the fundamental assumption discussed above. This helps this calibration process to conform to Oliva's first criteria, which only treats truly unknown variables to the calibration process and does not overwrite other known variables. The second calibration then was carried out in accordance with Oliva's second criteria, which is to limit calibration to the smallest possible portion of the model. This second round of calibration was run for each domain to discover values for the 'mean' and 'stdev' variables that described the response distribution that facilitated the greatest fit between the model and the data. Given this, the primary difference between each of the domains studied in this model are different assumptions for the reaction distributions applied in each domain, and any differences in output can therefore be traced to the parameterization of these two variables. So, by splitting the calibration into two processes as has been done in this project, the outcomes of the first calibration routine produce estimated 'universal' values for the exponent and time to update reference condition variables, thereby isolating these parameterizations to the generic model; then the outcome of the second calibration routine isolates any differences among the domains to the shape of the distributions, as described by the mean and standard deviation. Further discussion of this will follow in the sections below, and further details of the calibration routines can be found in Appendix C.

Model Results

Following a full discussion of the model structure, calibrations, and consideration of its validity, the results from each of the seven domains studied in this research project are described below.

Airline Industry

Introduction:

The airline industry has felt an extreme impact due to COVID (Hotl & Mumbower, 2021). In the US, there were never any explicit regulations against domestic travel, though regulations in some states made domestic travel less appealing through quarantine requirements. International travel has been severely impacted due to federal regulations restricting travel for non-residents from many countries, currently including anyone coming from the EU, China, India, Brazil, or South Africa (United States Center for Disease Control, 2021). This domain will look at how COVID has impacted peoples demand for air travel.

Data:

The data used for this model comes from the Transportation Security Administration's statistics for number of passengers traveling through all US airports on a given day (United States Transportation Security Administration, 2021). The data is reported from January 1, 2019, providing a full year of pre-COVID data for comparison. As such, and due to the seasonal cyclicality of airline traffic, the post-COVID data has been normalized to the passenger traffic observed on the same day in 2019 so that the seasonal fluctuations are not considered in this model.

Model:

The model used in this domain utilizes the generic structure, but for this domain, an adjustment to the output has been made that substantially eliminates 90% of international travel since these restrictions have remained in place since the beginning of the pandemic. Thus, most international travel is not subject to the behavior model as it has remained categorically restricted. Additionally, an adjustment has been made to the generic model in this case to reflect the fact that demand for air travel is raised much slower than it is lost. Changes in COVID can cause rapid declines in air travel as it is a relatively quick process for either the airline to cancel flights or the passenger to cancel their tickets. However, as the situation improves, demand will catch up more slowly due to the time it takes to plan air travel and schedule flights in response to the increased indicated demand. Thus, behavior in this domain is assumed to contract with a delay of 10 days and expand with a delay of 45 days. The modified model is pictured below in Figure 27 and the changes from the generic structure are highlighted in yellow to reflect the adjustments discussed above:

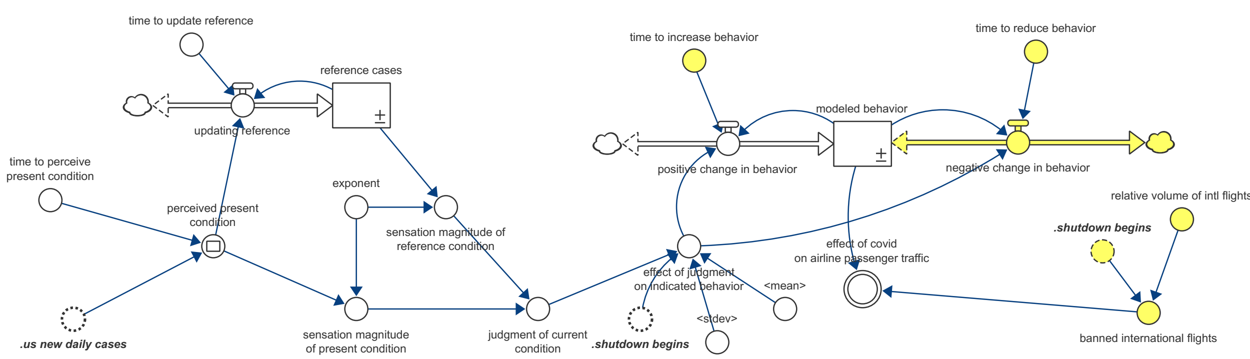


Figure 27: Modified generic structure for the airline industry.

Calibration:

This domain was subject to the standard calibration procedure as described in the calibration section and Appendix C; no modifications were made to the standard procedure.

Results:

Figure 28 shows he results of the model (red) compared to the historical data (blue) below. Additionally, the distribution and cumulative distribution curves that were used in this domain are shown below.

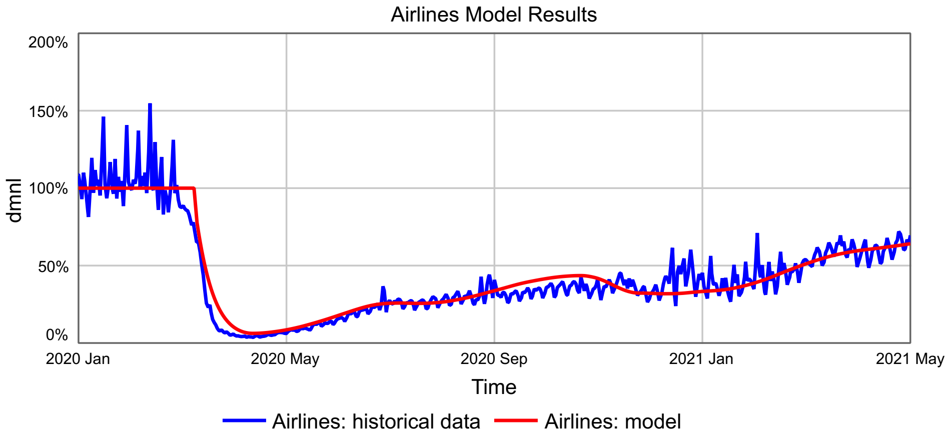


Figure 28: Historical data vs. simulated data when the model is applied to the airline industry

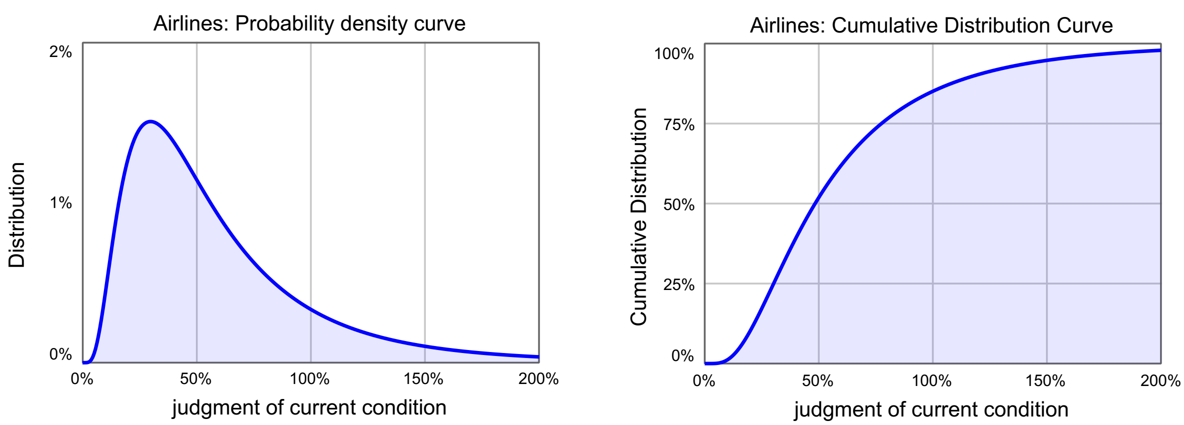


Figure 29: Probability Distribution and Cumulative Distribution of reaction to COVID in the airline industry.

Discussion:

The results of the model indicate a good fit to the historical data. The model fits less well during the period of the holiday, though this could be due to the fact that the holiday's skewed the decision-making behavior by altering the motivation for travel that resulted in a different risk/reward appraisal. This is untested speculation as to what causes the difference, but on the whole, the results match very well, with an R^2 value of 0.863.

Restaurant Industry

Introduction:

The pandemic has hit the restaurant industry from two different angles: changes in consumer demand and impact of strict government regulations. In this domain, only dine-in behavior is considered. Given the affront on the industry from both the demand side and the supply side (government enforced supply restrictions to capacity and operations) This model will primarily consider the impacts due to demand. Even though it is shown that government restrictions are also subject to the same general forces affecting individual behavior (Djulbegovic B, 2020 Oct), so there is potential overlap of the model to both effects here, the model will certainly underestimate behavior levels during periods whereby substantially all dine-in restaurants were forced to close.

Data:

The ‘behavior level’ in this domain is estimated using changes in dine-in revenue reported by restaurants as compared to their pre-COVID levels. The data comes from Opentable.com, a popular restaurant reservation app used in the United States, and shows day to day aggregate dine-in revenue as a percentage of revenue on the same day in 2019 (OpenTable, 2021).

Model:

No adjustments have been made to the generic model in this case, though it is worth noting that this domain has been arrayed by state. The results displayed here represent a weighted average (weighted by state population) of the results from each individual state; where the COVID cases from each state were used as the input to the model. This is an important distinction, since the situation in a particular state is much more likely to affect behavior (and restrictions) than the situation in the US as a whole. Therefore, this model has been disaggregated and run on the state level, and then aggregated up to the US as a whole. The exact same parameterization is used for each state; therefore, the value in disaggregation is purely to account for how the local COVID situation would impact behavior, not to account for potential local differences in parameter values.

Calibration:

This domain was subject to the standard calibration procedure as described in the calibration section and Appendix C; no modifications were made to the standard procedure.

Results:

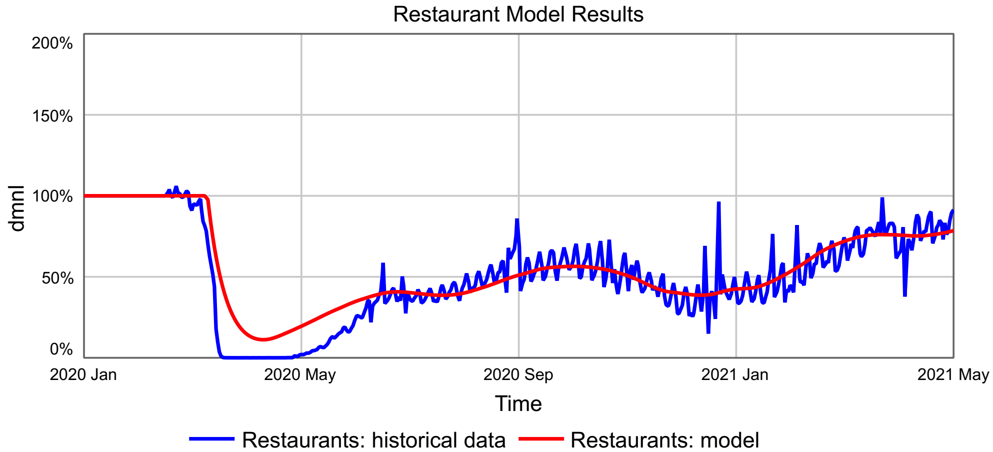


Figure 30: Historical data vs. simulated data when the model is applied to the restaurant industry

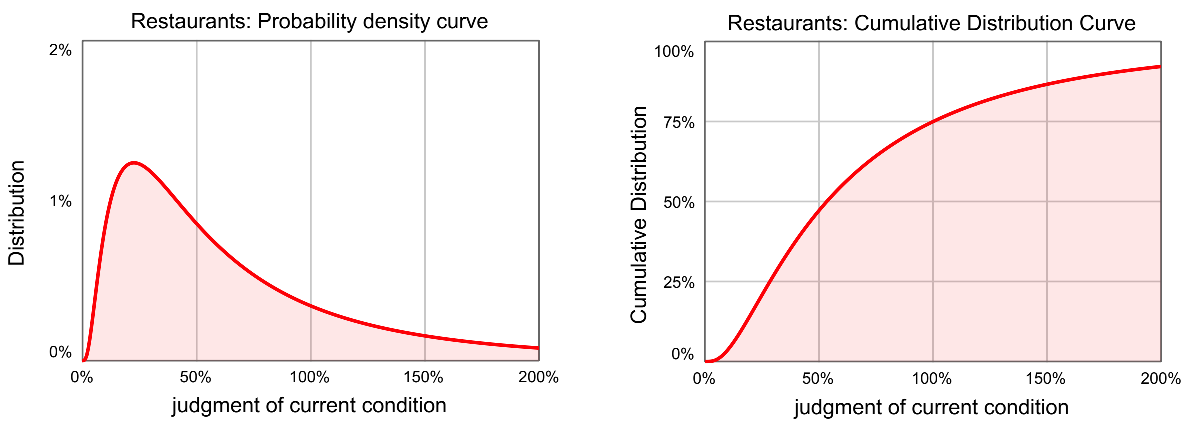


Figure 31: Probability Distribution and Cumulative Distribution of reaction to COVID in the restaurant industry.

Discussion:

The results of this domain indicate a strong fit to the historical data. Although the model overestimates demand in the initial period of the pandemic, this is due to the fact that substantially all states had categorically restricted dine-in restaurants from opening. An analysis of the state-by-state results show a similar issue on the state-wide level when the model overestimates periods where restrictions obviously precluded any supply from being made available. Overall, considering the entire US, the model has an R^2 value of 0.771, indicating a good correlation between the model and the data. Appendix D shows the state-by-state results of the model. Unsurprisingly, the model over and underestimates results in many states due to the ignorance of possible locally-specific parameter values in this model. One such plausible difference, which was outside of the boundary of this model, but which may offer an explanation of the divergence on the state-by-state level, is that of how the politics of the particular state affected behavior in that state (Akovall & Yilmaz, 2020); (Pew Research Center, 2020); (Hallas, Hatibie, Majumdar, Pyarali, & Hale, 2020). For instance, New York was known for a particularly strong lockdown, so being that this was not considered in the model, it is unsurprising that the model overestimates the level of behavior (Figure 32 below). On the other end of the spectrum, Florida was known for particularly weak lockdown measures, so it is unsurprising that this model would underestimate the true level of demand (Figure 32 below).

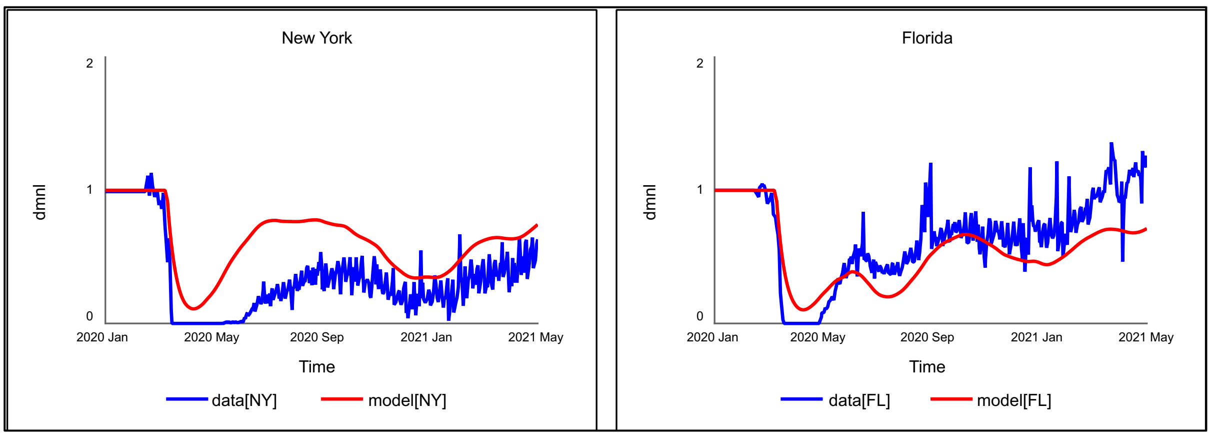


Figure 32: State-specific results for New York and Florida

In general, the state-specific results show that the model produces reasonable results (adjusting for other local factors) and is generally able to identify the timing of the peaks and valleys in behavior and the direction and scale by which demand moves during the pandemic. Refer to Appendix D for more results.

Workplace mobility

Introduction:

Many workplaces have had to temporarily or permanently shut down, or have offered 'work from home' arrangements with their employees. Therefore, there has been a significant decline in people going to a physical workplace. This represents a different kind of domain from those studied so far in that this domain does not represent consumer demand, but represents more employee and employer adaptations of work behavior in response to COVID.

Data:

Google publishes mobility data for workplaces. The data is expressed as a percentage of a baseline level of workplace mobility, calculated using the average mobility from the beginning of 2020, before the pandemic started (Google LLC, n.d.). For this project, the data has been rescaled from a baseline of 0 (with declines going negative and increases going positive) to a scale of 0 – 100 (where 100 represents the baseline value and subsequent changes are scaled accordingly).

Model:

No significant changes were made to the generic model.

Calibration:

To calibrate the model to the data, a 10-day smooth of the data was compared to a 10-day smooth of the model results. This was done to smooth out the extreme daily variability in the data caused by weekends. Additionally, the other sharp decreases in mobility as seen in the data are due to public holidays. The effect of these was not adjusted for in the calibration process, though they likely have some impact on the results. Further research could adjust for this effect and likely get a more realistic behavior pattern. Other than these points, the calibration routine followed the standard process.

Results:

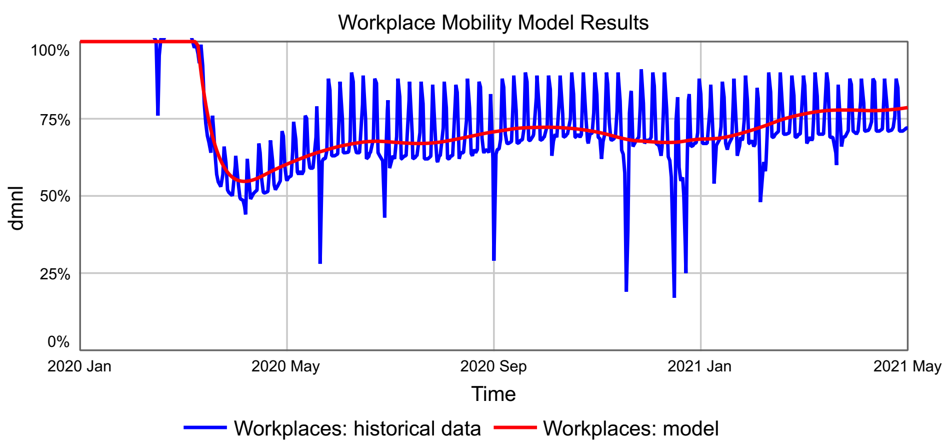


Figure 33: Historical data vs. simulated data when the model is applied to workplace mobility

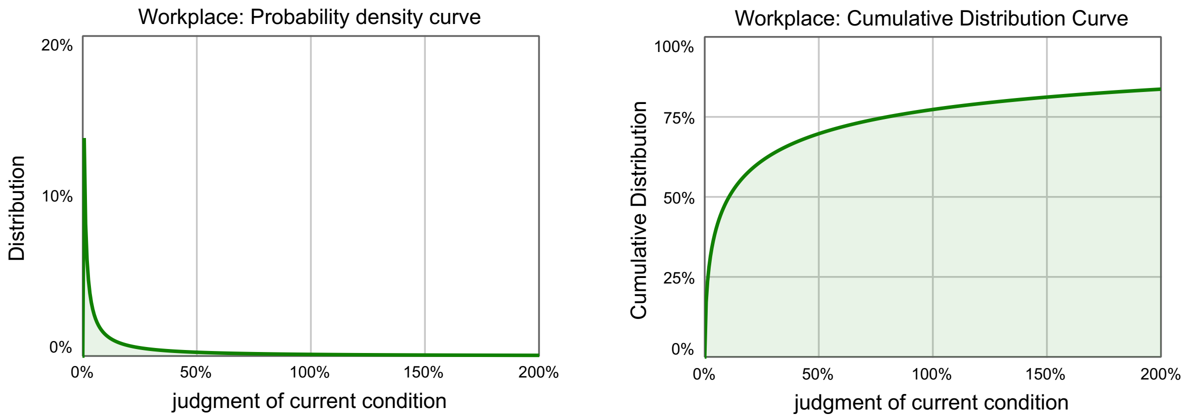


Figure 34: Probability Distribution and Cumulative Distribution of reaction to COVID in workplace mobility.

Discussion:

The model is able to fit the historical data quite well, both on the US level as a whole, as pictured in Figure 34 above, and to a lesser extent on a state-wide basis. The model output correlates strongly to the data, with an R^2 value of 0.857. Additionally, insights can be gained from the shape of the distribution curve, which shows that behavior in workplace mobility settles around 75% of the baseline level on average if the judgment of current condition value is 100%. As the situation changes, there is limited flexibility of behavior, but only if the situation were to get very bad would more dramatic declines in workplace mobility be observed. On the other end, the situation will have to improve dramatically if mobility is to surpass 90% of its baseline level.

Retail and Recreation Mobility

Introduction:

This sector looks at a very broad swath of behavior related to going to retail and recreation locations. This can include malls, restaurants, movie theaters, stores, and many other possible locations that fall under this general category.

Data:

Google publishes mobility data for retail and recreation. The data is expressed as a percentage of a baseline level of retail and recreation mobility, calculated using the average mobility from the beginning of 2020, before the pandemic started (Google LLC, n.d.). For this project, the data has been rescaled from a baseline of 0 (with declines going negative and increases going positive) to a scale of 0 – 100 (where 100 represents the baseline value and subsequent changes are scaled accordingly).

Model:

No significant changes were made to the generic model.

Calibration:

To calibrate the model to the data, a 10-day smooth of the data was compared to a 10-day smooth of the model results. This was done to smooth out the daily variability in the data likely caused by weekends. Other than this modification, the calibration routine followed the standard process.

Results:

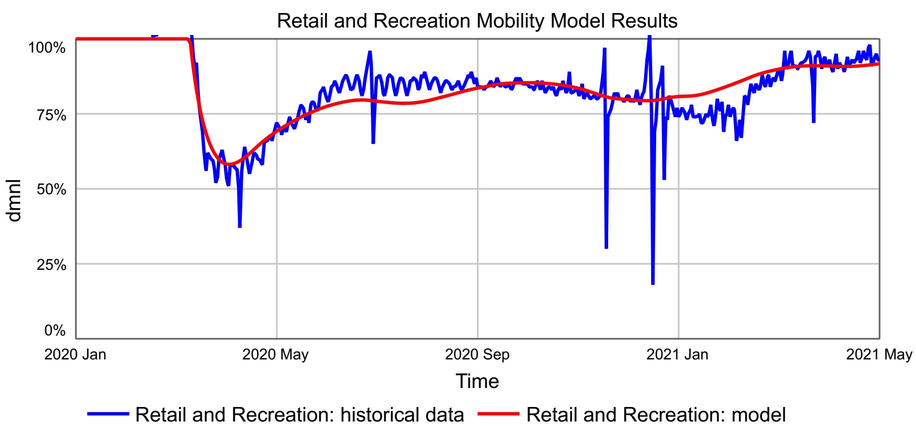
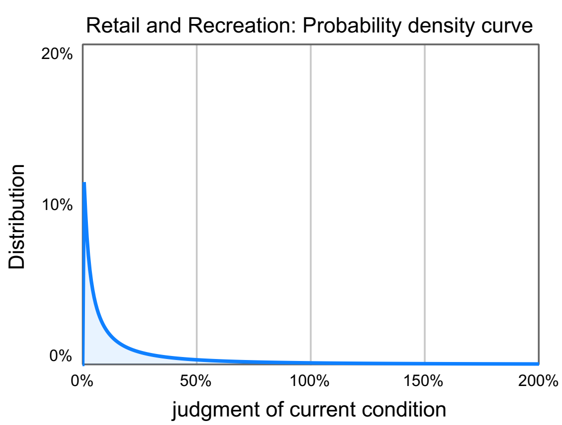


Figure 35: Historical data vs. simulated data when the model is applied to retail and recreation mobility



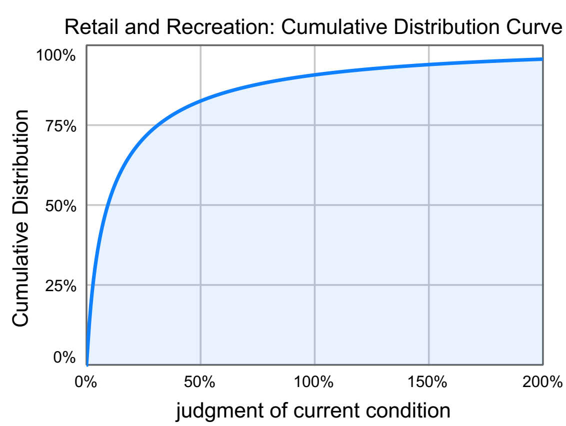


Figure 36: Probability Distribution and Cumulative Distribution of reaction to COVID in the retail and recreation mobility.

Discussion:

Given the broad scope of this domain compared to, for example, the restaurant domain which specifically looks at demand for dine-in, it would be expected the model might not calibrate as nicely to this particular domain. In fact, the model generally tracks the behavior well (R^2 value of 0.782), though with some discrepancies at times. Particularly, the model does not show as strong of a rebound coming out of the first wave, and the model does not show as severe of a drop going into the third wave. A state-by-state analysis of this domain finds that most states have undergone a very similar development as it pertains to retail and recreation mobility. Some states saw a surge in mobility (which this model would not replicate but would pull up the national average as seen in Figure 35 above). Some states had very different developments from what the model predicted, but typically the model tracked very well the state-by-state scenario. See Appendix D for state-by-state results. Further investigation would be needed to look into the discrepancies of certain states, that are certainly affecting the final output shown here.

Grocery and Pharmacy Mobility

Introduction:

The grocery and pharmacy domain tracks how many people were found to be going to grocery stores and pharmacies. It was included in this model due to the fact that it is known that grocery and pharmacy mobility has seen very little impact overall due to COVID, so it seemed to be an interesting case to test the model against.

Data:

Google publishes mobility data for grocery and pharmacies. The data is expressed as a percentage of a baseline level of grocery and pharmacy mobility, calculated using the average mobility from the beginning of 2020, before the pandemic started (Google LLC, n.d.). For this project, the data has been rescaled from a baseline of 0 (with declines going negative and increases going positive) to a scale of 0 – 100 (where 100 represents the baseline value and subsequent changes are scaled accordingly).

Model:

No significant changes were made to the generic model.

Calibration:

To calibrate the model to the data, a 10-day smooth of the data was compared to a 10-day smooth of the model results. This was done to smooth out the daily variability in the data likely caused by weekends. Other than this modification, the calibration routine followed the standard process.

Results:

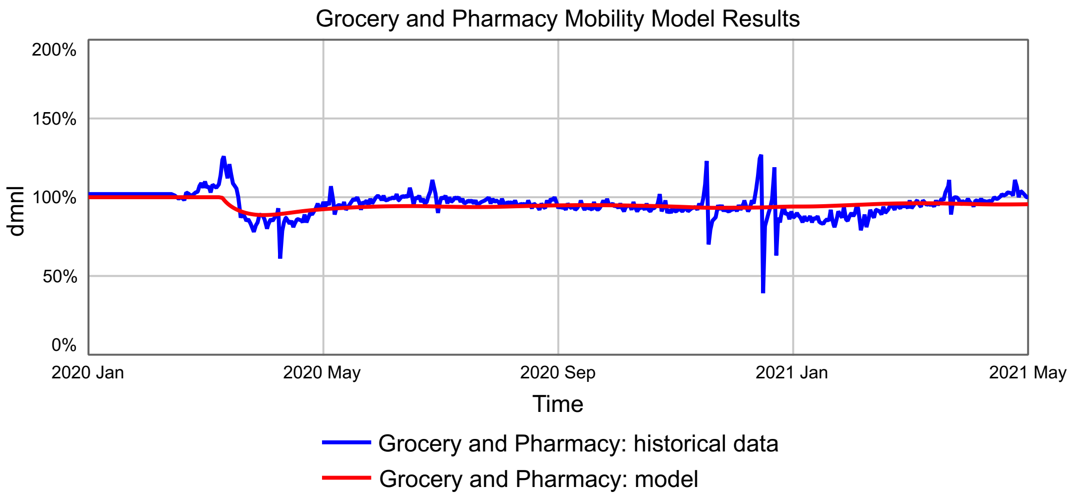


Figure 37: Historical data vs. simulated data when the model is applied to grocery and pharmacy mobility

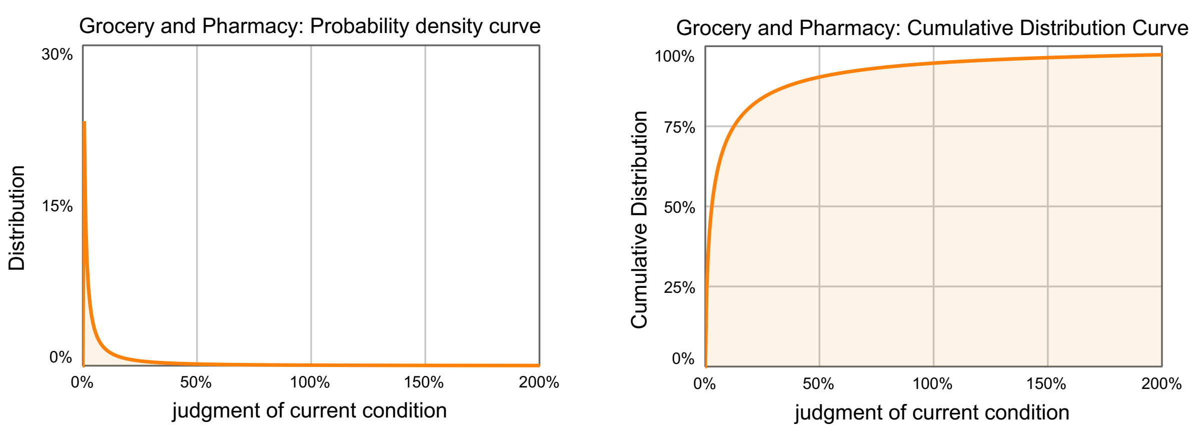


Figure 38: Probability Distribution and Cumulative Distribution of reaction to COVID in grocery and pharmacy mobility.

Discussion:

The model is not capable of producing as good of a behavioral fit in this domain due to a fundamental limitation of the model in not being able to account for situations in which behavior actually increases above the pre-pandemic baseline as a result of COVID. Additionally, this sector does not fully account for additional variables and processes likely driving people's need to go to grocery stores or pharmacies.

As seen in the US data and state level data, there are periods of increased behavior over the baseline, which this model will not replicate. It could also be that this domain needs additional model structure (as in the senior housing domain presented later in this analysis section) to fully explain the behavior patterns observed. The reality is that people go grocery shopping to stock up on groceries. Initially, there was a strong trend of people stocking up and hoarding food items as the nature of the pandemic was highly uncertain. People then maintain an inventory of food at their homes and will go shopping again only once the supplies in their homes are sufficiently depleted. This indicates additional model structure may be necessary to account for this. Regardless, the model is able to roughly be calibrated to the data (although only with an R^2 value of 0.28) and the resulting distribution curve does make sense in this situation. It suggests that people's behavior in grocery and pharmacy mobility is almost completely unaffected by COVID; which makes sense in that grocery shopping is a necessary activity and would only be reduced if the situation was so severe that people were afraid even to go out and perform the most necessary errands.

Transit Station Mobility

Introduction:

Transit stations represent a very broad category of places, such as bus stops, train stations, airports, taxi stands, subways, etc. Generally, this domain will capture to what extent people are traveling around. The category is broad but represents an interesting case to apply the model to.

Data:

Google publishes mobility data for transit stations. The data is expressed as a percentage of a baseline level of transit station mobility, calculated using the average mobility from the beginning of 2020, before the pandemic started (Google LLC, n.d.). For this project, the data has been rescaled from a baseline of 0 (with declines going negative and increases going positive) to a scale of 0 – 100 (where 100 represents the baseline value and subsequent changes are scaled accordingly).

Model:

No significant changes were made to the generic model.

Calibration:

To calibrate the model to the data, a 10-day smooth of the data was compared to a 10-day smooth of the model results. This was done to smooth out the daily variability in the data likely caused by weekends. Other than this modification, the calibration routine followed the standard process.

Results:

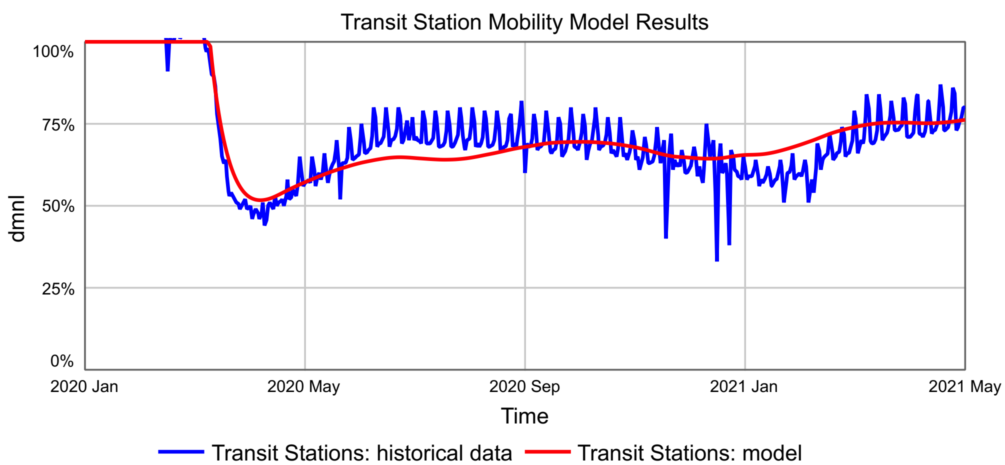


Figure 39: Historical data vs. simulated data when the model is applied to transit station mobility.

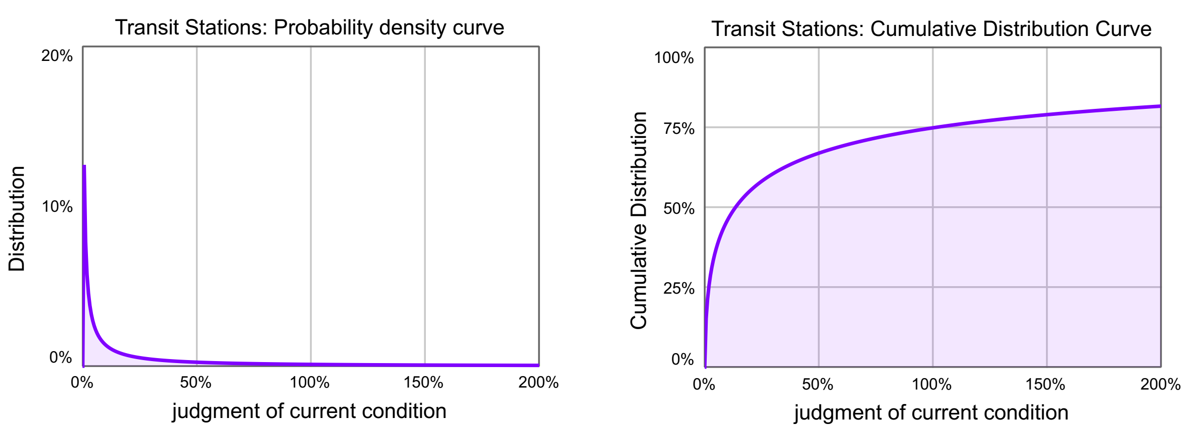


Figure 40: Probability Distribution and Cumulative Distribution of reaction to COVID in transit station mobility.

Discussion:

The model of the transit mobility domain did not provide as close of a fit to the real data, apparently for many of the same reasons as discussed in the retail and recreation domain. Additionally, there may be an element of seasonality in the data that is not properly adjusted for (similar to what was done in the airline domain). These factors aside, the mode does produce an R^2 value of 0.624, which tells that the model still is capturing a significant portion of the behavior.

The Senior Housing Industry: an extended application of the model component

Introduction:

The senior housing industry has bet hit by many factors due to COVID. These include loss of residents due to pre-mature deaths caused by COVID, decreased people moving in due to fear of infection, and increased costs due to government regulations to name just a few of the prominent challenges. (Shaver, 2020) As indicated in the preface of this paper, analyzing the impact of COVID on the senior housing industry was the initial inspiration for this research, so it will be included here, though in a very different manner from the other sectors. This domain analyses to a deeper level how the change in behavior due to COVID has interacted with how the senior housing industry works to produce the observed historical data, which will be occupancy in senior housing facilities. This domain perhaps best serves as an example of the potential utility of this research: that the model component developed here can be plugged into larger models to solve deeper problems.

Data:

Reliable, daily data about people's decision to move into a senior housing facility is not available for the US as a whole, so instead, to estimate the impact of COVID on move-in behavior, proxy data will be used. This domain looks to operating data from the largest provider of senior housing in the United States, Brookdale Senior Living, which operates over 62,000 beds in 41 US states (Brookdale Senior Living INC, 2021). Throughout the pandemic, Brookdale has reported its overall occupancy percentage across its portfolio, which is assumed to be representative of the entire US due to the scale and the presence of its operations in the US.

Model:

The following model structure (Figure 41) was introduced to represent the basic structure of the Senior Housing Industry. The model is a very basic pipeline model showing how leads are generated, and in turn move in to represent occupancy in the facility. Occupancy is the primary operating metric and is a stock value, while demand and the decision to move in represents a flow value. In addition to COVID's effect on move-ins (represented by the red variable), there was also a strong impact of COVID on move-outs in the US senior housing industry due to fatalities. It is estimated that up to 34% of all COVID deaths that have occurred in the US occurred in senior housing facilities (The New York Times, 2021).

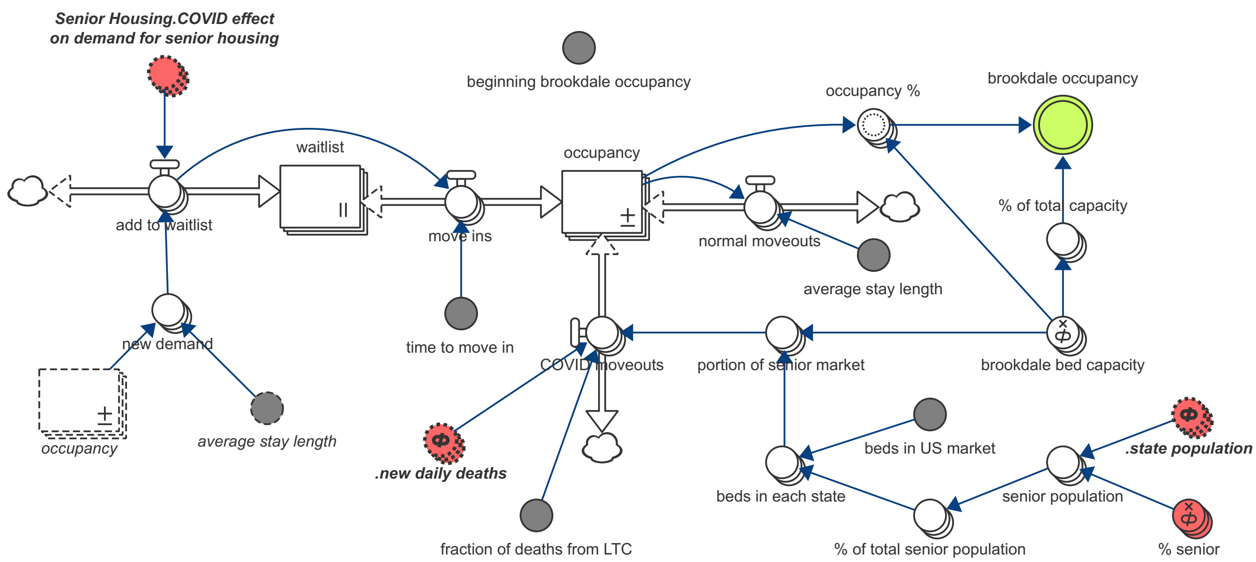


Figure 41: Stock and Flow diagram of the Senior Housing Industry sub-model

Calibration:

This domain was subject to the standard calibration procedure as described in the calibration section and Appendix C; no modifications were made to the standard procedure other than that the model was calibrated from time 0 – 456 due to data only being available until this date.

Results:

In the results, the modeled occupancy of the senior housing industry is compared with the actual reported occupancy. In contrast with the other domains studied in this research, these results don't show the behavioral outcome relative to the pre-pandemic baseline; rather they show the true (modeled) occupancy percentage of senior housing homes given changes in move-in rates relative to the baseline. The graph to the left (Figure 42) shows what the generic model assumes as the change in move-ins from the baseline and then this is plugged into the industry model to produce the overall occupancy results as shown in Figure 43 below.

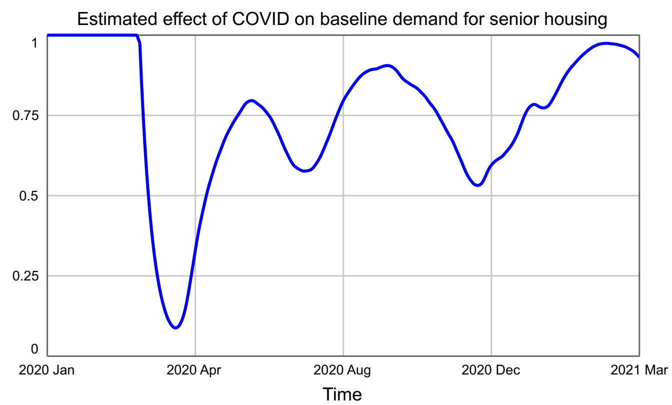


Figure 42: Effect of COVID on baseline move-ins to senior housing

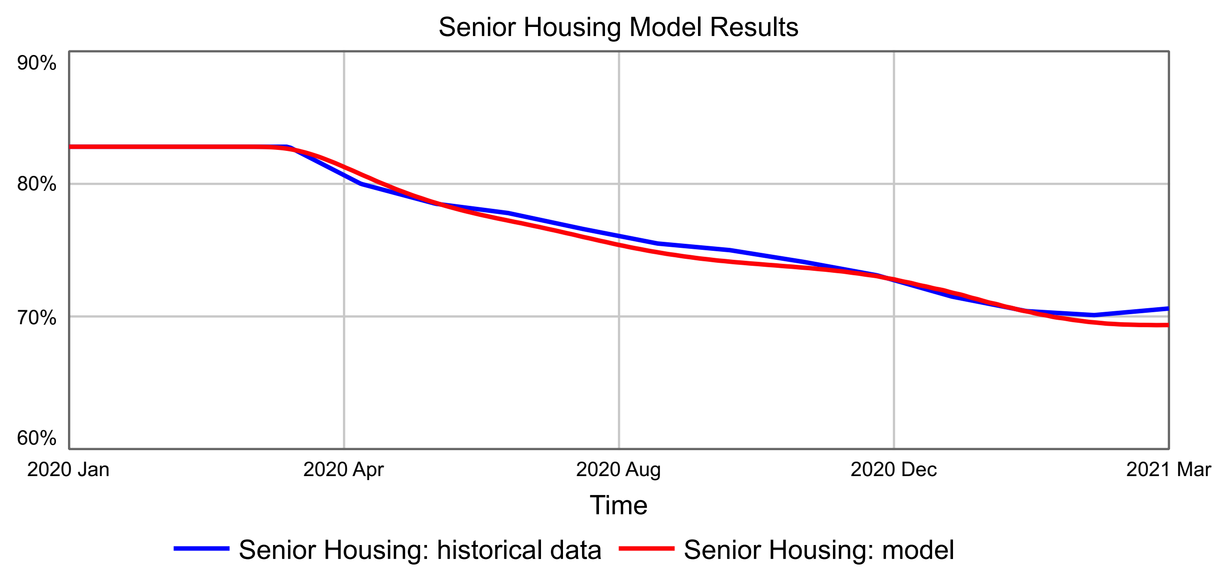


Figure 43: Historical data vs. simulated data when the model is applied to the Senior Housing industry.

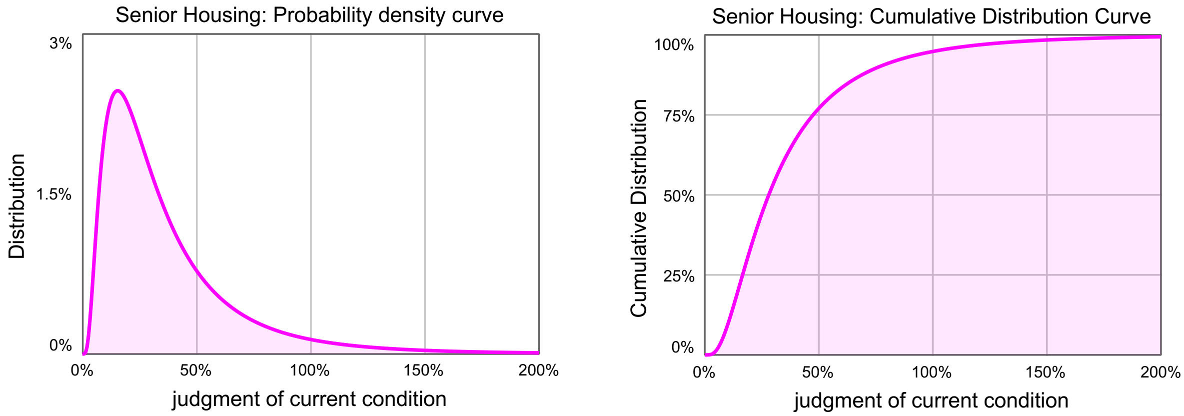


Figure 44: Probability Distribution and Cumulative Distribution of reaction to COVID in the Senior Housing industry.

Discussion:

This domain demonstrates the model components potential utility in being incorporated into larger models. In this case, to understand senior housing occupancy, one needs to take into account move-in patterns and move-out patterns. In this case both have been impacted by COVID, but the impact of COVID on move-in patterns is really just one piece of this particular analysis. So, this component can be used to estimate the move-in side, data about deaths can be used to estimate the impact on move-outs (due to deaths), and the basic industry structure can be brought in to tell the full story of how occupancy has been impacted over time due to COVID.

Analysis of All results

Contribution of calibration

The calibration process (discussed in the model description section of this paper) provides a twofold benefit to estimating and validating the parameters in this model:

1. As Oliva has suggested, the calibration can be used to test the structure of the model itself (Oliva, Model Calibration as a Testing Strategy, 2001). Given that reasonable parameterization of the model in different domains can reproduce the historically observed behavior, confidence can be gained that the structure does plausibly represent the real-world system, and that the structure is generally applicable, through different

parameterizations, to many different domains. In this case, the calibration of the model has not disproven the hypothesis put forth in this research.

2. Second, given confidence in the structure, the automated calibration routine used here can provide reasonable estimates of real-world variables that would otherwise be very difficult to estimate. The structure put forth in this project, when subjected to proper and reasonable calibration routines, can offer estimated values for the following parameters:
    a. **Time to update reference condition**- How fast is the process of people 'growing accustomed' to a certain level of COVID?
    b. **Exponent**- What would be a reasonable estimate for the power law relationship between the objective number of cases and the 'sensation magnitude' produced by those cases? (Slovic, 2007); (Stevens, 1986)
    c. **Effect of judgment of indicated behavior** (or the reaction distribution)- For the possible range of severity of the COVID situation at any given time, what is the estimated distribution of reactions in a given population for a given domain. By calibrating the mean and the standard deviation of the log-normal distribution used in each domain, the model can reasonably estimate the shape of this distribution.

Significance of estimated response distribution curves

The variability among the distribution curves in each domain provides interesting insight into how behavior is effected by the same COVID situation in different domains. The shape of the distribution curves (shown in Figure 45 on the next page) can offer several insights, including:

1. The general range of sensitivity of a population's behavior in a particular domain to the current level of COVID.
2. The proportion of the population willing to re-engage in normal decision making when the judgment value is one
3. Identify a potential long-term decrease in behavior activity as long as COVID remains a current issue
4. Identify potential thresholds below which any further decline in the COVID situation would cause increasingly decreased levels of behavior.

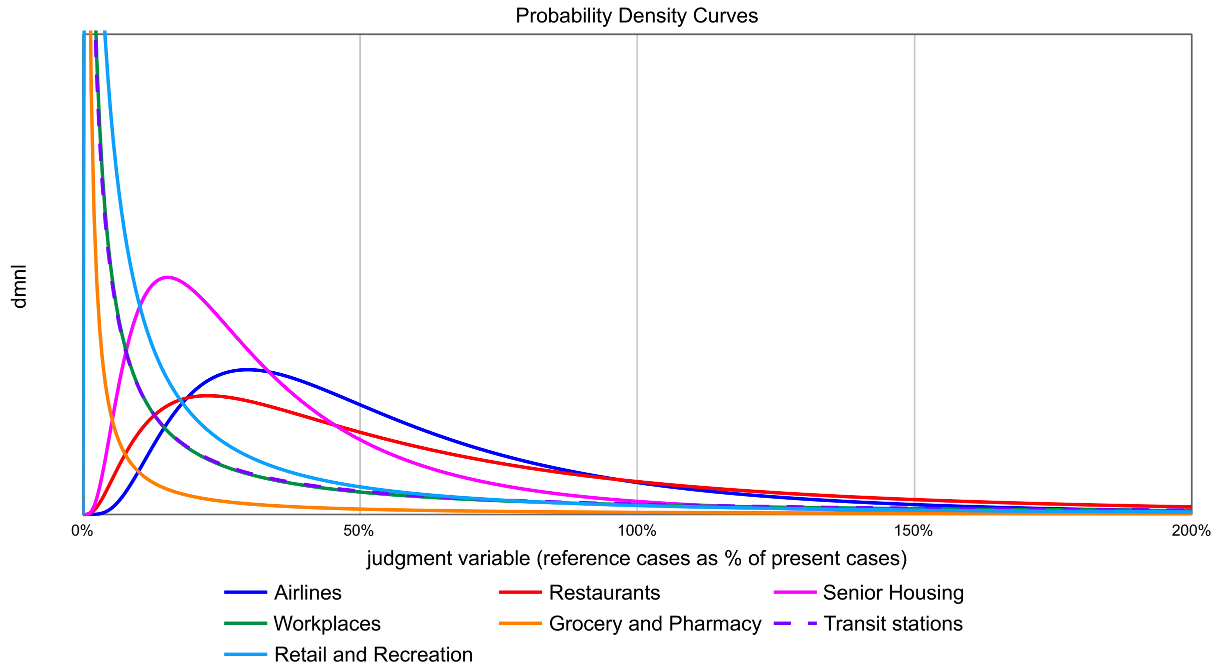


Figure 45: The estimated distribution curves for each of the seven domains studied in this model.

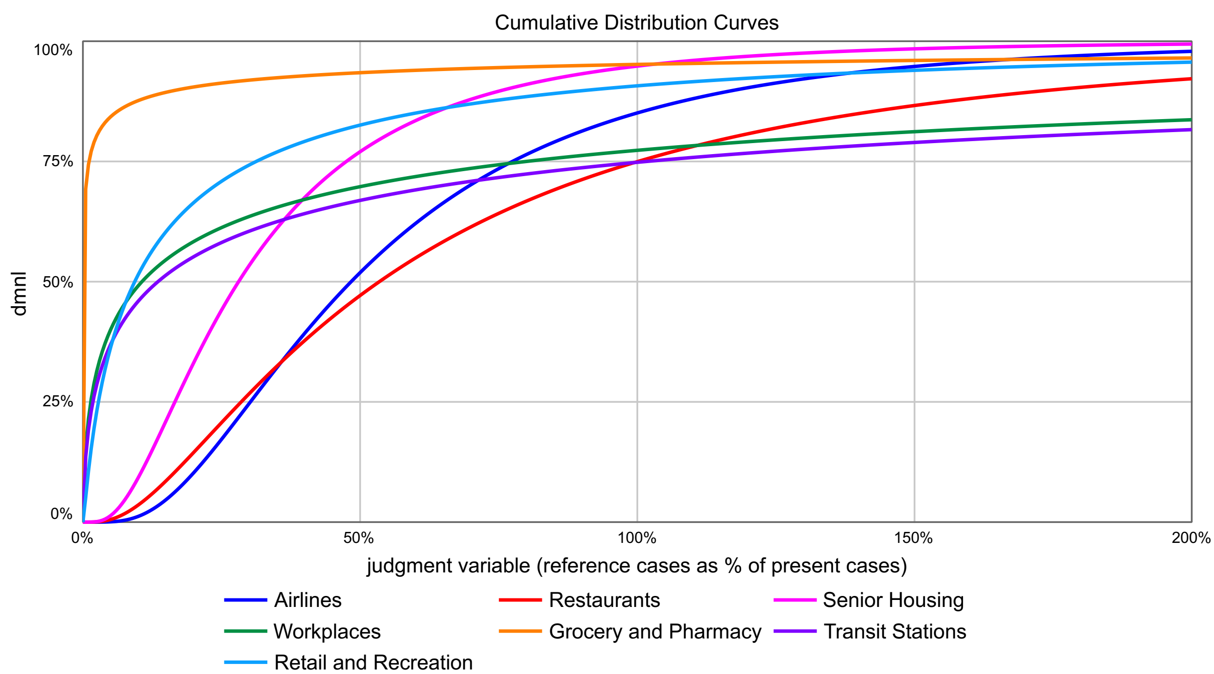


Figure 46: The estimated cumulative distribution curves for each of the seven domains studied in this model.

Comparing the shapes of the distribution curves of the various domain introduces some interesting characteristics of the domains. At one extreme, there is the curve produced by the grocery and pharmacy domain, which indicates that within a wide range of possible COVID scenarios, there will be little change in demand. It is only as the judgment variable approaches 0 (the worst possible case scenario) that people would begin to dramatically alter their behavior patterns. On the other end of the spectrum would be restaurants, whose curve suggests that even at a judgment value of 1, it is only expected that roughly 75% of people would be dining-out normally. As the situation improves from here, modest gains would be expected; however, as the situation deteriorates, significant reductions of dining out is to be expected until a point at which there would be almost no dining out at all if the situation were bad enough (perhaps around 10% to 20%). Therefore, people's decision to dine-out is extremely sensitive to different [reasonably expected] levels of COVID. In order to better understand the meaning of the distribution curves, below describes the general characteristics of the curves and what real-world insights they may hold

Pictured below are examples of four different probability density and cumulative probability curves produced with different combinations of mean and standard deviation values.

- The **mean value** (ranges from -3.59 to -0.626 among the domains studied here) generally indicates the average impact that COVID has on decreasing behavior levels in a particular domain. . A higher value (moving closer toward, or past 0) indicates that a lower proportion of the population would engage in 'normal' behavior at any given level of COVID; a lower value will indicate the opposite. A sufficiently low value would indicate that there would be no substantial impact of COVID on a particular behavior whereas a sufficiently high value would indicate that the presence of COVID has substantially eliminated a particular behavior.
- The **standard deviation value** (ranges from 0.698 to 2.99 among the domains studied here) generally indicates the range of variability among the population's response to levels of COVID. Low values for standard deviation imply that the population acts more in unison, so the behavior levels become more sensitive to the COVID situation around the mean; high values imply a wider distribution of behaviors, so the behavior changes in a smoother manner as the COVID situation changes. An extreme value of 0 for the standard deviation would indicate that the entire population changes its behavior in unison, whereas a sufficiently high value would indicate that all behavioral responses are observable at all levels of COVID.

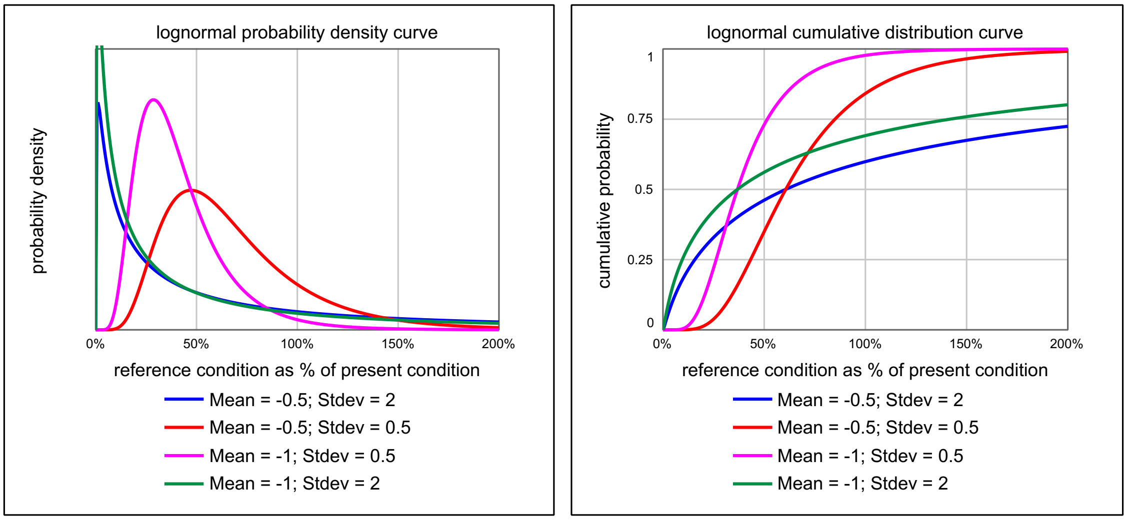


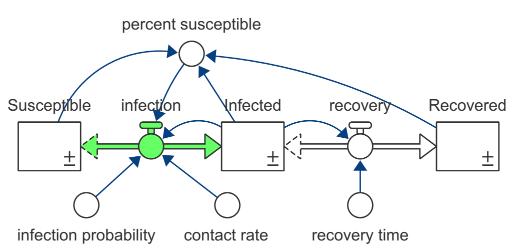
Figure 47: Examples of four different log-normal distributions

Table 5: Profiles of four types of log-normal distribution curves

	Low Mean Value	High Mean Value
High Standard Deviation Value	A distribution with a low mean and high standard deviation indicates that society predominantly retains its normal behavior patterns regardless of the COVID situation, the high standard deviation creates the conditions whereby behavior would only drop substantially if the situation got especially severe; yet will only return to fully normal after the pandemic is fully over. Examples here include necessary domains, such as grocery.	A high mean and standard deviation indicates that on average the population is more reluctant to re-engage in normal behavior, regardless of the current situation, however due to the high level of variability, there is a relatively smooth change in behavior as COVID changes. Examples here include necessary, yet flexible domains, such as workplaces. Generally, going to work is not dependent on COVID, though if many places are allowing remote work, it could lower the average mobility in workplaces.
Low Standard Deviation Value	A low mean and low standard distribution would produce a very interesting behavior pattern whereby the population acts in unison around one particular level of COVID. No examples of this were found in this research project and it seems unlikely that such a scenario would exist in the US. It is possible that in a country such as China, with high levels social conformity and extremely low tolerance for COVID, that such a pattern could exist.	A high mean value and low standard deviation indicates that for a population to engage in normal behavior, the situation has to be fairly good. Additionally, there is less variation among the population in their response, so there is a higher elasticity between the COVID situation and behavior. Such a distribution is more likely to resemble a normal distribution, therefore producing an *S*-shaped cumulative distribution curve. Examples here likely include discretionary domains, such as restaurants and airlines as we have seen in this research.

Behavioral response estimated by the model under various hypothetical COVID scenarios: For the sake of better understanding the model structure and how behavioral responses change in response to the COVID situation, this section will analyze the model's behavior given several different, hypothetical COVID scenarios. The reason for this hypothetical testing is that it can be difficult to parse out the actual trends in behavior patterns given the messy, organic development of the true COVID situation; therefore, some simple hypothetical situations are input to the model so that the resulting behavior patterns can be clearly identified. Seven different hypothetical scenarios were tested and are summarized in Table 6 and Figure 49 below.

Table 6: Extreme Conditions of COVID input

Run	Test Input
Run 1	STEP(1000, 10)-STEP(1000, 310)
Run 2	STEP(10000, 10)-STEP(10000, 310)
Run 3	RAMP(100, 10)+RAMP(-200, 310)
Run 4	10000+SINWAVE(10000, 100)
Run 5	STEP(25000, 10)+RAMP(-100, 10, 260)
Run 6	10^(TIME/100)
Run 7	Infection curve (from a basic SIR model)  **Figure 48: SIR model to create an infection rate test input**

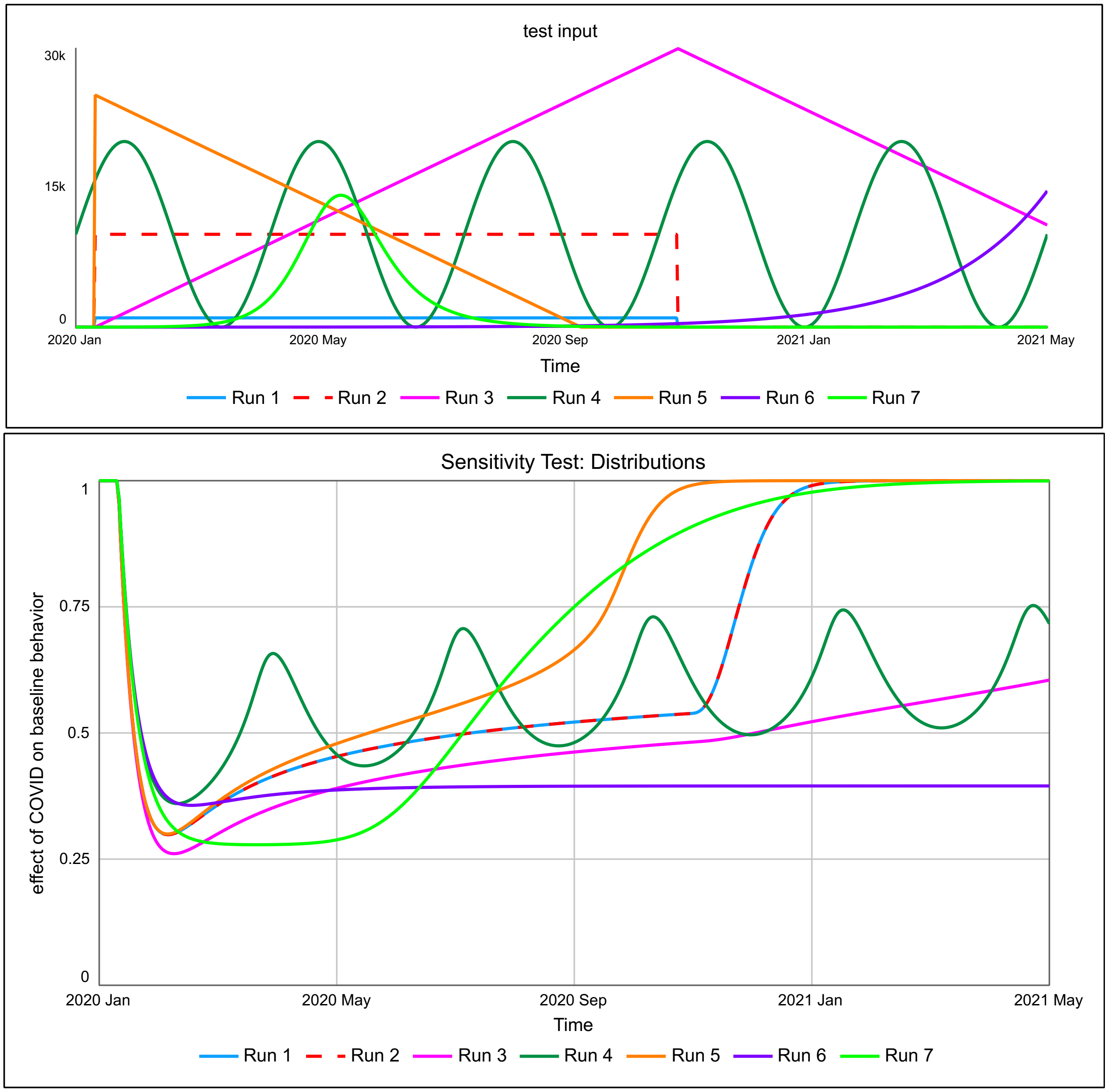


Figure 49: Extreme Conditions test of COVID input

There are a handful of interesting insights we gain about the model by subjecting it to these hypothetical COVID developments:

1. It is not the scale of cases that counts in this case, but rather the shape and speed of the development.

For instance, consider Run 1 and Run 2. Both runs assume COVID cases immediately jump up on day 10, remain steady at that level for 300 days and then jump back down to 0. The difference in each case is that the scale by which cases jump up under each scenario is different by a factor of 10. This makes sense mathematically given that the judgment is ultimately determined as a ratio of two values that grow by an exponential delay process. So, all else being equal, inputs on two different scales will produce the same ratio (reference over perceived present). Does this make sense realistically though? To some extent yes, and to some extent no. It is worth remembering that a fundamental feature of the COVID pandemic is its identification as a global pandemic. Therefore, COVID carries with it an extreme weight of importance that does indeed cause people to react drastically even to a few cases (as we saw in the beginning of the pandemic). The declaration by the WHO of COVID as a global pandemic represented a paradigm shift in how people and governments viewed the news about COVID; this is why the 'shutdown begins' variable must be included in the model, since there wasn't large scale impact to behavior in the US until after the declaration of a global pandemic or state of emergency was declared. After this point, the reaction seems to be independent of the number of cases. In fact, countries the world over generally reacted with tight lockdowns and restrictions, regardless of the actual severity of the spread of the virus in that country.

2. The adjustment over time of the reference condition causes a reduction in response over time, all else held equal.

There is a reduction in the impact of COVID over time due to the impact of the reference condition. This demonstrates a growing level of comfortability with some amount of COVID over time no matter how the pandemic develops. In Run 4, even with a steady fluctuation in the number of infections, each progressive wave prompts a lesser impact to behavior. Interestingly, in Run 3, even a linearly increasing number of cases still results in a reduced response over time. Only in Run 6, which assumes an exponentially increasing number of infections, is there not an effect of decreasing behavioral impact; instead, the behavior just remains steadily low. So, essentially the model produces no behavior pattern that can decrease further than the initial decrease at the outset of the pandemic.

3. A change in the exponent variable effects the response according to the scale of the pandemic at any given time.

The exponent refers to Steven's power law, in other words, the effect of our own understanding of the case numbers being distorted by the incomprehensibly large numbers involved. The effect of this must be demonstrated with a sensitivity run that compares the results of different scenarios assuming different exponents. Figure 50 to the right shows the result of the sensitivity analysis using the US actual cases as the input. Exponents ranging incrementally from 0.25 (Run 1) to 0.75 (Run 11) were used to generate these results.

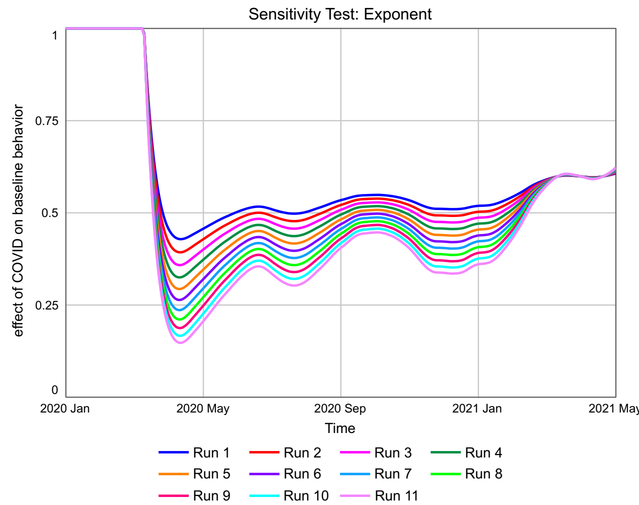


Figure 50: Sensitivity analysis results: Exponent

While the exponent is not likely to change, it is interesting when considered in combination with point 2 above. A change in the exponent variable adjusts for the diminished response as the *scale* of the pandemic increases, while the reference condition adjusts for the diminished response *over time* as the pandemic carries on. As the exponent decreases, the impact of the pandemic on behavior lessens. In FIGURE above, the same situation can prompt a weak response (Run 1) or a strong response (Run 11) depending on the effect of this bias. Therefore, the primary cognitive mechanisms at play here effectively diminish the assessed severity both as it increases in scale and as it goes on in time. So, the point of strongest behavior impact happens right at the beginning of the pandemic before these cognitive effects begin to corrode its assessed severity.

Summary of parameters

This section discusses what differences among the domains might mean from a practical and theoretical standpoint. Table 7 below summarizes the parameter values used in each domain.

Table 7: Parameterizations and other adjustment of the model for each domain studied.

Domain	Mean	Stdev	Other adjustments to the model or calibration routine
Airlines	-0.726	0.698	*The adjustment times for demand were adjusted so that increases and decreases in demand happened with different delays.
Restaurants	-0.626	0.930	None
Workplaces	-2.24	2.99	None to the model, though a smoothed version of the data was used for calibration and the period of the holidays (from Thanksgiving through New Year's) was removed for calibration.
Retail and Recreation	-2.37	1.79	None to the model, though a smoothed version of the data was used for calibration.
Grocery and Pharmacy	-3.59	2.20	None to the model, though a smoothed version of the data was used for calibration.
Transit Stations	-2.00	2.99	None to the model, though a smoothed version of the data was used for calibration.
Senior Housing	-1.27	0.78	None to the generic structure, but in this case the calibrated values considered how the basic industry structure of the senior housing industry responds to changes in number of move-ins, which was determined by the generic model component developed in this research.

Implications of Findings

Overview

The primary hypothesis of this research project is that a general model can be developed to sufficiently explain the historically observed behavior patterns at an aggregate population level in a variety of different domains and geographies merely by accounting for the fundamental cognitive mechanisms governing how people perceive, understand, and respond to information about COVID.

After a thorough analysis of the model and its results when tested across various domains and geographies, the hypothesis is supported with a sufficient degree of confidence. A general model has been developed that can offer a causal explanation of how real-world behavior patterns in a variety of domains and geographies have emerged from some fundamental cognitive mechanisms governing how people perceive, understand, and respond to information about COVID. This model has suggested the cognitive mechanisms likely at play and demonstrated that they can plausibly explain how behavior patterns are influenced by COVID. This section will reflect on the practical and theoretical implications of the findings from this model as well as review its limitations and the further research that can be done. After this the conclusions will summarize the answers to the original research questions posited in the introduction.

Practical and Theoretical Implications:

This research rests on the assumption that there are a handful of basic cognitive processes that people go through to update their behavior and decisions in light of the current pandemic situation. A model that brings together these processes could be used to understand in general terms how a populations perceptions, judgments, and reactions to the virus change as the pandemic situation continues to evolve. Given that the model utilizes general cognitive mechanisms as the means of determining how a behavior will change in response to a change in the COVID situation, it should then also work in general circumstances if it is to be held to be plausibly valid. Therefore, the model should be generally applicable and should be able to explain how people in different demographic groups, in different geographic locations update their behavior in a variety of different domains or situations as a result of changes in COVID. Such a model will inevitably lump together many specific, real-world effects under the umbrella of just a few general effects, but this is appropriate for the purposes of this model and there are many practical and theoretical insights that can come from this model. The points below represent the most interesting findings from this research:

Simulate future Covid Scenarios

The model could be used to test how future developments of the COVID situation are likely to affect behavior. While assessing the predictive capacity of the model was not an objective of this research, if the structure is held to be valid, it should produce appropriate output for future scenarios. It could, for example, estimate how big an additional wave would need to be to cause behavior to drop to a certain level. This could also be of use to business managers as they try to estimate the range of possible outcomes for how COVID could continue to impact their business.

Implications for policy makers

Policy makers can benefit from the insights of this model as they craft policies to limit the spread of the virus and its impact to the economy. This model demonstrates that the best opportunity for intervention occurs right at the beginning of a pandemic, as this is where people's responses are most sensitive to the situation. From the testing of hypothetical COVID developments, it was found that it should not be expected, that behavior will change more dramatically than the beginning of the pandemic.

Estimation of the distribution curves, Steven's exponent, and time to update reference.

While it is very plausible that the cognitive mechanisms identified in this research projects are at play, quantifying those phenomena can be quite difficult. While this project does not claim to offer precise values for these numbers, it does offer a reasonable basis for plausibly estimating their values. The estimation of the distribution curves is a particularly interesting insight as it quantifies in a distribution curve the differences in reaction from domain to domain. In this case, insights can be gained for how a domain influences behavior (e.g., Is the domain necessary or discretionary and is it flexible or inflexible?); and insights can be gained for how a population is likely to respond to COVID in that situation (e.g., Are there threshold levels where behavior becomes very sensitive to COVID? Is there a more or less permanent drop in behavior levels as long as COVID is a prevalent issue?) Additionally, the distribution curves could be used in and of themselves in other research and despite that they were developed indirectly through the models structure, they could be estimated and corroborated in future studies by means of empirical testing, similarly to the research presented in the literature review (see (Franzen & Wöhner, 2021; Dryhurst, et al., 2020))

Use in other modeling projects

An important practical implication of this research is its potential to be incorporated into other research projects. This point is given its own section due to the depth in which it will be discussed in comparison to the other points listed above. A stated objective of this project was to build a *generally applicable* model component that could be plugged into other more comprehensive models analyzing specific problems. An example of this potential is demonstrated in the 'Senior Housing' domain of this project. Another example would be for domains whereby the baseline level of behavior is suspected to be changing over time. In this model, it is assumed that the baseline level of behavior remains fixed at its pre-pandemic level; however, the baseline in many domains is likely undergoing a dramatic structural transformation that will permanently shift what is considered to be 'normal'. Overlaying this model, which tracks the short-term responses to COVID with a model which estimates the long-term change in the baseline may produce more compelling insights. In other words, this model could potentially be used to help parse out permanent shifts in behavior modes from those directly caused by COVID. Additionally, there may be additional feedback loops that can be drawn through extended model structures, whereby the other model(s) could, for instance, be used to estimate changes in the future COVID situation based on how people behave or estimate how some of the other parameter values might change over time in response to other effects. Figure 51 below demonstrates how this model could be incorporated into, extended by, or otherwise enhanced by combining it with additional model structure.

Therefore, this model could be copied and pasted into other models, though it will be crucial to make certain modifications and undertake a thoughtful assessment and thorough testing of its usefulness, validity, and impact when combined with other model structure. Figure 51 and following steps outline how it can be incorporated into other models.

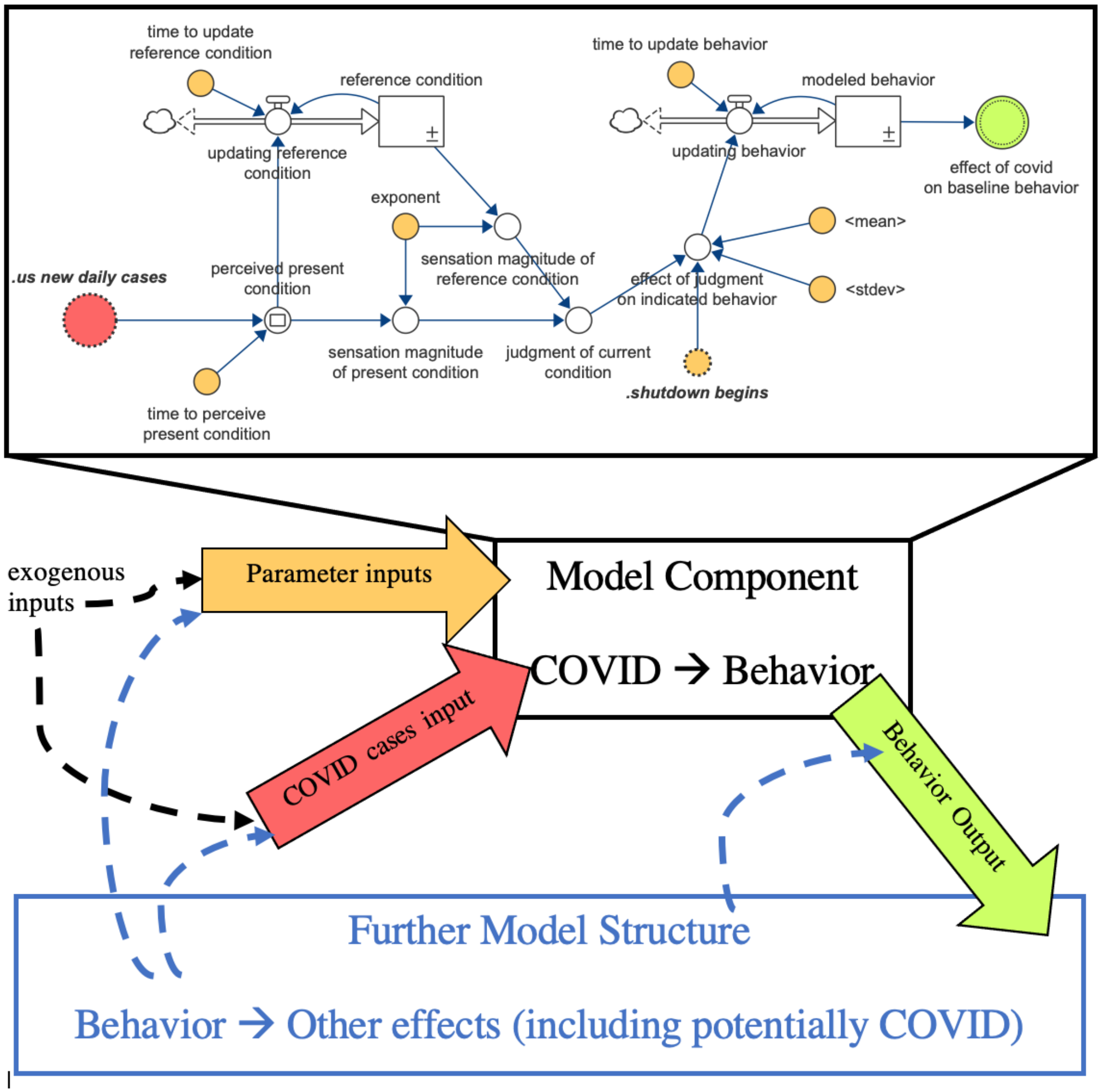


Figure 51: Diagram showing the potential incorporation of this model into a larger model structure.

1. **Obtain the required inputs-** The key input to this component is daily reported COVID cases for a particular geographic region under consideration. Either historical data, or an exogenous or endogenous estimate for future COVID cases should be plugged in as the input to this model.
2. **Calibrate the parameters-** Until further experimental and empirical research is done to validate the parameters used in this model, the values used in this model represent the

best estimates for what they are likely to be (these values include all exogenous parameters except the parameters describing the distribution curve, which is known to vary from domain to domain). The parameters describing the distribution curve will need to be calibrated to the particular case under research. Ideally, one would have a historical reference mode of behavior to which this model could be calibrated. If so, one could follow the calibration procedures described in Appendix C for direction on how to estimate the distribution curves.

3. **Plug the output of this model (behavior level) into another model sector-** Once the COVID input is determined and parameters are estimated, the resulting behavior pattern can be modeled, which can be useful input into other model structures (as demonstrated in the Senior Housing example).
4. **Analyze, Validate, and Test-** Of course, there will need to be extensive analysis, validation, and testing of this model structure as it is plugged into other models. This should be done for this individual component after it is adapted, calibrated, and parameterized according to the specific domain in which it is used, and this should be done to the model as a whole to be sure it is behaving as expected and producing reasonable output. Additionally, this model should only be used with a full understanding of its limitations, which are described in the following section.
5.

Model Limitations:

While the model can offer some interesting insights, its limitations and any reservations as to its applicability should be fully disclosed. The primary limitations are summarized below:

- *The model analyzes only one effect, where several effects are likely at play*
  This model uses COVID cases as an input and processes this input through one cognitive 'pathway' to produce the behavioral output. This is certainly a simplification of the real-world processes that are going on. The reality is that multiple inputs are being considered (COVID cases, deaths, hospitalizations, personal experience, among many others) and people undergo several different cognitive processes to shape their behavior to the situation. For instance, the behavioral chain of events presented in Gkini's, model shows very explicitly the risk assessment processes going on in people's minds (Gkini, 2020).

On the other hand, this model wraps all such considerations into an assumed distribution of outcomes. There is certainly a benefit to modeling such processes more explicitly than is done here, and it would lead to a more in-depth structural understanding of the decision-making process. Additionally, because this model only analyzes one effect, it is possible (or likely) that the model is misattributing a certain amount of the effect to this cognitive process, when in reality there may be a change in the baseline (as discussed above) that is fundamentally shifting the true behavior patterns over time. For example, government restrictions have been seen to plausibly follow the same patterns that populations follow (Djulbegovic B, 2020 Oct), there is still an important distinction between the organic response of a population versus the imposed restrictions that force a certain response. The restaurant sector provides an interesting example of this in that the model expects low, but not zero, dining in during the worst parts of the pandemic. In this case, government restrictions certainly lowered the behavior of dining-out beyond what some people may have wanted. In other words, this model mostly gets at the organic, demand side effects of COVID, when there are also supply-side effects that should be accounted for as well.

- *Does not mathematically allow for a transition between lower or higher demand.*
  From a mathematical standpoint, this model does not allow for analysis of any domains for which behavior has increased from the baseline. Naturally, this means that the model cannot also explain behavior patterns that have been observed to increase and decrease from the baseline (as is seen in certain individual states in some of the mobility data used in this project (see Appendix D for additional information).
- *Is the model ultimately a black box?*
  There is a possibility that this model does not produce true structural understanding and is more functioning as a black box model. Townsend et al. describe a common phenomenon of model *mimicry* whereby a model is able to produce the historical behavior, and a plausible structural explanation is provided, yet the effects produced by the model (even if they are correct) are due to fundamentally different processes than those posited in the hypothesis (Townsend, Wenger, & Houpt, 2018). This is certainly not the ideal outcome of a system dynamics model, so much additional empirical testing should be conducted to

further validate that this model does in fact produce the right behavior *for the right reasons*, as Oliva asserts these models must do (Oliva, 2001).

Future Research Opportunities:

As mentioned throughout this paper, a huge opportunity exists for further application and testing of this model. It should be applied to more domains, more geographic regions (both to different countries, and to different scales of regions), and should be included as a component in more specific and complex models. If the model continues to hold up under a variety of different applications, then this would both extend the usefulness and the validity of the model. Additionally, as the cognitive processes described in this model are not fundamentally processes belonging only to behavior under a pandemic, the model could be useful in other types of large-scale, ongoing disaster situations whereby people's behavior must be constantly adapted due to the conditions of the prevailing crisis. Perhaps additional examples of such crises could be identified, and this model adapted to that situation.

There is potential to use this research to not only quantify differences from one domain to another, but to also quantify differences from one geographic region to another. For instance, if a substantial drop in demand is observed in a particular industry, it may not be so clear to what extent the drop was caused by imposed government restrictions, genuine human response, or a combination of both. Being that the purpose of this model has been to estimate the aggregate behavioral response of a population to COVID, it may not be so important to consider these two effects separately, especially if it can be shown that aggregate individual response and government response are subject to the same types of response mechanisms. However, we should expect that the output of this model may certainly produce biased results if it is to, for instance, ignore the effects that a particularly strong or weak lockdown may have on aggregate response within a state. Also, while this model will not be parameterized to specific geographic locations, it could reasonably follow that specific geographic parameterization may be appropriate and capture the differences in individual and government response from one region to another, say for example differences in very liberal versus very conservative states (Akovall & Yilmaz, 2020).

Finally, future research should include specific, empirical testing of the assumptions made in this model. By conducting surveys or other studies, it may be possible to corroborate the assumptions made in this model, thus building additional confidence in its usefulness and further extending the theories underlying the cognitive processes used in this model. For instance, further investigation and testing could be undertake to more precisely estimate Steven's exponent as it pertains to COVID. Additionally, the shapes of the distribution curves hold interesting potential for further exploration into how they can be used to categorize differences from domain to domain (or as mentioned above, from region to region), and how they can be extended into other situations, for instance estimation of risk perception distribution in other areas outside of COVID.

Conclusion

This research project has offered an explanation as to how the COVID pandemic has impacted behavior patterns in a variety of domains and geographic regions within the US. After a thorough review of the cognitive mechanisms most likely responsible for shaping people's behavior, as well as other leading theories about what might be impacting behavior patterns in the midst of COVID, a simulation model was developed to replicate these cognitive mechanisms and other theories to test if they can explain the real-world behavior patterns that have emerged from COVID. The model developed in this project shows how behavior in several domains changes as a direct result of changes in the COVID situation. The model is able to quantify the effect of the cognitive processes that shape a population's response to incoming news about COVID and offers valuable theoretical and practical implications for business leaders, policy makers, and others looking to better understand how COVID is impacting people's behavior and decision making. Furthermore, the model component developed here can be plugged into other models that are studying more specific effects of COVID on other areas of society and require a model structure that can translate the COVID situation into some change in behavior.

To better summarize the findings of this research in an organized manner, the original research questions listed in the introduction will be revisited and answered below:

1. *How does a populations behavior change on the aggregate level in response to changes in the pandemic?*

   This project has demonstrated that behavior patterns can be reasonably estimated given the news about COVID cases.

   a. *Can a generic simulation model be developed and utilized that approximates for a variety of domains how these behavior patterns result from changes in COVID?*

      The behavioral results of the model developed in this research suggest that a generic model can be used to show how behavior in a variety of different domains is impacted by COVID. The model, under different parameterizations, is able to reproduce a wide variety of behavior modes across several different types of domains.

b. *Can such a model provide a better understanding of how the level of behavior could develop under different, hypothetical COVID scenarios?*

   After the model had been tested, calibrated, and validated using the historical COVID cases (both at the national and state levels), hypothetical COVID scenarios were passed into the model to gain better understanding as to how behavior adapts overtime under a variety of different situations (including exponential growth, cycles, and linear, steady state developments of different scales and directions. Doing this revealed a clear effect of people getting used to COVID over time, thus offering a theoretical, model-based validation of the 'pandemic fatigue' phenomenon. Additionally, it revealed what kinds of COVID developments would cause certain behavior patterns, such as exponential growth causing a steady level of behavior.

c. *What are the implications of this analysis for policy-makers or industry leaders as they create short and mid-term strategies to combat the effects of COVID?*

   The model produces interesting insights for public policy makers and industry leaders as they engage in strategic planning in the midst of COVID. Based on the results of the model, we can expect a people to grow more and more comfortable with COVID and as a result, continue to engage in more normal behavior patterns as time goes on *regardless of if the situation continues to worsen overall*. Additionally, the model can be calibrated to specific domains to allow for scenario testing of future potential COIVD developments and their expected impact on behaviors. Public health officials could incorporate this model into existing COIVD projection models to estimate how behaviors in other domains outside of immediate health behaviors could impact the spread of the infection. Finally, it shows that when future pandemics or crises come, the time of greatest leverages is in the initial stages of the pandemic, so such opportunities for action should not be wasted in the future.

2. *Are there specific cognitive mechanisms or heuristics that can be used to offer a causal explanation of how people's behavior changes in response to the COVID pandemic?*

This project has shown that modeling some of the relevant cognitive mechanisms and heuristics is capable of offering a causal explanation of the processes that shape people's response to COVID.

   a. *Can such cognitive mechanisms be adequately represented in a simulation model?*

      Several cognitive mechanisms have been successfully brought together into this model, including perception, anchoring and habituation, Steven's power law of psychophysics, and the estimated distribution of populations risk assessment and behavioral outcomes given a situation. Each of these have been mathematically represented in a reasonable and theoretically sound manner.

   b. *Can a populations behavioral response be sufficiently explained by only considering the cognitive mechanisms that shape a response given the current information about the pandemic?*

      A handful of relevant cognitive mechanisms have been identified and unified into a causal model that is capable of reproducing the observed behavior patterns. Of course, there are several known factors that have fallen outside of the boundary of this model (and some simple and obvious ones have been included), by accounting for how a population perceives, understands, and acts on information, and by accounting for differences from domain to domain, these cognitive mechanisms can explain a significant portion of the responses that have been witnessed throughout the pandemic. It is reasonable to expect that more detailed models that bring in additional known factors would further improve the behavioral fit and estimations of the real-world distribution curves.

3. *Are there meaningful differences in a population's behavioral response in different domains?*

   The model has revealed that a generic structure can be applied to a wide variety of domains despite the known differences among those domains.

   a. *Can such differences be quantified in a meaningful way?*

      The primary difference that has been quantifiably singled out among the domains is in the way that people respond to the COVID situation. While it is reasonable to expect that in all domain people will perceive the situation the same, of course there are differences among the domains in terms of how necessary or discretionary the domain is, as well as how flexible or inflexible people are in adapting their behavior in that domain. These differences can be adequately reflected in the shape of the log-normal distribution used to describe a populations expected response in a domain under different COVID situations. By calibrating each domain with a distribution curve characterized by a specific mean and standard deviation, the same model structure is able to replicate behavior under many very different domains.

b. *Can such a quantification also be used to offer insights regarding people's cognitive mechanisms under different situation?*
   The mean and standard deviation values that characterize each domains behavioral distributions have significant meaning in and of themselves as to how a population responds in that domain. It has been shown that necessary and largely inflexible domains such as grocery and pharmacy mobility is characterized by a high mean and low standard deviation; likewise, domains with a low mean and high standard deviation are typically very flexible and discretionary domains, such as restaurants and airlines.
c. *Could such a model be utilized in crisis situations beyond the covid pandemic?*
   While not explicitly proven in this research project, there is good reason to believe that the model developed here could have application beyond this COVID pandemic. Since the model reflects general cognitive processes rather than anything specific to COVID (or even a pandemic for that matter), it is reasonable to expect that the model could be adapted and useful in estimating potential population-wide behavioral responses to other large-scale, ongoing, and societally transformative crisis situations.

This concludes the findings of this research project. While COVID will likely come to represent a paradigm shift in our expectations of what it means to live in a global society, it will not likely be the last such shift in this generation. The problems facing the world are becoming much more global and complex; we must be able to understand how people will react to these problems as they emerge and evolve if we are to have a hope of managing and overcoming these problems of ever greater scale and frequency in our collective future. I hope this research has taken one small step forward toward a greater understanding of this and that it inspires others to study further. Thank you for taking the time to read this paper.

Bibliography

Akovall, U., & Yilmaz, K. (2020, December 10). *Polarised pandemic response and Covid-19 connectedness across US states*. Retrieved from voxeu.org: https://voxeu.org/article/polarised-pandemic-response-and-covid-19-connectedness-across-us-states

American Psychological Association. (n.d.). *APA Dictionary of Psychology*. Retrieved from dictionary.apa.org: https://dictionary.apa.org/affect

Anaki, D., & Sergey, J. (n.d.). Predicting health behavior in response to the coronavirus disease (COVID-19): Worldwide survey results from early March 2020. *PLoS One, 16*(1).

Barlas, Y. (1996). Formal Aspects of Model Validity and Validation in System Dynamics. *System Dynamics Review, 12*(3), 183-210.

Breeding, B. (2021, Januеary). *The Cost of Long-Term Care and How Long It's Needed*. Retrieved from buenavidaestates.org: https://www.buenavidaestates.org/what-long-term-care-costs-and-how-long-you-need-it/

Brookdale Senior Living. (2021, March). *Brookdale Reports March 2021 Occupancy*. Retrieved from brookdaleinvestors.com: https://s26.q4cdn.com/858530099/files/doc_news/2021/04/Brookdale-Reports-Mar-2021-Occupancy.pdf

Brookdale Senior Living INC. (2021, March). *10-K filing for year ended December 31, 2020 for BKD*. Retrieved from sec.gov: https://www.sec.gov/ix?doc=/Archives/edgar/data/1332349/000133234921000045/bkd-20201231.htm

Campos-Mercade, P., Meier, A. M., Schneider, F. H., & Wengström, E. (2021, March). Prosociality predicts health behaviors during the COVID-19 pandemic. *Journal of Public Economics, 195*.

Constantin, M., Saxon, S., & Yu, J. (2020, August). *Reimagining the $9 Trillion tourism economy: What will it take?* Retrieved from Mckinsey.com: mckinsey.com/~/media/McKinsey/Industries/Travel%20Transport%20and%20Logistics/Our%20Insights/Reimagining%20the%209%20trillion%20tourism%20economy%20what%20will%20it%20take/Reimagining-the-9-trillion-tourism-economy_what-will-it-take-vF.pdf

Crabtree, S. (2020, October 19). *Americans' Social Distancing Habits Have Tapered Since July*. Retrieved from Gallup: https://news.gallup.com/poll/322064/americans-social-distancing-habits-tapered-july.aspx

Davis, D. N. (2008, March). Linking perception and action through motivation and affect. *Journal of Experimental & Theoretical Artificial Intelligence, 20*(1), 37-60.

de Gooyert, V. (2018). Developing dynamic organizational theories; three system dynamics based research strategies. *Quality and Quantity, 53*, 653-666.

Djulbegovic B, W. D. (2020 Oct). Evaluation of the U.S. governors' decision when to issue stay-at-home orders. *Journal of Evaluation in Clinical Practice. 2020 Oct;26(5).*

Dryhurst, S., Schneider, C. R., Kerr, J., Freeman, A. L., Recchia, G., van der Bles, A., . . . van der Linden, S. (2020, May 5). Risk perceptions of COVID-19 around the world. *Journal of Risk Research, 23*(7-8 (Covid Special Issue)), 994-1006.

Dyer, J., & Blas, K. (2020). Public risk perception and emotion on Twitter during the Covid-19 pandemic. *Applied Network Science 5.*

Forrester, J. W., & Senge, P. (1980). Tests for Building Confidence in System Dynamics Models.

Franzen, A., & Wöhner, F. (2021). Coronavirus risk perception and compliance with social distancing measures in a sample of young adults: Evidence from Switzerland. *PLoS ONE, 16*(2).

Funk, S., Salathé, M., & Jansen, V. A. (2010, May 26). Modelling the influence of human behaviour on the spread of infectious diseases: a review. *Journal of the Royal Society Interface, 7*(50), https://doi.org/10.1098/rsif.2010.0142.

Gkini, C. (2020, August 12). *Health Behaviour Theories and the Norwegian response to COVID-19: a System Dynamics Modeling approach*. Retrieved from bora.uib.no: https://hdl.handle.net/1956/23665

Google LLC. (n.d.). "*Google COVID-19 Community Mobility Reports*". Retrieved May 2021, from https://www.google.com/covid19/mobility/

Guszkowski, J. (2020, August). *4 TRENDS DEFINING DELIVERY DURING COVID-19*. Retrieved from https://www.restaurantbusinessonline.com/operations/4-trends-defining-delivery-during-covid-19

Hallas, L., Hatibie, A., Majumdar, S., Pyarali, M., & Hale, T. (2020, December). *Variation in US states' responses to COVID-19*. Retrieved May 2021, from https://www.bsg.ox.ac.uk/sites/default/files/2020-12/BSG-WP-2020-034-v2_0.pdf

Homer, J. (2020, March 21). *Jack Homer Vensim Covid models*. Retrieved from metasd.com: Retrieved from: https://metasd.com/2020/03/model-covid-19-us/

Hotl, S., & Mumbower, S. (2021, March). The impact of COVID-19 on domestic U.S. air travel operations and commercial airport service. *Transportation Research, Interdisciplinary Perspectives, 9*.

isee Systems . (2021). Stella and iThink Version 2.1.1 with Loops that Matter TM. *Software Documentation*. isee Systems.

Lehman, C. (2020, September 22). *Many Metrics to Measure COVID-19, Which are Best?* Retrieved from webmd.com: https://www.webmd.com/lung/news/20200922/many-metrics-to-measure-covid-19-which-are-best

Limpert, E., Stahel, W. A., & Abbt, M. (2001, May). Log-normal Distributions across the Sciences: Keys and Clues. *BioScience, 51*(5).

Luna-Reyes, L., & Anderson, D. L. (2004). Collecting and analyzing qualitative data for system dynamics: methods and models. *System Dynamics Review*, 271-296.

Manoogian III, J., & Benson, B. (2017). *Every Single Cognitive Bias in One Infographic*. Retrieved from visualcapitalist.com: https://www.visualcapitalist.com/every-single-cognitive-bias/

Monterey Institute. (n.d.). *Introduction to Natural and Common Logarithms*. Retrieved from http://www.montereyinstitute.org/courses/DevelopmentalMath/COURSE_TEXT2_RESOURCE/U18_L3_T1_text_final.html

NCAL National Center for Assisted Living. (2019). *Assisted Living: A Growing Aspect of Long Term Care*. Retrieved from ahcancal.org: https://www.ahcancal.org/Advocacy/IssueBriefs/NCAL_Factsheet_2019.pdf

O'hara, D. (2020, November). *Paul Slovic observes the 'psychic numbing' of COVID-19*. Retrieved from American Psychological Association: https://www.apa.org/members/content/covid-19-psychic-numbing

Oliva, R. (1995). *A Vensim® Module to Calculate Summary Statistics for Historical Fit*. Massachussetts Institute of Technology, Sloan School of Management. Massechussetts Institute of Technology.

Oliva, R. (2001). Model Calibration as a Testing Strategy. *European Journal of Operational Research*, 552-568.

OpenTable. (2021). *The restaurant industry in recovery*. Retrieved from OpenTable: https://www.opentable.com/state-of-industry

Patki, V., Banasal, A., & Basavaraja, G. V. (2020). COVID-19: The war against the invisible enemy. *Journal of Pediatric Critical Care, 7*(7), S1-S2.

Pearce, N., Vandenbroucke, J. P., VanderWeele, T. J., & Greenland, S. (2020). Accurate Statistics on COVID-19 Are Essential for Policy Guidance and Decisions. *American Journal of Public Health, 110*(7), 949-951.

Pew Research Center. (2020, June). *Republicans, Democrats Move Even Further Apart in Coronavirus Concerns*. Retrieved from pewresearch.org: https://www.pewresearch.org/politics/2020/06/25/republicans-democrats-move-even-further-apart-in-coronavirus-concerns/

PRB. (2018). *Which US States Have the Oldest Populations?* Retrieved from prb.org: https://www.prb.org/which-us-states-are-the-oldest/

Schoenberg, W. (2021, May 11). Head Developer, Isee Systems. (W. Noyes, Interviewer)

Selka, S., Bojan, B., Milan, O., Dušanka, M., Dejan, P., & Snežana, S. (2020). Daily Monitoring of Emotional Responses to the Coronavirus Pandemic in Serbia: A Citizen Science Approach. *Frontiers in Psychology*, 2133.

Shaver, L. (2020, November). *The Pandemic Continues to Challenge Senior Housing*. Retrieved from globest.com: https://www.globest.com/2020/11/10/the-pandemic-continues-to-challenge-senior-housing/?slreturn=20210427124620

Simon, H. A. (1990). Bounded Rationality. In M. M. Eatwell J., *Utility and Probability*. London: Palgrave, Macmillan.

Slovic, P. (2007, April). "If I look at the mass I will never act": Psychic numbing and genocide. *Judgement and Decision Making, 2*(2), 79-95.

Soofi, M., Najafi, F., & Karami-Matin, B. (2020). Using Insights from Behavioral Economics to Mitigate the Spread of COVID-19. *Applied Health Economics and Health Policy*, 345-350.

Sterman, J. (1986). Expectation Formation in Behavioral Simulation Models. *Behavioral Science Jornal of the Society for General Systems Research*, 190-211.

Sterman, J. (2000). *Business Dynamics: Systems Thinking and Modeling for a Complex World*. United States: Jeffrey J. Shelstad.

Sterman, J. D. (1984, Winter). Appropriate Summary Statistics for Evaluating the Historical Fit of System Dynamics Models. *Dynamica, 10*(2), 51-66.

Stevens, S. S. (1986). *Psychophysics: Introduction to its perceptual, neural, and social prospects*. New York: Transaction Publishers.

Sydhagen, P. B. (2017). *How Can We Distinguish Perception from Cognition? The Perceptual Adaptation Hypothesis*. Retrieved from duo.uio.no: https://www.duo.uio.no/bitstream/handle/10852/58422/Sydhagen.pdf?sequence=1&isAllowed=y

The New York Times. (2021, April 28). *Nearly One-Third of U.S. Coronavirus Deaths Are Linked to Nursing Homes*. Retrieved from nytimes.com: https://www.nytimes.com/interactive/2020/us/coronavirus-nursing-homes.html

Townsend, J. T., Wenger, M., & Houpt, J. (2018). Uncovering Mental Architecture and Related Mechanisms in Elementary Human Perception, Cognition, and Action. In *Stevens' Handbook of Experimental Psychology and Cognitive Neuroscience* (pp. 429-458). John Wiley & Sons, Inc.

U.S. state and local government responses to the COVID-19 pandemic. (2020). Retrieved from wikipedia.com: https://en.wikipedia.org/wiki/U.S._state_and_local_government_responses_to_the_COVID-19_pandemic

United States Census Bureau. (2019, July). *State Population Totals and Components of Change: 2010-2019*. Retrieved from census.gov: https://www.census.gov/data/tables/time-series/demo/popest/2010s-state-total.html

United States Center for Disease Control. (2021, April 30). *Travelers Prohibited from Entry to the United States*. Retrieved from cdc.gov: https://www.cdc.gov/coronavirus/2019-ncov/travelers/from-other-countries.html

United States Center for Disease Control. (2021). *United States COVID-19 Cases and Deaths by State over Time*. Retrieved from dev.scorata.com: https://dev.socrata.com/foundry/data.cdc.gov/9mfq-cb36

United States Transportation Security Administration. (2021). *TSA checkpoint travel numbers (current year(s) versus prior year/same weekday)*. Retrieved from https://www.tsa.gov/coronavirus/passenger-throughput

US Bureau of Transportation Statistics. (2020, June 11). *2019 Traffic Data for U.S. Airlines and Foreign Airlines U.S. Flights - Final, Full-Year*. Retrieved from bts.gov: https://www.bts.gov/newsroom/final-full-year-2019-traffic-data-us-airlines-and-foreign-airlines

Volker, T., Weiss-Cohen, L., Filkukova, P., & Ayton, P. (2021, February). *Cognitive Predictors of Precautionary Behavior During the COVID-19 Pandemic*. Retrieved from frontiersin.org: https://www.frontiersin.org/articles/10.3389/fpsyg.2021.589800/full

von Neumann, J., & Morgenstern, O. (1944). *Theory of games and economic behavior*. Princeton, NJ: Princeton University Press.

World Health Organization. (2020, March 11). Retrieved from who.int: https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020

Zwizlocki, J. J. (2009). *Sensory Neuroscience: Four Laws of Psychophysics*. Syracuse, NY: Springer.

Appendices

Appendix A: Model Documentation

Start Time: 0 (January 1, 2020)
End Time: 500 (May 14, 2021)
Time Units: Days
DT: 1/16
Integration Method: Euler's
Software version: Stella Architect 2.1.1

The model has 229 (5001) variables (array expansion in parenthesis).
In root model and 7 additional modules with 14 sectors.
Stocks: 20 (726)
Flows: 23 (829)
Converters: 186 (3446)
Constants: 59 (577)
Equations: 150 (3698)
Graphicals: 0 (0)
There are also 4191 expanded macro variables.

Top-Level Model:

new_daily_cases[state] = NAN
UNITS: cases/day
DOCUMENT: This data comes from the United States CDC API (Socrata) and represents the daily new recorded deaths for each of the 50 US states plus Washington DC. (United States Center for Disease Control, 2021)

new_daily_deaths[state] = NAN
UNITS: people/day
DOCUMENT: This data comes from the United States CDC API (Socrata) and represents the daily new recorded deaths for each of the 50 US states plus Washington DC. (United States Center for Disease Control, 2021)

sample_data = IF
"switch_1_=_senior_housing_2_=_restaurants_3_=_airlines_4_=_mobility[sector]" = 1
THEN Senior_Housing.brookdale_historical ELSE IF
"switch_1_=_senior_housing_2_=_restaurants_3_=_airlines_4_=_mobility[sector]" = 2
THEN Restaurants.us_dinein_revenue ELSE IF
"switch_1_=_senior_housing_2_=_restaurants_3_=_airlines_4_=_mobility[sector]" =3
THEN Airlines.normalized_demand ELSE Mobility.us_mobility_data[work]
UNITS: dmnl

sample_model_results = IF
"switch_1_=_senior_housing_2_=_restaurants_3_=_airlines_4_=_mobility[sector]" = 1
THEN brookdale.brookdale_occupancy ELSE IF
"switch_1_=_senior_housing_2_=_restaurants_3_=_airlines_4_=_mobility[sector]" = 2
THEN Restaurants.effect_of_covid_on_decision_to_dine_out ELSE IF
"switch_1_=_senior_housing_2_=_restaurants_3_=_airlines_4_=_mobility[sector]" = 3
THEN Airlines.effect_of_covid_on_airline_passenger_traffic ELSE
Mobility.effect_of_covid_on_mobility[work]
UNITS: dmnl

shutdown_begins = 71
UNITS: day
DOCUMENT: For simplicity, it is assumed that the pandemic began to effect behavior patterns within the entire US on March 11, 2020, the day that COVID was declared a global pandemic by the WHO. Until this day, the model will produce no effect on demand. (World Health Organization, 2020)

state_population[state] = NAN
UNITS: people
DOCUMENT: Population data as of 2019 by US state. This is used to calculate weighted averages when aggregating state-wide model results into an overall US result. (United States Census Bureau, 2019)

State	population	State	population	State	population
[AL]	4,903,185	[LA]	4,648,794	[OH]	11,689,100
[AK]	731,545	[ME]	1,344,212	[OK]	3,956,971
[AZ]	7,278,717	[MD]	6,045,680	[OR]	4,217,737
[AR]	3,017,825	[MA]	6,949,503	[PA]	12,801,989
[CA]	39,512,223	[MI]	9,986,857	[RI]	1,059,361
[CO]	5,758,736	[MN]	5,639,632	[SC]	5,148,714
[CT]	3,565,287	[MS]	2,976,149	[SD]	884,659
[DE]	973,764	[MO]	6,137,428	[TN]	6,833,174
[FL]	21,477,737	[MT]	1,068,778	[TX]	28,995,881
[GA]	10,617,423	[NE]	1,934,408	[UT]	3,205,958
[HI]	1,415,872	[NV]	3,080,156	[VT]	623,989
[ID]	1,787,065	[NH]	1,359,711	[VA]	8,535,519
[IL]	12,671,821	[NJ]	8,882,190	[WA]	7,614,893
[IN]	6,732,219	[NM]	2,096,829	[WV]	1,792,147
[IA]	3,155,070	[NY]	19,453,561	[WI]	5,822,434
[KS]	2,913,314	[NC]	10,488,084	[WY]	578,759
[KY]	4,467,673	[ND]	762,062	[DC]	705,749

"switch_1_=_senior_housing_2_=_restaurants_3_=_airlines_4_=_mobility[sector]" = 2
UNITS: dmnl

us_new_daily_cases = SUM(new_daily_cases)
UNITS: cases/day
DOCUMENT: This variable sums the total new daily cases from each individual US state into an aggregated US amount.

us_new_daily_deaths = SUM(new_daily_deaths)
UNITS: people/day
DOCUMENT: This variable sums the total new daily deaths from each individual US state into an aggregated US amount

Generic_Model:

DOCUMENT: This module contains the generic model structure used throughout this research project. Here it is not applied to any particular domain nor is it arrayed. Additional graphs, analysis, and supporting structures can be found in this variable. All documentation as to the generic structure of this model will be found here.

modeled_behavior(t) = modeled_behavior(t - dt) + (updating_behavior) * dt
INIT modeled_behavior = 1
UNITS: dmnl
DOCUMENT: The modeled demand is the final output variable of this model and represents what the model would project the overall level of demand to be given the current and historical COVID situation in light of the various cognitive biases applied in this model. It is this output that will be evaluated against the real-world data to judge the behavioral validity of this model.
The stock is initialized with a value of 1, meaning that behavior is assumed to start in a steady state at 100% of its pre-pandemic level.

reference_condition(t) = reference_condition(t - dt) + (updating_reference_condition) * dt

INIT reference_condition = 0

UNITS: cases/day

DOCUMENT: The idea of a reference condition comes from John Sterman's expectation formation paper. The basic idea here is that the reference condition represents the recent memory of an ongoing condition. The formulation here utilizes a first order exponential delay process meaning that the most recent information is weighted most heavily, and older information is discounted at an exponential rate. The reference condition is a key part of the basic TREND function as Sterman describes in his paper (Sterman, 1986).

Functionally this would represent what people would consider to be the average condition over some backwards looking period-- that period being determined by the 'time to update reference condition' variable.

The practical implication of this variable is that the reference condition, which will be the standard by which the present condition is compared to later on in the model, does in fact change over time and can represent the level to which people grow comfortable with a certain number of COVID cases.

The stock is initialized with a value of 0 since the model begins well before the pandemic starts.

updating_behavior = ((effect_of_judgment_on_indicated_behavior)-modeled_behavior)/time_to_update_behavior

UNITS: dmnl/days

DOCUMENT: The flow here is determined by a basic goal/gap formulation characteristic of a first order delay process.

updating_reference_condition = (perceived_present_condition-reference_condition)/time_to_update_reference_condition

UNITS: cases/day/days

DOCUMENT: The flow here is determined by a basic goal/gap formulation characteristic of a first order delay process.

"<mean>" = -.5

UNITS: dmnl

DOCUMENT: The value here describes the mean of the lognormal distribution drawn in the 'effect of judgment on indicated behavior' variable. This variable is calibrated to each specific domain and is explained more thoroughly in the written report.

See appendix B for sensitivity analysis

See appendix C for the calibration procedure used

"<stdev>" = 2

UNITS: dmnl

DOCUMENT: The value here describes the standard deviation of the lognormal distribution drawn in the 'effect of judgment on indicated behavior' variable. This variable is calibrated to each specific domain.

See appendix B for sensitivity analysis

See appendix C for the calibration procedure used

effect_of_covid_on_baseline_behavior = MIN(1, modeled_behavior)

UNITS: dmnl

DOCUMENT: This is the output variable. In this case, it is equivalent to the 'modeled demand' stock, but in other cases, this is where the aggregation of state specific results would take place to produce a result for the US as a whole or this is where additional particular adjustment calculations may take place to match the output data to the reference mode data.

effect_of_judgment_on_indicated_behavior = IF TIME <.shutdown_begins THEN 1 ELSE NORMALCDF(-99, LN(judgment_of_current_condition+1e-12), "<mean>", "<stdev>")

UNITS: dmnl

DOCUMENT: The purpose of this variable is to translate the 'judgment of current condition' into an indicated demand level. This is a complex calculation and requires a proper accounting for the fact that at any level of 'judgement of current condition' there is a distribution of people who would or would not change their behavior at that given level. This variable evaluates the cumulative probability of a lognormal distribution with a given mean and standard deviation (calibrated to the particular domain) at a given z value (where z is the value given by 'judgment of current condition').

We assume that behavior in this case represents a simple 'yes' or 'no' decision on the part of the individual people in the population, and we are looking at the proportion of the population that chooses 'yes' or 'no'. Note that this model scales normal behavior to whatever levels were typical before the pandemic began. Thus, everything is scaled to the pre-pandemic levels and expressed as a percentage of pre-pandemic behavior. In most cases in this research, the terms behavior and demand are used interchangeably; so that 100% represents everyone who would have normally made a 'yes' decision makes a 'yes' decision currently.

The following 3 criteria point toward a lognormal distribution (Limpert, Stahel, & Abbt, 2001):

1. If 'judgment of current condition' were to equal 0, then 0 percent of the population should engage in normal behavior. Thus, there is no possibility for negative values.
2. the mean value is low
3. the variance among the population is high

An additional criterion is presented here:

4. Only if 'judgment of current condition' were to equal infinity (meaning COVID has completely disappeared), would we expect 100% of the population should engage in normal behavior.

It is assumed that this effect will only register once an official crisis has been declared. When a global pandemic was declared and the US federal and state governments began enforcing various restrictions, it represented a paradigm shift in how a population made their decisions. Thus, the effect is deactivated until the official start of the pandemic, at which point it is turned on and left on indefinitely.

exponent = .5
UNITS: dmnl
DOCUMENT: The exponent is used in Steven's Power Law to calculate the relationship between an objective real world stimulus intensity and its value of its sensory intensity (Zwizlocki, 2009). In this case Steven's Power Law is being extended from the realm of physical stimuli to non-physical stimuli; thus, the number of cases in the perceived present condition and the reference condition are considered the stimuli and the exponent will be used to calculate the sensation magnitude of each, respectively. When an exponent of less than 1 is used, it implies that the sensed magnitude of the stimulus will increase at an exponentially decreasing rate compared to the actual magnitude of the stimulus. Thus, we can say that low numbers of cases will be perceived more accurately than high numbers of cases, which will be increasingly discounted the larger the stimulus gets. Utilizing Steven's Power Law in this way corresponds to research in the field of 'psychic numbing' that as the magnitude of a catastrophe increases, the emotional response increases only marginally so (Slovic, 2007).

It is assumed for this model that the same exponent can be used here regardless of the domain to which it is applied, since the exponent refers to the particular stimulus. While there certainly can be variation of the exponent within a particular stimulus (depending on its sensory context and the stakes of accurately judging the condition), it will be assumed for simplicity that all domains assessed in this model will utilize an estimated exponent value of 0.5 and that any small error in estimation (if variation were in fact to be expected) would be compensated for by a slight change to the '<stdev>' variable (explained below).

It was known beforehand that this variable should be a value between 0 and 1 based on the theoretical implication of Slovic's research on psychic numbing (see (Slovic, 2007).) This value was then roughly estimated to be 0.5 for all domains by performing a calibration routine for each individual domain whereby 'time to update reference condition', 'exponent', '<mean>', and '<stdev>' were all calibrated at once to find a value for each that produced the best behavioral fit to the data. After doing this for each domain discussed in this research project, the calibrated exponent variable fell roughly within a range of 0.3 to 0.7, so an average value of 0.5 was assumed to be adequate here to describe all domains. Sensitivity analysis further revealed that opposite changes in both the 'exponent' variable and the '<stdev>' variable could produce similar behavioral changes within a certain range. This ultimately made calibration difficult when both these values were allowed to be changed, since a change in one variable could be compensated for to a large extent by an opposite change in the other. Therefore, the decision was to fix the 'exponent' value at a value that was deemed appropriate for all domains (0.5), and then allow the burden of producing variability in the model output, all else being equal, thus fell upon the '<mean>' and '<stdev>' variables. This is further theoretically justified in that it is fully expected that there will be wild variations in the distributions of outcomes (as represented by the 'effect of judgment on indicated behavior' variable) from domain to domain, so the variables describing the distribution should bear the weight of calibration much more than the 'exponent' variable which is much more commonly known to be relatively stable with little difference between values within the same stimulus.

extreme_condition = STEP(100000, 10)-STEP(100000, 730)
UNITS: cases/day
DOCUMENT: test input used in extreme conditions testing

judgment_of_current_condition = sensation_magnitude_of_reference_condition//sensation_magnitude_of_present_condition
UNITS: dmnl
DOCUMENT: This is a simple comparison of the 'sensation magnitude of reference condition' to the 'sensation magnitude of present condition'. The result is a ratio of the reference over the present condition. A value of 1 would indicate that it is perceived that the present condition is equivalent to the reference condition, and thus under control. A value approaching 0 would indicate that the reference condition is much few cases than the present condition; thus, this would indicate a worst-case scenario. A value approaching infinity would indicate that the reference condition represents many more cases than the present condition; thus, this would indicate a very safe and favorable scenario.

This equation borrows somewhat from John Sterman's Expectation Formation paper (Sterman, 1986); except in this case people are not using the present and reference conditions to estimate a future trend, they are rather using these to judge a current condition.

lognormal_cumulative_distribution_curve = NORMALCDF(-99, LN(RAMP(0.01)+1e-12),"<mean>", "<stdev>")
UNITS: dmnl
DOCUMENT: The equation for drawing a lognormal cumulative probability density curve was given by Billy Schoenberg, who offered an adaptation of the NORMALCDF built-in function in Stella (Schoenberg, 2021) (Isee Systems , 2021). Then an input of the ramp(.01) function was given for the z argument so that when plotted over time, it would draw a cumulative probability density curve with the given mean and standard deviation. The x axis should be interpreted as a dimensionless axis and divided by 100.

lognormal_probability_density_curve = (1//(RAMP(.01)*"<stdev>"*SQRT(2*PI)))*(EXP(1)^(-.5*(((LN(RAMP(.01))-"<mean>"))//"<stdev>")^2))
UNITS: dmnl
DOCUMENT: The equation for drawing a lognormal probability density curve was taken from https://www.real-statistics.com/normal-distribution/log-normal-distribution/. Then an input of the ramp(.01) function was given for the z argument so that when plotted over time, it would draw a probability density curve with the given mean and standard deviation. The x axis should be interpreted as a dimensionless axis and divided by 100.

perceived_present_condition = SMTH3(.us_new_daily_cases, time_to_perceive_present_condition) {DELAY CONVERTER}
UNITS: cases/day
DOCUMENT: The perceived present condition is assumed to be a third order exponential delay of the total new daily cases. A third order delay is used to account for the fact that there are many stages in the process between collecting data and it being perceived by the public. (Sterman, Business Dynamics: Systems Thinking and Modeling for a Complex World, 2000)

sensation_magnitude_of_present_condition = DELAY(perceived_present_condition^exponent, DT)
UNITS: cases/day
DOCUMENT: As explained in the 'exponent' variable, this variable calculates the sensory magnitude of the 'perceived present condition' by taking the stimulus and raising it to the exponent. This is calculated using Steven's Power Law, which states that:
*sensation magnitude = constant * stimulus^ exponent* (Zwizlocki, 2009)
The constant is irrelevant in this model since in the 'judgment of current condition' variable, the result of this equation will be divided by the result of the same equation applied to the 'reference condition'. Both the exponent and constant are assumed to be the same in both cases since they are both the same kind of stimuli. Since the constant is applied linearly in the equation, they will cancel each other out when it comes to the 'comparison' calculation. Note that the unit error here does is not due to a real dimensional inconsistency, but due to the difficulty the software has in assessing the units of equations utilizing non-integer exponents. The effect of this variable is to distort the objective cases per day into the sensed cases per day, no unit transformation should result from this calculation.

sensation_magnitude_of_reference_condition = reference_condition^exponent
UNITS: cases/day
DOCUMENT: As explained in the 'exponent' variable, this variable calculates the sensory magnitude of the 'reference condition' by taking the stimulus and raising it to the exponent. This is calculated using Steven's Power Law, which states that:
*sensation magnitude = constant * stimulus^ exponent* (Zwizlocki, 2009)
The constant is irrelevant in this model since in the 'judgment of current condition' variable, the result of this equation will be divided by the result of the same equation applied to the 'perceived present condition'. Both the exponent and constant are assumed to be the same in both cases since they are both the same kind of stimuli. Since the constant is applied linearly in the equation, they will cancel each other out when it comes to the 'judgment of current condition' calculation. Note that the unit error here does is not due to a real dimensional inconsistency, but due to the difficulty the software has in assessing the units of equations utilizing non-integer exponents. The effect of this variable is to distort the objective cases per day into the sensed cases per day, no unit transformation should result from this calculation.

time_to_perceive_present_condition = 10

UNITS: days
DOCUMENT: This represents the average amount of time that it takes for a population within the given region to perceive the real level of COVID cases. This delay time can account for the time needed to collect, aggregate, and publish the final data figures as well as the time it takes for people to hear of the news of the new daily cases. This number is assumed to be 10 days, though the real number may be more or less depending on the reporting procedures in the given region or depending on how interested people are in keeping up to date with the latest figures. Sensitivity testing on this variable reveals that the model is not particularly sensitive in terms of behavior mode as this variable is adjusted up or down. See Appendix B for more details.

time_to_update_behavior = 10
UNITS: days
DOCUMENT: This variable represents how long on average it takes to change one's demand or consumption behavior in response to updated signals coming from the COVID situation. A first order process is used here, so it assumes most people will update their behavior rather quickly with some waiting potentially a few weeks to change their behavior (whether it is increasing or decreasing).

time_to_update_reference_condition = 360
UNITS: days
DOCUMENT: This variable represents the time frame by which the reference condition is formed (Sterman, 1986).

A short delay time here would indicate that the reference condition is based on a fairly recent period of time and thus the reference condition would be liable to change quickly as the actual situation changed quickly. Conversely, a longer delay time would indicate that the reference condition is based on a much longer backwards looking time horizon and that the older information is discounted much slower. This would mean the reference condition moves very slowly compared to the present condition.

While this variable theoretically could be different when assessed in different domains, for this model it is assumed that all domains use a value of 360 days. Sensitivity testing reveals that changes in this variable as well as the '<mean>' variable both can affect the final 'modeled behavior' in similar ways. Therefore, any reduction in 'time to update reference condition' can to some extent be offset by an adjustment to the assumed '<mean>' variable. Since it is fully expected that the '<mean>' variable will be different from domain to domain, and since calibration techniques are not able to properly differentiate between these two variables, the decision was made to fix the value of this variable and let the '<mean>' variable bear the burden of calibration for this model.

However, in order to determine the value of 360, each domain was calibrated with this variable, along with the 'exponent', '<mean>', and '<stdev>' variables subject to change. After testing each domain separately, most came in around 360 days with the exception of one or two outliers. Thus 360 will be assumed for all of them and any required adjustment from this variable will be accounted for by slight changes to the '<mean>' variable.

Airlines:

DOCUMENT: This sector applies the model structure to the airline industry in the US, looking specifically at how the COVID pandemic has affected demand for air travel. The analysis here looks at overall US cases and produces an estimated demand over time for the entire US. This sector need not be aggregated by state, since local COVID conditions are not as likely to influence a decision to travel than overall COVID conditions for the US as a whole.

modeled_behavior(t) = modeled_behavior(t - dt) + (positive_change_in_behavior - negative_change_in_behavior) * dt
INIT modeled_behavior = 1
UNITS: dmnl
DOCUMENT: Refer to generic model

reference_cases(t) = reference_cases(t - dt) + (updating_reference) * dt
INIT reference_cases = 0
UNITS: cases/day
DOCUMENT: Refer to generic model

negative_change_in_behavior = MAX(0, ((modeled_behavior)-effect_of_judgment_on_indicated_behavior)/time_to_reduce_behavior)
UNITS: dmnl/days
DOCUMENT: Refer to generic model
For the airline industry, it should not be assumed that the behavior in this case (traveling by plane) can expand or contract at the same rate. While in other domains, this may be true, the reality in airlines is that flights can very quickly be canceled and passengers may very quickly decide to cancel or reschedule their itinerary, however it usually takes at least few weeks to plan air travel. Thus, if the COVID situation worsens, demand (and supply) of air travel can quickly be lost, however it will take longer to build back up again (since people need to plan and book in advance and additional flights must be scheduled in advance). Therefore, loss of demand will happen with a 10-day delay time (as in all other domains) yet will only be gained back again with a 45-day delay time.

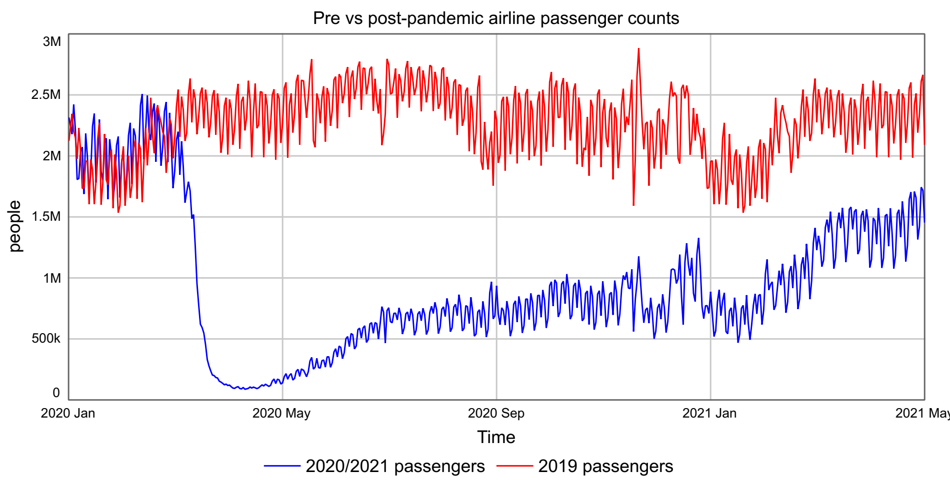
positive_change_in_behavior = MAX(0, ((effect_of_judgment_on_indicated_behavior)-modeled_behavior)/time_to_increase_behavior)
UNITS: Per Day
DOCUMENT: Refer to generic model
For the airline industry, it should not be assumed that the behavior in this case (traveling by plane) can expand or contract at the same rate. While in other domains, this may be true, the reality in airlines is that flights can very quickly be canceled and passengers may very quickly decide to cancel or reschedule their itinerary, however it usually takes at least few weeks to plan air travel. Thus, if the COVID situation worsens, demand (and supply) of air travel can quickly be lost, however it will take longer to build back up again (since people need to plan and book in advance and additional flights must be scheduled in advance). Therefore, loss of demand will happen with a 10-day delay

time (as in all other domains) yet will only be gained back again with a 45-day delay time.

updating_reference = (perceived_present_condition-reference_cases)/time_to_update_reference
UNITS: cases/day/days
DOCUMENT: Refer to generic model

"2019_passengers" = 1908805
UNITS: people
DOCUMENT: Data taken from the Transportation Security Administration website for passenger counts going through all US airports on each day in 2019.
(United States Transportation Security Administration, 2021)
Refer to FIGURE

"2020_passengers" = 689951
UNITS: people
DOCUMENT: Data taken from the Transportation Security Administration website for passenger counts going through all US airports on each day in 2020.
(United States Transportation Security Administration, 2021)
Refer to FIGURE



"<mean>" = -.726
UNITS: dmnl
DOCUMENT: Refer to generic model.
The calibration routine produced a value of -0.73
Details of the calibration routine used can be found in appendix C
Details of the sensitivity analysis can be found in appendix B

"<stdev>" = .698
UNITS: dmnl
DOCUMENT: Refer to generic model.
The calibration routine produced a value of 0.69

Details of the calibration routine used can be found in appendix C
Details of the sensitivity analysis can be found in appendix B

airlines_lognormal_cumulative_distribution_curve = NORMALCDF(-99, LN(RAMP(0.01)+1e-12),"<mean>", "<stdev>")
UNITS: dmnl
DOCUMENT: Refer to generic model

airlines_lognormal_probability_density_curve = (1//(RAMP(.01)*"<stdev>"*SQRT(2*PI)))*(EXP(1)^(-.5*(((LN(RAMP(.01))-"<mean>"))//"<stdev>")^2))
UNITS: dmnl
DOCUMENT: Refer to generic model

banned_international_flights = 1+STEP(-relative_volume_of_intl_flights, .shutdown_begins)
UNITS: dmnl
DOCUMENT: This variable enforces the supply restriction after the pandemic has begun and leaves it in place during the horizon of this model.

effect_of_covid_on_airline_passenger_traffic = modeled_behavior*banned_international_flights
UNITS: dmnl
DOCUMENT: This is the modeled level of demand for airline travel based upon the output of the model developed for this research project.
Special assumptions include an adjustment down for international travel, two different delay times for positive or negative changes in demand, and using total US cases as the input to the model.

effect_of_judgment_on_indicated_behavior = IF TIME <.shutdown_begins THEN 1 ELSE NORMALCDF(-99, LN(judgment_of_current_condition+1e-12), "<mean>", "<stdev>")
UNITS: dmnl
DOCUMENT: Refer to generic model

exponent = .5
UNITS: dmnl
DOCUMENT: Refer to generic model

judgment_of_current_condition = (sensation_magnitude_of_reference_condition//sensation_magnitude_of_present_condition)
UNITS: dmnl
DOCUMENT: Refer to generic model

normalized_demand = "2020_passengers"/"2019_passengers"

UNITS: dmnl
DOCUMENT: This variable expresses the actual demand seen from January 1, 2020 to present by taking the number of passengers observed during this time frame divided by the number of passengers observed on the same day of the year in 2019. This produces a normalized stream of data that expresses the level of demand compared to pre-pandemic levels, expressed as a percentage. Doing this also removes seasonal variations in the data.

perceived_present_condition = SMTH3(.us_new_daily_cases, time_to_perceive_present_condition) {DELAY CONVERTER}
UNITS: cases/day
DOCUMENT: Refer to generic model

relative_volume_of_intl_flights = (241.3/1052.8)*.9
UNITS: dmnl
DOCUMENT: An adjustment is made in this model that assumes a near complete elimination of international travel due to strict border controls that have been in place since the onset of the pandemic. As of May 2021, most of these travel restrictions remain in place (United States Center for Disease Control, 2021). Therefore, it is assumed that this segment of air travel will not rebound until these restrictions are broadly lifted, despite the demand that may exist for international travel. This percentage is calculated using passenger data from 2019 (US Bureau of Transportation Statistics, 2020), and it is assumed that 90% of this demand is suppressed due to ongoing border controls.

sensation_magnitude_of_present_condition = DELAY(perceived_present_condition^exponent, DT)
UNITS: cases/day
DOCUMENT: Refer to generic model

sensation_magnitude_of_reference_condition = reference_cases^exponent
UNITS: cases/day
DOCUMENT: Refer to generic model

time_to_increase_behavior = 45
UNITS: days
DOCUMENT: Refer to generic model
In this case the assumption of 45 days is only applied to a gain in demand for air travel, losses are treated separately.

time_to_perceive_present_condition = 10
UNITS: days
DOCUMENT: Refer to generic model

time_to_reduce_behavior = 10
UNITS: days
DOCUMENT: Refer to generic model

In this case the assumption of 10 days is only applied to a loss in demand for air travel, gains are treated separately.

time_to_update_reference = 360
UNITS: days
DOCUMENT: Refer to generic model

Mobility:

DOCUMENT: This sector analyzes Google mobility data. The data is available in 6 broad categories (four of which are used in this model) and is available on a statewide level. The model is applied at a statewide level to the mobility data and is also aggregated to the US as a whole. Whereas the restaurant and airlines sectors explicitly represent consumption behavior, the mobility data represents where people spend their time. We can infer their decision making based on where they are spending time, though this data is perhaps not as neat of a fit to the purpose of this model.

Note that most variables in this module are arrayed by both state and mobility sector (workplaces, retail and recreation, grocery and pharmacy, and transit stations).

modeled_behavior[mobility_category, state](t) = modeled_behavior[mobility_category, state](t - dt) + (updating_behavior[mobility_category, state]) * dt
INIT modeled_behavior[mobility_category, state] = 1
UNITS: dmnl
DOCUMENT: Refer to generic model.
Note: this stock (as are most variables in this module) is arrayed by both state and mobility sector.

reference_cases[mobility_category, state](t) = reference_cases[mobility_category, state](t - dt) + (updating_reference[mobility_category, state]) * dt
INIT reference_cases[mobility_category, state] = 0
UNITS: cases/day
DOCUMENT: Refer to generic model

updating_behavior[mobility_category, state] = ((effect_of_judgment_on_indicated_behavior)-modeled_behavior)/time_to_update_behavior[mobility_category]
UNITS: Per Day
DOCUMENT: Refer to generic model

updating_reference[mobility_category, state] = (perceived_present_condition-reference_cases)/time_to_update_reference[mobility_category]
UNITS: cases/day/days
DOCUMENT: Refer to generic model

"<mean>"[work] = -2.24

UNITS: dmnl
DOCUMENT: Refer to generic model.
The calibration routine produced the following values for each of the mobility sectors:
workplaces (work): -2.24
retail and recreation (retail): -2.37
grocery and pharmacy (grocery): -3.56
transit stations (trans):-2.00
Details of the calibration routine used can be found in appendix C
Details of the sensitivity analysis can be found in appendix B

"<mean>"[retail] = -2.37
UNITS: dmnl
DOCUMENT: Refer to generic model.
The calibration routine produced the following values for each of the mobility sectors:
workplaces (work): -2.24
retail and recreation (retail): -2.37
grocery and pharmacy (grocery): -3.56
transit stations (trans):-2.00
Details of the calibration routine used can be found in appendix C
Details of the sensitivity analysis can be found in appendix B

"<mean>"[grocery] = -3.56
UNITS: dmnl
DOCUMENT: Refer to generic model.
The calibration routine produced the following values for each of the mobility sectors:
workplaces (work): -2.24
retail and recreation (retail): -2.37
grocery and pharmacy (grocery): -3.56
transit stations (trans):-2.00
Details of the calibration routine used can be found in appendix C
Details of the sensitivity analysis can be found in appendix B

"<mean>"[trans] = -2
UNITS: dmnl
DOCUMENT: Refer to generic model.
The calibration routine produced the following values for each of the mobility sectors:
workplaces (work): -2.24
retail and recreation (retail): -2.37
grocery and pharmacy (grocery): -3.56
transit stations (trans):-2.00
Details of the calibration routine used can be found in appendix C
Details of the sensitivity analysis can be found in appendix B

"<stdev>"[work] = 2.99
UNITS: dmnl
DOCUMENT: Refer to generic model.

The calibration routine produced the following values for each of the mobility sectors:
workplaces (work): 2.99
retail and recreation (retail): 1.79
grocery and pharmacy (grocery): 2.2
transit stations (trans): 2.99
Details of the calibration routine used can be found in appendix C
Details of the sensitivity analysis can be found in appendix B

"<stdev>"[retail] = 1.79
UNITS: dmnl
DOCUMENT: Refer to generic model.
The calibration routine produced the following values for each of the mobility sectors:
workplaces (work): 2.99
retail and recreation (retail): 1.79
grocery and pharmacy (grocery): 2.2
transit stations (trans): 2.99
Details of the calibration routine used can be found in appendix C
Details of the sensitivity analysis can be found in appendix B

"<stdev>"[grocery] = 2.2
UNITS: dmnl
DOCUMENT: Refer to generic model.
The calibration routine produced the following values for each of the mobility sectors:
workplaces (work): 2.99
retail and recreation (retail): 1.79
grocery and pharmacy (grocery): 2.2
transit stations (trans): 2.99
Details of the calibration routine used can be found in appendix C
Details of the sensitivity analysis can be found in appendix B

"<stdev>"[trans] = 2.99
UNITS: dmnl
DOCUMENT: Refer to generic model.
The calibration routine produced the following values for each of the mobility sectors:
workplaces (work): 2.99
retail and recreation (retail): 1.79
grocery and pharmacy (grocery): 2.2
transit stations (trans): 2.99
Details of the calibration routine used can be found in appendix C
Details of the sensitivity analysis can be found in appendix B

"calibration_variable_(data)" = IF TIME > 320 AND TIME < 380 THEN 0 ELSE smoothed_us_workplaces
UNITS: dmnl

DOCUMENT: This variable excludes the period of the holidays (from roughly Thanksgiving around day 320 to after New Year's around day 380) so that the unique behavior pattern caused by the holiday season is not included in the calibration.

"calibration_variables_(model)"[work] = IF TIME > 320 AND TIME < 380 THEN 0 ELSE SMTH1(effect_of_covid_on_mobility[work], 10)
UNITS: dmnl
DOCUMENT: This variable applies certain transformations to the output of the model so that it can be more accurately calibrated to the actual data. Since the actual data contains significant day to day variation, the actual data has been smoothed by 10 days; therefore, the model output must also be smoothed by 10 days so that it is equally distorted. Additionally, for the workplaces sector, the period of the holidays (from roughly Thanksgiving around day 320 to after New Year's around day 380) has been excluded since the holidays have driven behavior patterns that are outside of the scope of this model. All of these transformations are only done so that the software can calibrate to the actual trends and not to the noise or to known external factors beyond COVID that may be impacting the trends.

"calibration_variables_(model)"[retail] = SMTH1(effect_of_covid_on_mobility[retail], 10)
UNITS: dmnl
DOCUMENT: This variable applies certain transformations to the output of the model so that it can be more accurately calibrated to the actual data. Since the actual data contains significant day to day variation, the actual data has been smoothed by 10 days; therefore, the model output must also be smoothed by 10 days so that it is equally distorted. Additionally, for the workplaces sector, the period of the holidays (from roughly Thanksgiving around day 320 to after New Year's around day 380) has been excluded since the holidays have driven behavior patterns that are outside of the scope of this model. All of these transformations are only done so that the software can calibrate to the actual trends and not to the noise or to known external factors beyond COVID that may be impacting the trends.

"calibration_variables_(model)"[grocery] = SMTH1(effect_of_covid_on_mobility[grocery], 10)
UNITS: dmnl
DOCUMENT: This variable applies certain transformations to the output of the model so that it can be more accurately calibrated to the actual data. Since the actual data contains significant day to day variation, the actual data has been smoothed by 10 days; therefore, the model output must also be smoothed by 10 days so that it is equally distorted. Additionally, for the workplaces sector, the period of the holidays (from roughly Thanksgiving around day 320 to after New Year's around day 380) has been excluded since the holidays have driven behavior patterns that are outside of the scope of this model. All of these transformations are only done so that the software can calibrate to the actual trends and not to the noise or to known external factors beyond COVID that may be impacting the trends.

"calibration_variables_(model)"[trans] = SMTH1(effect_of_covid_on_mobility[trans], 10)
UNITS: dmnl
DOCUMENT: This variable applies certain transformations to the output of the model so that it can be more accurately calibrated to the actual data. Since the actual data contains significant day to day variation, the actual data has been smoothed by 10 days; therefore, the model output must also be smoothed by 10 days so that it is equally distorted. Additionally, for the workplaces sector, the period of the holidays (from roughly Thanksgiving around day 320 to after New Year's around day 380) has been excluded since the holidays have driven behavior patterns that are outside of the scope of this model. All of these transformations are only done so that the software can calibrate to the actual trends and not to the noise or to known external factors beyond COVID that may be impacting the trends.

data[state] = workplaces+1
UNITS: dmnl
DOCUMENT: This variable holds the real data to be plotted state by state.

effect_of_covid_on_mobility[mobility_category] = MIN(1, SUM(percentage_of_total_population_per_state[*]*modeled_behavior[mobility_category,*]))-1
UNITS: dmnl
DOCUMENT: This variable shows the effect of covid on mobility for the US as a whole by taking a weighted average (weighted by state population) of the modeled results. This variable is arrayed by each of the domains (workplaces, retail and recreation, grocery and pharmacy, and transit stations) that are covered in this module.

effect_of_judgment_on_indicated_behavior[mobility_category, state] = IF TIME <.shutdown_begins THEN 1 ELSE NORMALCDF(-99, LN(judgment_of_current_condition+1e-12), "<mean>"[mobility_category], "<stdev>"[mobility_category])
UNITS: dmnl
DOCUMENT: Refer to generic model

exponent[work] = .5
UNITS: dmnl
DOCUMENT: Refer to generic model

exponent[retail] = .5
UNITS: dmnl
DOCUMENT: Refer to generic model

exponent[grocery] = .5
UNITS: dmnl
DOCUMENT: Refer to generic model

exponent[trans] = .5
UNITS: dmnl
DOCUMENT: Refer to generic model

grocery_and_pharmacy[state] = NAN
UNITS: dmnl
DOCUMENT: Mobility data from Google. It tracks by state the number of people that passed through grocery store or pharmacy locations and is expressed as a percentage relative to the number of people found in the same places during the pre-pandemic period of January and February 2020 (Google LLC, n.d.)

judgment_of_current_condition[mobility_category, state] = (sensation_magnitude_of_reference_condition//sensation_magnitude_of_present_condition)
UNITS: dmnl
DOCUMENT: Refer to generic model

mobility_lognormal_cumulative_distribution_curve[mobility_category] = NORMALCDF(-99, LN(RAMP(0.01)+1e-12),"<mean>", "<stdev>")
UNITS: dmnl
DOCUMENT: Refer to generic model

mobility_lognormal_probability_density_curve[mobility_category] = (1//(RAMP(.01)*"<stdev>"*SQRT(2*PI)))*(EXP(1)^(-.5*(((LN(RAMP(.01))-"<mean>"))//"<stdev>")^2))
UNITS: dmnl
DOCUMENT: Refer to generic model

model[state] = modeled_behavior[work,state]
UNITS: dmnl
DOCUMENT: This variable holds the modeled data to be plotted state by state.

perceived_present_condition[mobility_category, state] = SMTH3(.new_daily_cases[state], time_to_perceive_present_condition[mobility_category]) {DELAY CONVERTER}
UNITS: cases/day
DOCUMENT: Refer to generic model

percentage_of_total_population_per_state[state] = .state_population/SUM(.state_population)
UNITS: dmnl
DOCUMENT: This variable expresses each states' population as a percentage of the total US population.

retail_and_recreation[state] = NAN
UNITS: dmnl

DOCUMENT: Mobility data from Google. It tracks by state the number of people that passed through retail and recreation locations and is expressed as a percentage relative to the number of people found in the same places during the pre-pandemic period of January and February 2020 (Google LLC, n.d.)

sensation_magnitude_of_present_condition[mobility_category, state] = DELAY(perceived_present_condition^exponent[mobility_category], DT)
UNITS: cases/day
DOCUMENT: Refer to generic model

sensation_magnitude_of_reference_condition[mobility_category, state] = reference_cases^exponent[mobility_category]
UNITS: cases/day
DOCUMENT: Refer to generic model

smoothed_us_grocery_and_pharmacy = SMTH1(us_grocery_and_pharmacy, 10)
UNITS: dmnl
DOCUMENT: In order to smooth out the noise in this data to get a better calibration of the underlying trends happening in the data, the data was subjected to a 10 first order exponential delay.

smoothed_us_retail_and_recreation = SMTH1(us_retail_and_recreation, 10)
UNITS: dmnl
DOCUMENT: In order to smooth out the noise in this data to get a better calibration of the underlying trends happening in the data, the data was subjected to a 10 first order exponential delay.

smoothed_us_transit_stations = SMTH1(us_transit_stations, 10)
UNITS: dmnl
DOCUMENT: In order to smooth out the noise in this data to get a better calibration of the underlying trends happening in the data, the data was subjected to a 10 first order exponential delay.

smoothed_us_workplaces = SMTH1(us_workplaces, 10)
UNITS: dmnl
DOCUMENT: In order to smooth out the noise in this data to get a better calibration of the underlying trends happening in the data, the data was subjected to a 10 first order exponential delay.

time_to_perceive_present_condition[mobility_category] = 10
UNITS: days
DOCUMENT: Refer to generic model

time_to_update_behavior[mobility_category] = 10
UNITS: days
DOCUMENT: Refer to generic model

time_to_update_reference[work] = 360
UNITS: days
DOCUMENT: Refer to generic model

time_to_update_reference[retail] = 360
UNITS: days
DOCUMENT: Refer to generic model

time_to_update_reference[grocery] = 30
UNITS: days
DOCUMENT: Refer to generic model

time_to_update_reference[trans] = 360
UNITS: days
DOCUMENT: Refer to generic model

transit_stations[state] = NAN
UNITS: dmnl
DOCUMENT: Mobility data from Google. It tracks by state the number of people that passed through transit stations(including highway rest stops, subway stations, taxi stands, etc.) and is expressed as a percentage relative to the number of people found in the same places during the pre-pandemic period of January and February 2020 (Google LLC, n.d.)

us_grocery_and_pharmacy = NAN
UNITS: dmnl
DOCUMENT: Mobility data from Google. It tracks for the entire US the number of people that passed through grocery store or pharmacy locations and is expressed as a percentage relative to the number of people found in the same places during the pre-pandemic period of January and February 2020 (Google LLC, n.d.)
Refer to FIGURE

us_mobility_data[work] = us_workplaces
UNITS: dmnl

us_mobility_data[retail] = us_retail_and_recreation
UNITS: dmnl

us_mobility_data[grocery] = us_grocery_and_pharmacy
UNITS: dmnl

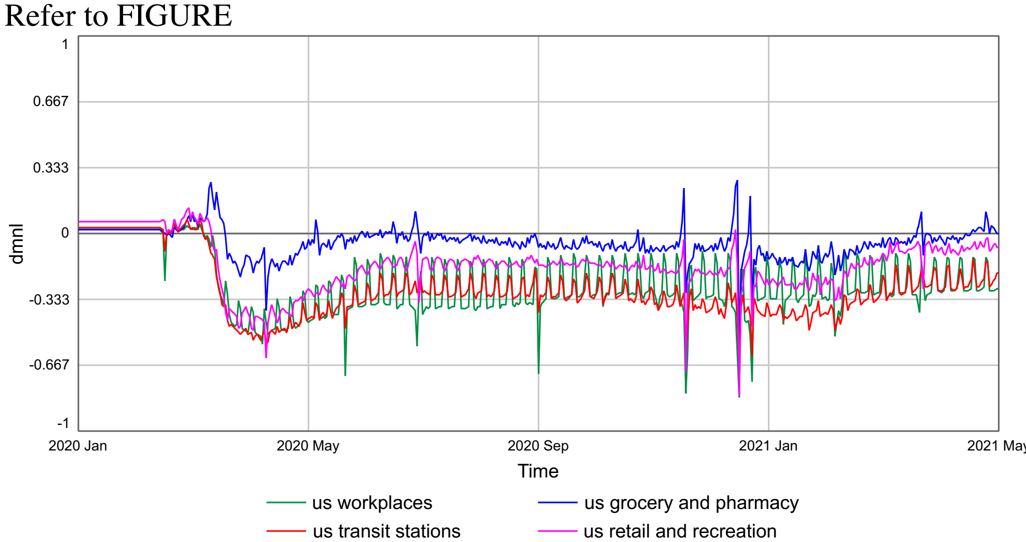
us_mobility_data[trans] = us_transit_stations
UNITS: dmnl

us_retail_and_recreation = NAN

UNITS: dmnl
DOCUMENT: Mobility data from Google. It tracks by state the number of people that passed through retail and recreation locations and is expressed as a percentage relative to the number of people found in the same places during the pre-pandemic period of January and February 2020 (Google LLC, n.d.)
Refer to FIGURE

us_transit_stations = NAN
UNITS: dmnl
DOCUMENT: Mobility data from Google. It tracks for the entire US the number of people that passed through transit stations(including highway rest stops, subway stations, taxi stands, etc.) and is expressed as a percentage relative to the number of people found in the same places during the pre-pandemic period of January and February 2020 (Google LLC, n.d.)
Refer to FIGURE

us_workplaces = NAN
UNITS: dmnl
DOCUMENT: Mobility data from Google. It tracks for the entire US the number of people that passed through workplace locations and is expressed as a percentage relative to the number of people found in the same places during the pre-pandemic period of January and February 2020 (Google LLC, n.d.)
Refer to FIGURE



workplaces[state] = NAN
UNITS: dmnl
DOCUMENT: Mobility data from Google. It tracks by state the number of people that passed through workplace locations and is expressed as a percentage relative to the number of people found in the same places during the pre-pandemic period of January and February 2020 (Google LLC, n.d.)

Restaurants:

DOCUMENT: This sector applies the model structure to the restaurant industry in the US, looking specifically at how the COVID pandemic has affected demand for dine-in spending. The analysis here is arrayed by state and then aggregated to overall US results. This is because the particular COVID situation within a state is much more likely to influence consumer behavior than the situation for the US as a whole. It is assumed that the overall daily revenue (as compared to 2019 revenue on the same day) can reasonably represent how consumer behavior has changed from day to day throughout the pandemic.

modeled_behavior[state](t) = modeled_behavior[state](t - dt) + (updating_behavior[state]) * dt
INIT modeled_behavior[state] = 1
UNITS: dmnl
DOCUMENT: This is the modeled level of demand for dining out at restaurants l based upon the output of the model developed for this research project. The results are achieved using new daily cases as the input and by adjusting the values of three parameters (time to update reference, exponent, and percentage at 1). This is the result for each individual state within the US
reference_cases[state](t) = reference_cases[state](t - dt) + (updating_reference[state]) * dt
INIT reference_cases[state] = 0
UNITS: cases/day
DOCUMENT: Refer to generic model

updating_behavior[state] = ((effect_of_judgment_on_indicated_behavior)-modeled_behavior)/time_to_update_behavior
UNITS: dmnl/days
DOCUMENT: Refer to generic model

updating_reference[state] = (perceived_present_condition-reference_cases)/time_to_update_reference
UNITS: cases/day/days
DOCUMENT: Refer to generic model

"<mean>" = -.626
UNITS: dmnl
DOCUMENT: Refer to generic model.
The calibration routine produced a value of -0.63
Details of the calibration routine used can be found in appendix C
Details of the sensitivity analysis can be found in appendix B

"<stdev>" = .93
UNITS: dmnl
DOCUMENT: Refer to generic model.
The calibration routine produced a value of 0.93
Details of the calibration routine used can be found in appendix C
Details of the sensitivity analysis can be found in appendix B

calibration_variable = IF TIME < .shutdown_begins THEN 1 ELSE IF TIME < 152 THEN 0 ELSE effect_of_covid_on_decision_to_dine_out
UNITS: dmnl
DOCUMENT: So that the calibration does not consider the unique period of time from end of March to end of May whereby substantially all states had full dine-in restrictions, this variable transforms the 'effect of covid on decision to dine out' variable so that it is 0 during the period from day 71 (the beginning of the pandemic) to day 152 (May 31, 2020). Thus, the calibration will focus on the time after day 152.
data[state] = SMTH1(dineinrevenue+1, 10)
UNITS: dmnl
DOCUMENT: This variable holds the real data to be plotted state by state.

dineinrevenue[state] = NAN
UNITS: dmnl
DOCUMENT: This data comes from OpenTable.com, a popular restaurant reservation platform in the United States. It has collected and published daily data estimating the percentage change in dine in customers for a variety of geographic regions since the start of the pandemic. The data is normalized to 2019 levels. In this variable, the data is arrayed by state. (OpenTable, 2021)
Refer to Appendix E for a state-by-state example of the data.

effect_of_covid_on_decision_to_dine_out = SUM(modeled_behavior*percentage_of_total_population_per_state)
UNITS: dmnl
DOCUMENT: This is the modeled level of demand for dining out at restaurants l based upon the output of the model developed for this research project. This is the aggregated result for the entire US calculated by taking a weighted average (weighted by population) of the results of each individual US state.

effect_of_judgment_on_indicated_behavior[state] = IF TIME <.shutdown_begins THEN 1 ELSE NORMALCDF(-99, LN(judgment_of_current_condition+1e-12), "<mean>", "<stdev>")
UNITS: dmnl
DOCUMENT: Refer to generic model

exponent = .5
UNITS: dmnl
DOCUMENT: Refer to generic model

judgment_of_current_condition[state] = (sensation_magnitude_of_reference_condition//sensation_magnitude_of_present_condition)
UNITS: dmnl
DOCUMENT: Refer to generic model

model[state] = SMTH1(modeled_behavior, 10)

UNITS: dmnl
DOCUMENT: This variable holds the modeled data to be plotted state by state.

perceived_present_condition[state] = SMTH3(.new_daily_cases, time_to_perceive_present_condition) {DELAY CONVERTER}
UNITS: cases/day
DOCUMENT: Refer to generic model

percentage_of_total_population_per_state[state] = .state_population/SUM(.state_population)
UNITS: dmnl
DOCUMENT: This variable expresses each states' population as a percentage of the total US population.

restaurants_lognormal_cumulative_distribution_curve = NORMALCDF(-99, LN(RAMP(0.01)+1e-12),"<mean>", "<stdev>")
UNITS: dmnl
DOCUMENT: Refer to generic model

restaurants_lognormal_probability_density_curve = (1//(RAMP(.01)*"<stdev>"*SQRT(2*PI)))*(EXP(1)^(-.5*(((LN(RAMP(.01))-"<mean>"))//"<stdev>")^2))
UNITS: dmnl
DOCUMENT: Refer to generic model

sensation_magnitude_of_present_condition[state] = DELAY(perceived_present_condition^exponent, DT)
UNITS: cases/day
DOCUMENT: Refer to generic model

sensation_magnitude_of_reference_condition[state] = reference_cases^exponent
UNITS: cases/day
DOCUMENT: Refer to generic model

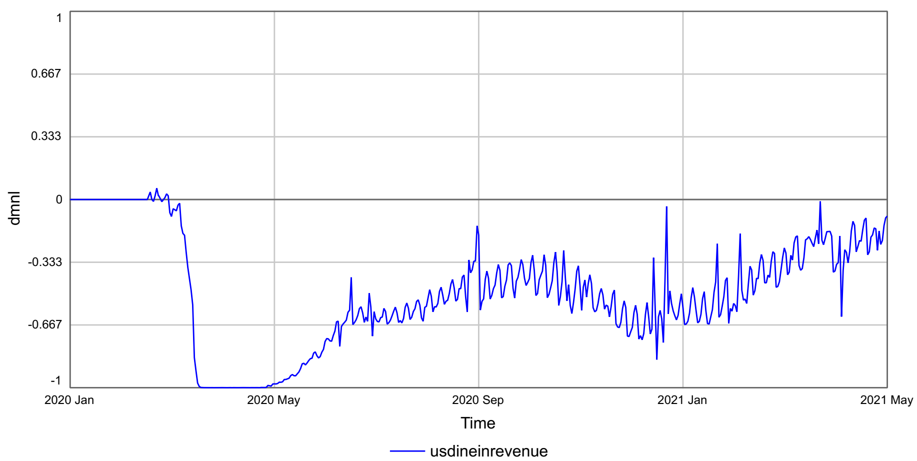
time_to_perceive_present_condition = 10
UNITS: days
DOCUMENT: Refer to generic model

time_to_update_behavior = 10
UNITS: days
DOCUMENT: Refer to generic model

time_to_update_reference = 360
UNITS: days
DOCUMENT: Refer to generic model

us_dinein_revenue = usdineinrevenue+1
UNITS: dmnl
DOCUMENT: This variable transforms the data to a scale of 0-1

usdineinrevenue = NAN
UNITS: dmnl
DOCUMENT: This data comes from OpenTable.com, a popular restaurant reservation platform in the United States. It has collected and published daily data estimating the percentage change in dine in customers for a variety of geographic regions since the start of the pandemic. The data is normalized to 2019 levels. (OpenTable, 2021)



Senior_Housing:

DOCUMENT: This sector analysis how COVID has impacted occupancy in Senior Housing facilities across the US. This case differs from the other cases used in this model in that it takes one step further into modeling how a change in demand caused by COVID would specifically affect the senior housing industry. Thus, additional model structure is introduced to analyze not only how COVID effects demand, but how that change in demand effects key operating metrics of the senior housing industry. This sector serves as an example of how the basic model component developed in this project can be used as a component in a more specific research project that analyses how the impact of COVID materializes in a specific situation/domain.

modeled_behavior[state](t) = modeled_behavior[state](t - dt) + (updating_behavior[state]) * dt
INIT modeled_behavior[state] = 1
UNITS: dmnl
DOCUMENT: Refer to generic model

reference_cases[state](t) = reference_cases[state](t - dt) + (updating_reference[state]) * dt
INIT reference_cases[state] = 0
UNITS: cases/day
DOCUMENT: Refer to generic model

updating_behavior[state] = ((effect_of_judgment_on_indicated_demand)-modeled_behavior)/time_to_update_behavior
UNITS: Per Day
DOCUMENT: Refer to generic model

updating_reference[state] = (perceived_present_condition-reference_cases)/time_to_update_reference
UNITS: cases/day/days
DOCUMENT: Refer to generic model

"<mean>" = -1.27
UNITS: dmnl
DOCUMENT: Refer to generic model.
The calibration routine produced a value of -1.35
Details of the calibration routine used can be found in appendix C
Details of the sensitivity analysis can be found in appendix B

"<stdev>" = .78
UNITS: dmnl
DOCUMENT: Refer to generic model.
The calibration routine produced a value of 0.86
Details of the calibration routine used can be found in appendix C
Details of the sensitivity analysis can be found in appendix B

brookdale_historical = NAN
UNITS: dmnl
DOCUMENT: This is the historical month end census data for Brookdale Senior Living, the largest provider of senior housing in the United States. The data comes from the company's website (Brookdale Senior Living, 2021)

date	time	occupancy
31-Mar-20	91	82.8%
30-Apr-20	121	80.0%
31-May-20	152	78.5%
30-Jun-20	182	77.8%
31-Jul-20	213	76.6%
31-Aug-20	244	75.5%
30-Sep-20	274	75.0%
31-Oct-20	305	74.1%
30-Nov-20	335	73.1%
31-Dec-20	366	71.5%
31-Jan-21	397	70.4%
28-Feb-21	425	70.1%
31-Mar-21	456	70.6%

COVID_effect_on_demand_for_senior_housing[state] = modeled_behavior
UNITS: dmnl

DOCUMENT: This is the output from the primary model of this research project. As a demonstration of its potential use in future research. It is being used in this domain as the input to a model that specifically looks at how the senior housing industry responds to changes in demand. The final output will be the occupancy percentages that result from the changes in demand predicted by the generic model presented here.

effect_of_judgment_on_indicated_demand[state] = IF TIME <.shutdown_begins THEN 1 ELSE NORMALCDF(-99, LN(judgment_of_current_condition+1e-12), "<mean>", "<stdev>")
UNITS: dmnl
DOCUMENT: Refer to generic model

exponent = .5
UNITS: dmnl
DOCUMENT: Refer to generic model

judgment_of_current_condition[state] = (sensation_magnitude_of_reference_condition//sensation_magnitude_of_present_condition)
UNITS: dmnl
DOCUMENT: Refer to generic model

perceived_present_condition[state] = SMTH3(.new_daily_cases, time_to_perceive_present_condition) {DELAY CONVERTER}
UNITS: cases/day
DOCUMENT: Refer to generic model

senior_housing_lognormal_cumulative_distribution_curve = NORMALCDF(-99, LN(RAMP(0.01)+1e-12),"<mean>", "<stdev>")
UNITS: dmnl
DOCUMENT: Refer to generic model

senior_housing_lognormal_probability_density_curve = (1//(RAMP(.01)*"<stdev>"*SQRT(2*PI)))*(EXP(1)^(-.5*(((LN(RAMP(.01))-"<mean>"))//"<stdev>")^2))
UNITS: dmnl
DOCUMENT: Refer to generic model

sensation_magnitude_of_present_condition[state] = DELAY(perceived_present_condition^exponent, DT)
UNITS: cases/day
DOCUMENT: Refer to generic model

sensation_magnitude_of_reference_condition[state] = reference_cases^exponent
UNITS: cases/day
DOCUMENT: Refer to generic model

time_to_perceive_present_condition = 10

UNITS: days
DOCUMENT: Refer to generic model

time_to_update_behavior = 10
UNITS: days
DOCUMENT: Refer to generic model

time_to_update_reference = 360
UNITS: days
DOCUMENT: Refer to generic model

Brookdale:

DOCUMENT: Brookdale Senior Living is the largest provider of Senior Living in the United States. Because it publishes timely data and is present in most of the United States, it is used to represent the entire US senior housing market.

occupancy[state](t) = occupancy[state](t - dt) + (move_ins[state] - COVID_moveouts[state] - normal_moveouts[state]) * dt
INIT occupancy[state] = brookdale_bed_capacity*beginning_brookdale_occupancy
UNITS: people
DOCUMENT: This stock represents the estimated occupancy (number of residents) who are living in Brookdale buildings in each state. It is initialized by taking the bed capacity in each state multiplied by the average occupancy percentage at the start of the pandemic.

waitlist[state](t) = waitlist[state](t - dt) + (add_to_waitlist[state] - move_ins[state]) * dt {NON-NEGATIVE}
INIT waitlist[state] = occupancy/average_stay_length*time_to_move_in
UNITS: people
DOCUMENT: This stock represents the group of people who have decided to move into senior housing but are not yet occupants of any facility. There is typically a period of a few weeks between the decision and the actual moving in. It is initialized in equilibrium

add_to_waitlist[state] = new_demand*(Senior_Housing.COVID_effect_on_demand_for_senior_housing)
UNITS: people/day
DOCUMENT: This represents the number of people who are expected to decide to move into an assisted living home. It is calculated by taking the normal equilibrium demand (new demand) multiplied by the effect of COVID on demand, which will effectively reduce the number who are added to the wait list as long as COVID remains.

COVID_moveouts[state] = ((.new_daily_deaths*fraction_of_deaths_from_LTC*portion_of_senior_market))
UNITS: people/day
DOCUMENT: This flow tracks how many moveouts have been specifically caused by COVID deaths. While it is not certain how many deaths are attributable to Brookdale

facilities, an average is used that is in line with national averages. The estimated COVID moveouts is calculated by taking the total number of deaths within a state, multiplied by the fraction of deaths from assisted living facilities (10%) times the portion of the senior housing market that Brookdale serves in that state.

move_ins[state] = DELAYN((add_to_waitlist), time_to_move_in, 3)
UNITS: people/day
DOCUMENT: This flow represents how many people are moving into Brookdale facilities.

normal_moveouts[state] = occupancy/average_stay_length
UNITS: people/day
DOCUMENT: This flow represents the normal number of people moving out.

"%_of_total_capacity"[state] = brookdale_bed_capacity/SUM(brookdale_bed_capacity)
UNITS: dmnl
DOCUMENT: This variable calculates the percentage of Brookdale's beds that are found in each state.

"%_of_total_senior_population"[state] = senior_population/SUM(senior_population)
UNITS: dmnl
DOCUMENT: The percentage of the total US population that is older than 65 years living in each US state

"%_senior"[state] = NAN
UNITS: dmnl
DOCUMENT: An estimate of the percentage of population in each US state that is over 65 years old. (PRB, 2018)

State	% senior	State	% senior	State	% senior
[AL]	16.9%	[LA]	15.4%	[OH]	17.1%
[AK]	11.8%	[ME]	20.6%	[OK]	15.7%
[AZ]	17.5%	[MD]	15.4%	[OR]	17.6%
[AR]	17.0%	[MA]	16.5%	[PA]	18.2%
[CA]	14.3%	[MI]	17.2%	[RI]	17.2%
[CO]	14.2%	[MN]	15.9%	[SC]	17.7%
[CT]	17.2%	[MS]	15.9%	[SD]	16.6%
[DE]	18.7%	[MO]	16.9%	[TN]	16.4%
[FL]	20.5%	[MT]	18.7%	[TX]	12.6%
[GA]	13.9%	[NE]	15.7%	[UT]	11.1%
[HI]	18.4%	[NV]	15.7%	[VT]	19.4%
[ID]	15.9%	[NH]	18.1%	[VA]	15.4%
[IL]	15.6%	[NJ]	16.1%	[WA]	15.4%
[IN]	15.8%	[NM]	17.5%	[WV]	19.9%
[IA]	17.1%	[NY]	16.4%	[WI]	17.0%
[KS]	15.9%	[NC]	16.3%	[WY]	16.5%
[KY]	16.4%	[ND]	15.3%	[DC]	15.0%

average_stay_length = 28*30.42 (Breeding, 2021)
UNITS: days

beds_in_each_state[state] = "%_of_total_senior_population"*beds_in_US_market
UNITS: beds
DOCUMENT: An estimate of the number of assisted living beds in each state by allocating the total number of beds in the US multiplied by the percentage of total elderly people living in each state. While some states have a higher or lower prevalence of assisted living beds than the national average, this will be a close enough approximation for the purpose of this model.

beds_in_US_market = 996100
UNITS: beds
DOCUMENT: An estimate of the number of licensed assisted living beds in the United States. (NCAL National Center for Assisted Living, 2019)

beginning_brookdale_occupancy = .828
UNITS: dmnl

brookdale_bed_capacity[state] = NAN
UNITS: beds
DOCUMENT: Number of beds operated by Brookdale per state, as of December 31, 2020 (Brookdale Senior Living INC, 2021)

State	# beds	State	# beds	State	# beds
[AK]	494	[KY]	283	[NY]	1,500
[AL]	804	[LA]	486	[OH]	2,971
[AK]	-	[KY]	899	[NY]	979
[AL]	2,153	[LA]	560	[OH]	1,805
[AK]	6,961	[KY]	-	[NY]	766
[AL]	3,380	[LA]	1,678	[OH]	532
[AK]	636	[KY]	538	[NY]	611
[AL]	-	[LA]	-	[OH]	-
[AK]	105	[KY]	386	[NY]	1,494
[AL]	6,384	[LA]	137	[OH]	9,023
[AK]	717	[KY]	3,401	[NY]	55
[AL]	-	[LA]	-	[OH]	1,206
[AK]	-	[KY]	-	[NY]	101
[AL]	548	[LA]	90	[OH]	2,833
[AK]	3,027	[KY]	1,147	[NY]	712
[AL]	830	[LA]	457	[OH]	93
[AK]	1,114	[KY]	256	[NY]	46

brookdale_occupancy = SUM("%_of_total_capacity"*occupancy_%)
UNITS: dmnl
DOCUMENT: This is the modeled occupancy percentage over time for Brookdale Senior Living given the output of the generic model (calibrated to the senior living industry) and the response of this output when taken as the demand input into the senior housing industry model.

fraction_of_deaths_from_LTC = .1
UNITS: dmnl
DOCUMENT: This variable represents an estimate for what percentage of COVID deaths are attributable to people living in assisted living facilities. While this number is not perfectly known, it is estimated to be around 10%.

According to The New York Times, 32% of all COVID deaths in the US have come from long term care facilities (The New York Times, 2021). This includes primarily assisted living as well as nursing homes. Nursing homes on average serve higher acuity residents, so it is expected the deaths will be skewed toward nursing homes over assisted living, and nursing homes account for a majority of long-term care facilities. Therefore, this model estimates that 10% of total COVID deaths are attributable to assisted living.

new_demand[state] = INIT(occupancy)/average_stay_length
UNITS: people/day
DOCUMENT: New demand is assumed to be a value that would keep the senior housing market in equilibrium given normal move-out rates. In the short term this is a reasonable assumption, though for longer term projections this should reflect the natural growth of the market.

occupancy_%[state] = occupancy//brookdale_bed_capacity
UNITS: dmnl
DOCUMENT: This calculates the occupancy percentage for Brookdale in each state it operates in

portion_of_senior_market[state] = brookdale_bed_capacity/beds_in_each_state
UNITS: dmnl
DOCUMENT: This variable estimates what percentage of assisted living beds in each state belong to Brookdale.

senior_population[state] = "%_senior"*.state_population
UNITS: people
DOCUMENT: An estimate of the total population over 65 years old in each US state.

time_to_move_in = 21
UNITS: days
DOCUMENT: It is assumed that it takes on average 3 weeks from the decision to move into senior housing to actually move in.

Theil_Statistics:

DOCUMENT: This is a module, developed by Rogelio Oliva, which calculates the Theil Statistics of a model's behavior mode with the reference mode of historical behavior. It is used to calculate the statistics of historical fit for the models in this research project. (Oliva)

count(t) = count(t - dt) + (add_one) * dt {NON-NEGATIVE}
INIT count = 1e-9
UNITS: unitless

Sum_Di(t) = Sum_Di(t - dt) + (add_Di) * dt {NON-NEGATIVE}
INIT Sum_Di = 0
UNITS: stats

Sum_Dsq(t) = Sum_Dsq(t - dt) + (add_Dsq) * dt {NON-NEGATIVE}
INIT Sum_Dsq = 0
UNITS: stats^2

"Sum_M-Dsq"(t) = "Sum_M-Dsq"(t - dt) + ("add_M-Dsq") * dt {NON-NEGATIVE}
INIT "Sum_M-Dsq" = 1e-9
UNITS: stats^2

Sum_Mi(t) = Sum_Mi(t - dt) + (add_Mi) * dt {NON-NEGATIVE}
INIT Sum_Mi = 0
UNITS: stats

Sum_Msq(t) = Sum_Msq(t - dt) + (add_Msq) * dt {NON-NEGATIVE}
INIT Sum_Msq = 0
UNITS: stats^2

Sum_MY(t) = Sum_MY(t - dt) + (add_MD) * dt {NON-NEGATIVE}
INIT Sum_MY = 0
UNITS: stats^2

Sum_PE(t) = Sum_PE(t - dt) + (add_PE) * dt {NON-NEGATIVE}
INIT Sum_PE = 0
UNITS: unitless

add_Di = Di/DT
UNITS: stats/days

add_Dsq = Di*Di/DT
UNITS: stats^2/days

"add_M-Dsq" = (Mi-Di)*(Mi-Di)/DT
UNITS: stats^2/days

add_MD = Mi*Di/DT
UNITS: stats^2/days

add_Mi = Mi/DT
UNITS: stats/days

add_Msq = Mi*Mi/DT
UNITS: stats^2/days

add_one = pick/DT
UNITS: Per Day

add_PE = IF Di > 0 OR Di < 0 THEN (((Mi-Di)/Di)^2)/DT ELSE 0

UNITS: Per Day

Bias = (Mm-Md)*(Mm-Md)/MSE
UNITS: unitless

Covariation = 2*Sm*Sd*(1-R)/MSE
UNITS: unitless

Data = .sample_data
UNITS: dmnl

Di = pick*Data*units_conversion
UNITS: stats

end = 5000 {any time greater than the end of the simulation run}
UNITS: days

Md = Sum_Di/count
UNITS: stats

Mdsq = Sum_Dsq/count
UNITS: stats^2

Mi = pick*Model*units_conversion
UNITS: stats

Mm = Sum_Mi/count
UNITS: stats

Mmd = Sum_MY/count
UNITS: stats^2

Mmsq = Sum_Msq/count
UNITS: stats^2

Model = .sample_model_results
UNITS: dmnl

MSE = "Sum_M-Dsq"/count
UNITS: stats^2

pick = PULSE(DT,start,1)*(STEP(1,start)-STEP(1,end+DT/2))
UNITS: unitless

R = (Mmd-Mm*Md)/(Sm*Sd+(1e-9))
UNITS: unitless

RMSPE = SQRT(Sum_PE/count)
UNITS: unitless

Rsq = R^2
UNITS: unitless

Sd = SQRT(Mdsq-Md*Md)
UNITS: stats

Sm = SQRT(Mmsq-Mm*Mm)
UNITS: stats

start = STARTTIME
UNITS: days

units_conversion = 1
UNITS: stats/dmnl

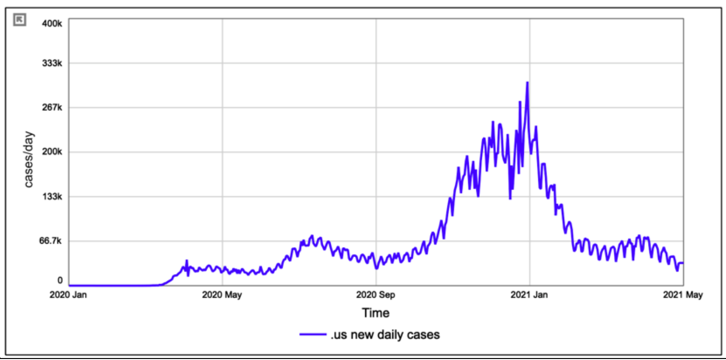
Variation = (Sm-Sd)*(Sm-Sd)/MSE
UNITS: unitless

Appendix B: Sensitivity Analysis Results

This appendix shows the results of sensitivity analysis run on all exogenous parameters of the generic model. A base case run is given below, and each sensitivity run utilizes these values and changes one of the values incrementally within a preset range that is described below in Table 8. A brief discussion about the insights of the sensitivity analysis will follow the results for each tested parameter.

Base Case Run (Generic Model Component Structure) :

Table 8: Standard values for the sensitivity analysis:

Variable	Base Case Value	Units
Total new daily cases	CDC data aggregated for the entire United States 	Cases/day
Time to perceive present condition	10	days
Time to update reference condition	360	days
Exponent	0.5	dmnl
Shutdown begins	71	days
<stdev>	2	dmnl
<mean>	-0.5	dmnl
Time to update demand	10	days

Time to Perceive Present Condition:

The follow are the results of the sensitivity analysis conduction on the 'time to perceive present condition' variable. The model was run in the base case except for changing the 'time to perceive present condition' variable incrementally from 0 to 30 as described in Table 9 below. As the length of time increases, the effect is an equivalent delay of the behavior mode of the model. The behavior model is not substantially changed due to changes in this variable. Given level of estimation and uncertainty around quantifying this variable, it is encouraging to see that errors in its estimation are not likely to have material results on the behavior of the model.

Table 9: Sensitivity values: Time to perceive present condition

	time to perceive present condition
Run 1	0
Run 2	3
Run 3	6
Run 4	9
Run 5	12
Run 6	15
Run 7	18
Run 8	21
Run 9	24
Run 10	27
Run 11	30

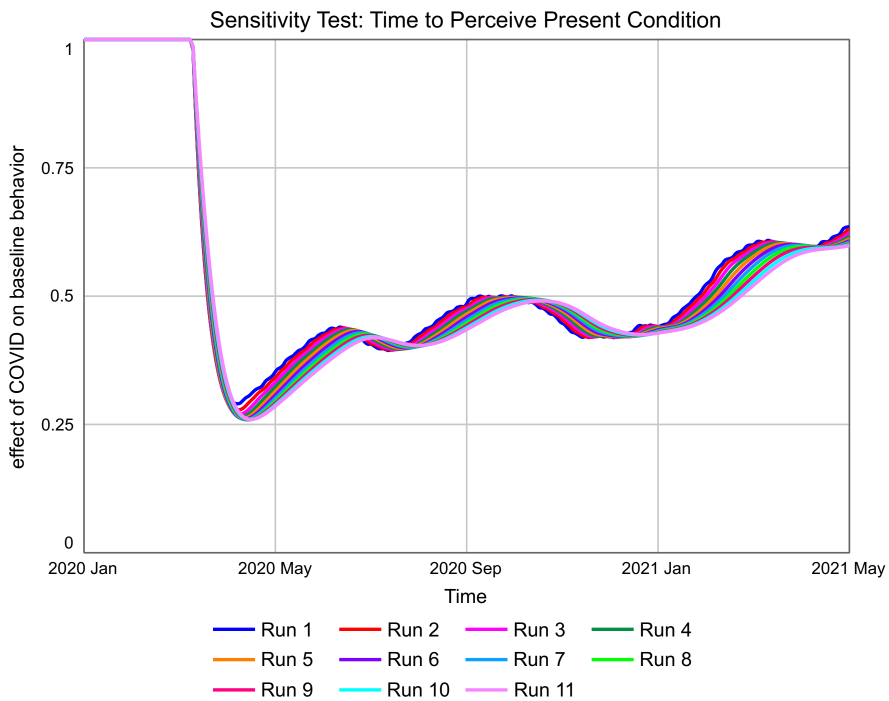


Figure 52: Sensitivity Analysis: Time to Perceive Present Condition

Time to Update Reference Condition

The following are the results of the sensitivity analysis conduction on the 'time to update reference condition' variable. The model was run in the base case except for changing the 'time to update reference condition' variable incrementally from 60 to 720 as described in TABLE below. As the length of time increases, it has the effect of lowering the output curve, though the strength of how much it increases or decreases does weaken over time; in other words, the lines converge slightly over time.

Table 10: Sensitivity values: time to update reference condition.

	time to update reference condition
Run 1	60
Run 2	120
Run 3	180
Run 4	240
Run 5	300
Run 6	360
Run 7	420
Run 8	480
Run 9	540
Run 10	600
Run 11	660
Run 12	720

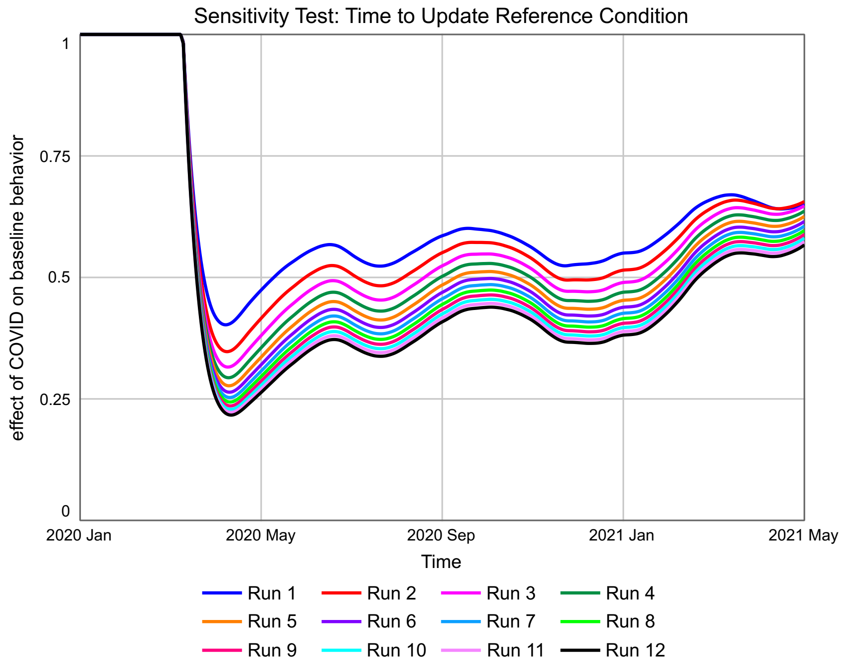


Figure 53: Sensitivity Analysis: Time to update reference condition

Exponent:

The exponent has the effect of exaggerating the peaks and valleys of the behavior mode. It has been tested incrementally from .25 to .75 and will stretch the behavior output further from whatever percentage a ‘judgment of current condition’ value of 1 would produce when passed through the distribution. In this example, this line runs at about effect of COVID on baseline behavior = 0.60. Lowering the exponent will draw all behavior closer to this line; raising it will distort behavior further from this line.

Table 11: Sensitivity values: Exponent

	exponent
Run 1	0.25
Run 2	0.3
Run 3	0.35
Run 4	0.4
Run 5	0.45
Run 6	0.5
Run 7	0.55
Run 8	0.6
Run 9	0.65
Run 10	0.7
Run 11	0.75

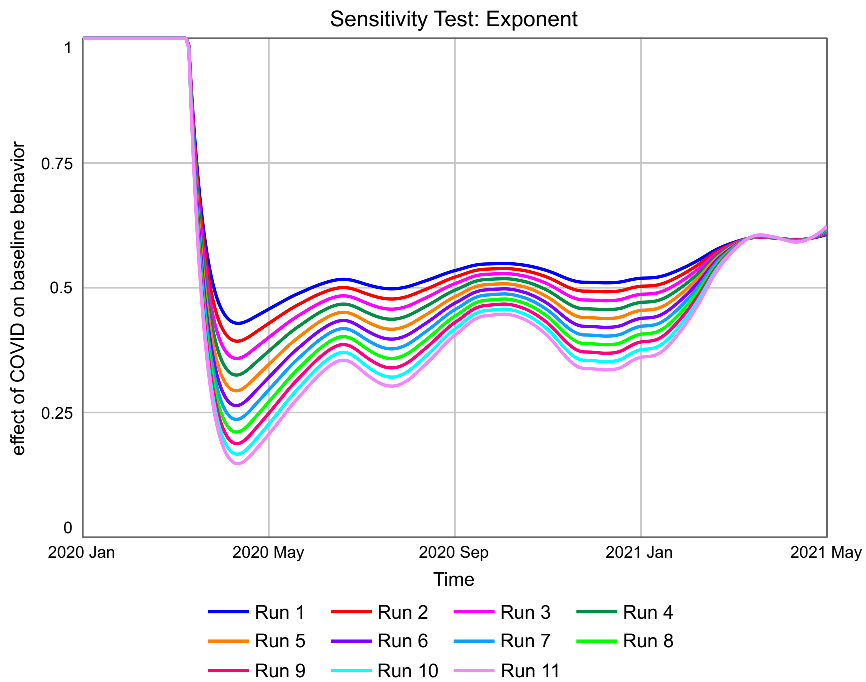


Figure 54: Sensitivity Analysis: Exponent

Stdev

The standard deviation value has been tested incrementally from 0.5 (a tight distribution) to 3.0 (a wide distribution). This variable has the effect of stretching the behavior mode further from the mean value. In the case below, the mean of the distribution used in the model was constant at -0.5, which indicates that the mean behavior level given all different judgment values is 0.5, so the larger the standard deviation, the closer the behavior will stay to the mean given a different judgment value.

Table 12: Sensitivity values: Stdev

	<stdev>
Run 1	0.5
Run 2	0.75
Run 3	1.0
Run 4	1.25
Run 5	1.5
Run 6	1.75
Run 7	2.0
Run 8	2.25
Run 9	2.5
Run 10	2.75
Run 11	3.00

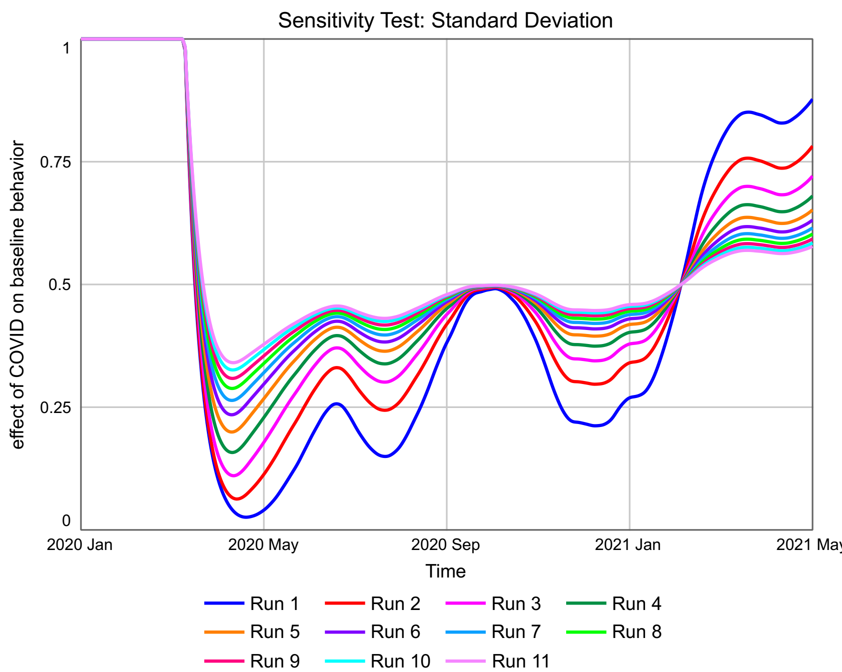


Figure 55: Sensitivity Analysis: Standard Deviation

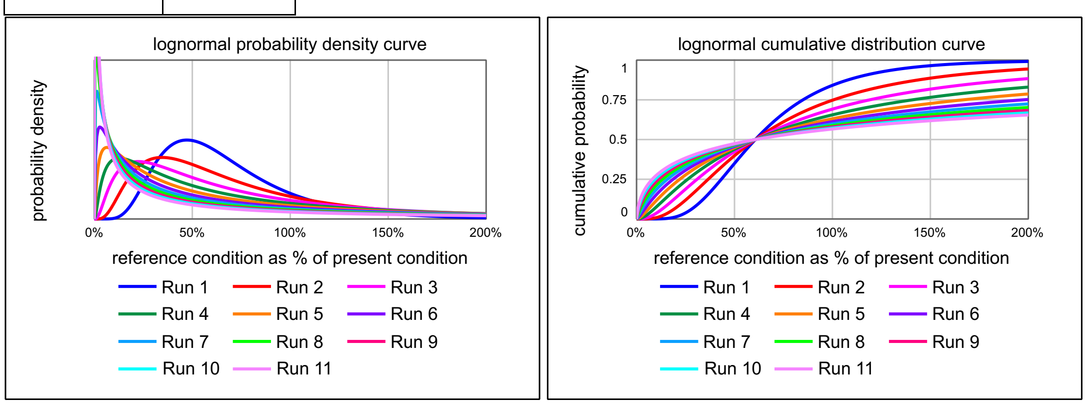


Figure 56: Sensitivity Analysis: Effect of change in the standard deviation on the shape of the probability and cumulative probability density curves

Mean

The mean of the lognormal distribution used in the model was analyzed with values ranging from -3.67 to -0.33 As the mean reduces, it means that behavior will be overall less impacted by COVID.

Table 13: Sensitivity values: Mean

	<mean>
Run 1	-3.67
Run 2	-3.33
Run 3	-3.0
Run 4	-2.67
Run 5	-2.33
Run 6	-2.0
Run 7	-1.67
Run 8	-1.33
Run 9	-1.0
Run 10	-0.67
Run 11	-0.33

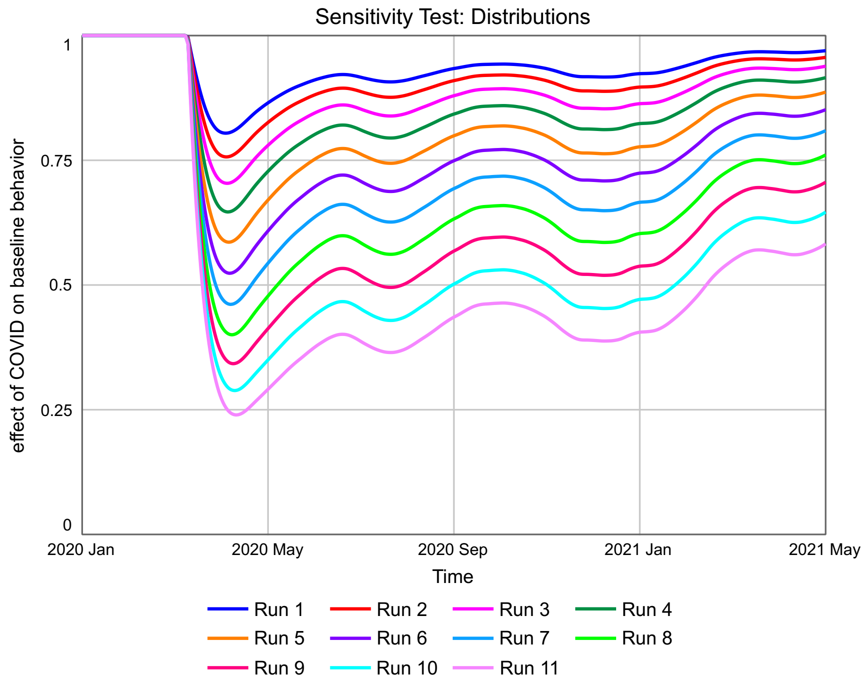


Figure 57: Sensitivity Analysis: Mean

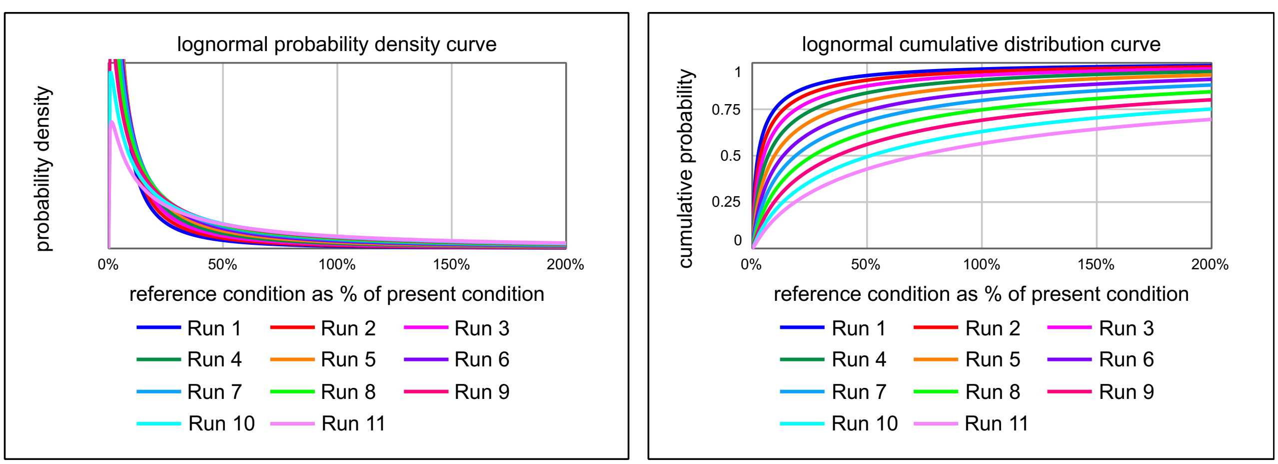


Figure 58: Sensitivity Analysis: Effect of change in the standard deviation on the shape of the probability and cumulative probability density curves

Time to Update Behavior

The time to update behavior was run with values ranging from 0 to 100 days. While it is not expected that in most cases the time to update behavior will vary that much (unless there is known to be considerable lag time between the indicated behavior and the actual behavior (as in the case of the airlines)), this analysis nonetheless demonstrates that the model is highly sensitive to this value, and even small changes of a few days may make a difference in the model output. The longer this delay, the smoother the output behavior will be.

Table 14: Sensitivity values: Time to update behavior

	time to update behavior
Run 1	0
Run 2	10
Run 3	20
Run 4	30
Run 5	40
Run 6	50
Run 7	60
Run 8	70
Run 9	80
Run 10	90
Run 11	100

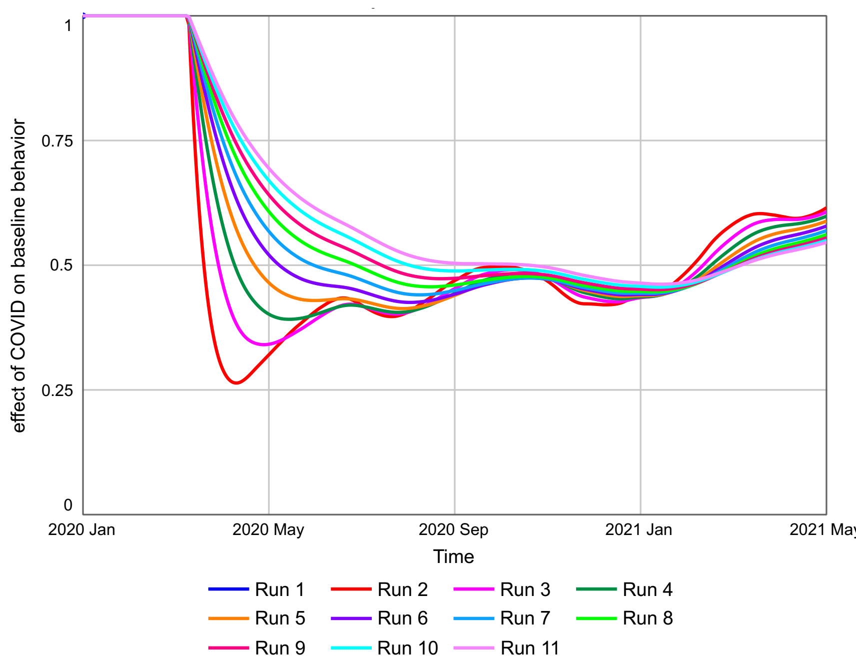


Figure 59: Sensitivity Analysis: Time to Update Behavior

Sensitivity of different combinations of distribution parameters

Table 15: Sensitivity values: distribution parameters

	Mean	Stdev
Run 1	-2.5	0.5
Run 2	-2.5	1
Run 3	-2.5	1.5
Run 4	-2.5	2
Run 5	-2.5	2.5
Run 6	-2	0.5
Run 7	-2	1
Run 8	-2	1.5
Run 9	-2	2
Run 10	-2	2.5
Run 11	-1.5	0.5
Run 12	-1.5	1
Run 13	-1.5	1.5
Run 14	-1.5	2
Run 15	-1.5	2.5
Run 16	-1	0.5
Run 17	-1	1
Run 18	-1	1.5
Run 19	-1	2
Run 20	-1	2.5
Run 21	-0.5	0.5
Run 22	-0.5	1
Run 23	-0.5	1.5
Run 24	-0.5	2
Run 25	-0.5	2.5

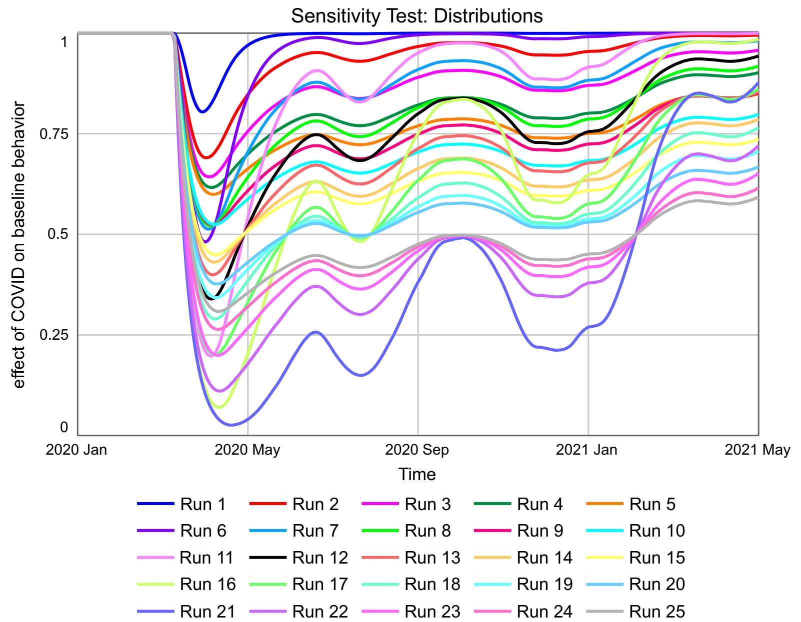


Figure 61: Sensitivity Analysis: Effect of different combinations of mean and standard deviation values on the model output

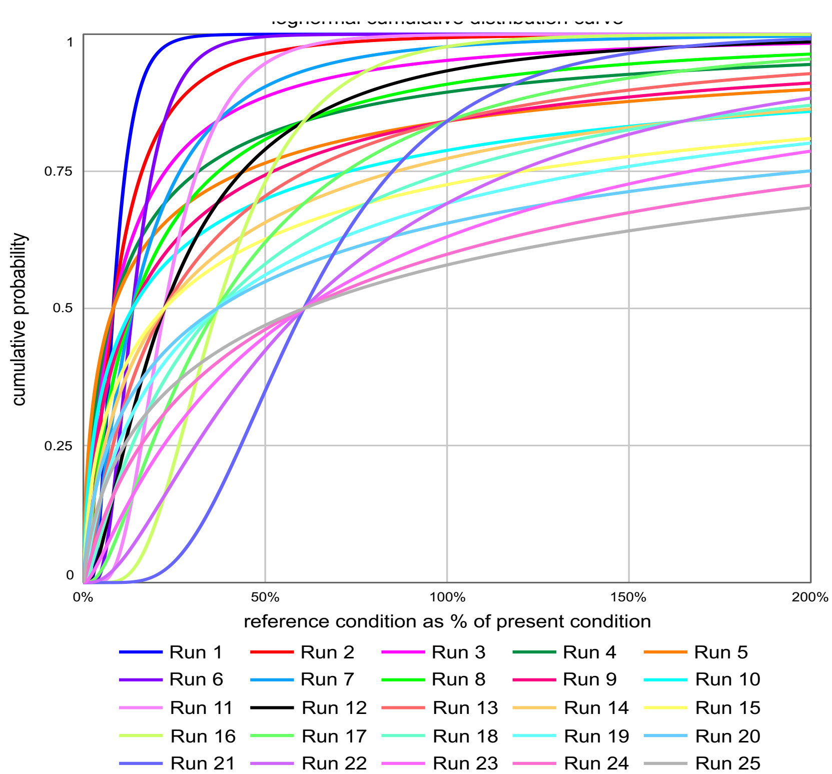


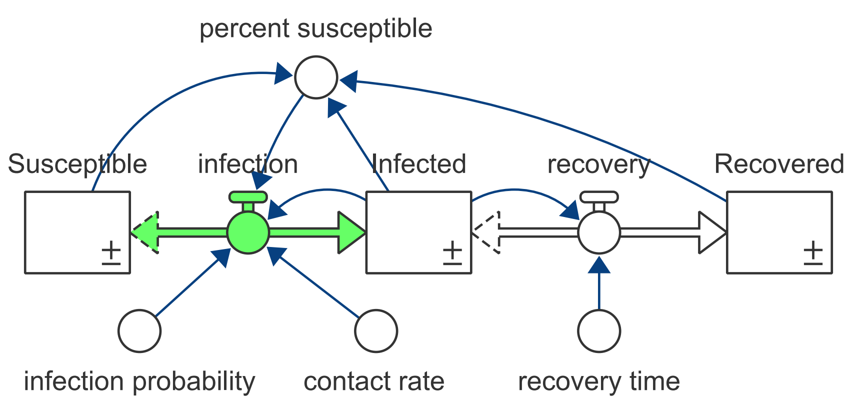
Figure 60: Sensitivity Analysis: Effect of different combinations of mean and standard deviation values on the respective cumulative distribution curves.

The results on the previous page indicate that just by utilizing a different combination of mean and standard deviation values, drastically different behavior can result from the model. Ultimately it is the power of these variables in combination with each other that calibrates the model so nicely in each of the domains.

Sensitivity of Daily Cases Input

This section tests how different hypothetical COVID developments would impact behavior patterns. It must be noted that the 'shutdown begins' variable has been changed to day 10 for each of these tests. A further discussion of this can be found in the body of the paper under the analysis section, but the results are shown again here as sensitivity analysis. As you can see, in all cases the onset of the pandemic causes behavior levels to drop it like it's hot.

Table 16: Sensitivity inputs to daily cases

Run	Equation
Run 1	STEP(1000, 10)-STEP(1000, 310)
Run 2	STEP(10000, 10)-STEP(10000, 310)
Run 3	RAMP(100, 10)+RAMP(-200, 310)
Run 4	10000+SINWAVE(10000, 100)
Run 5	STEP(25000, 10)+RAMP(-100, 10, 260)
Run 6	10^(TIME/100)
Run 7	Infection curve (from a basic SIR model) 

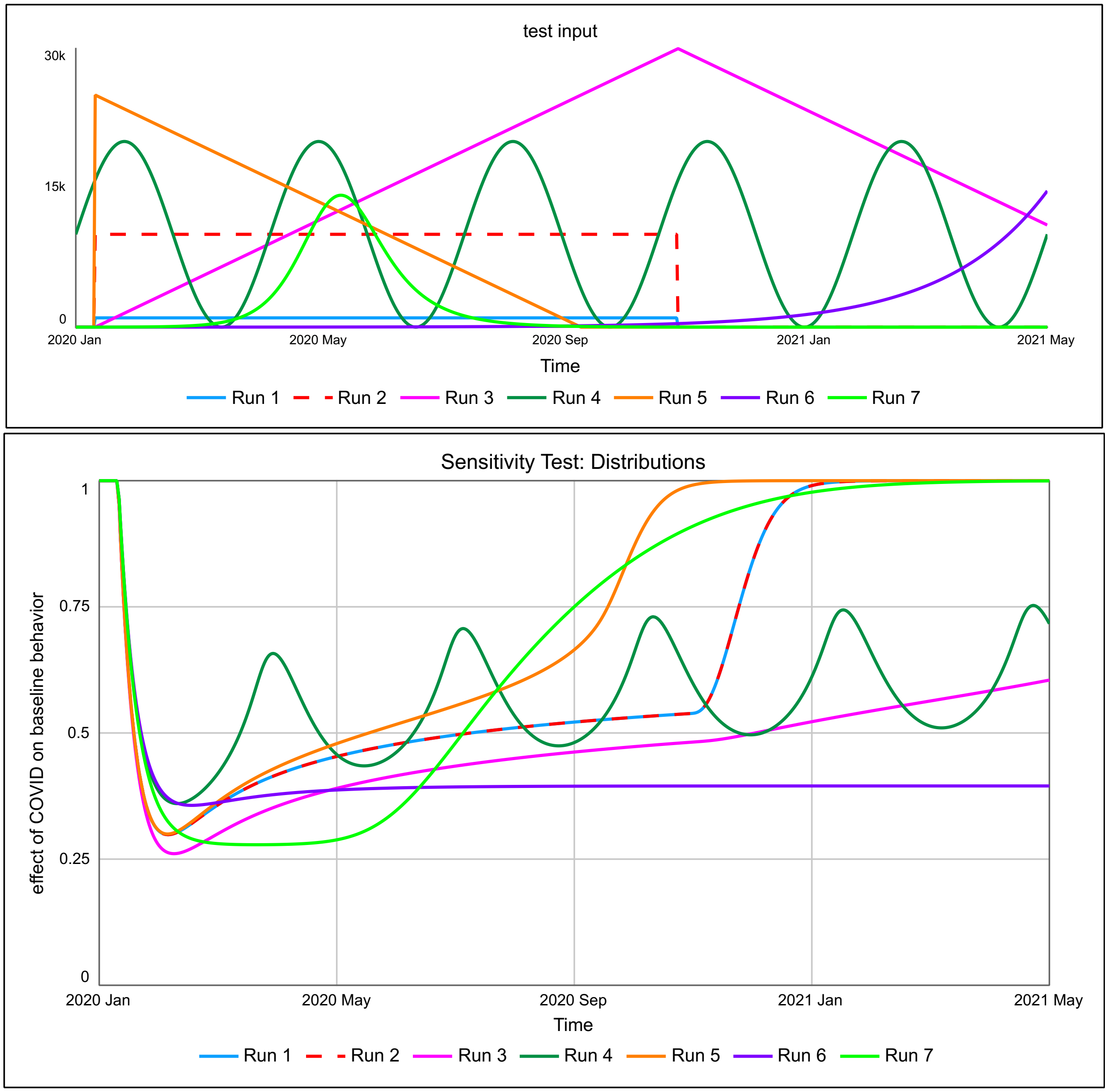


Figure 62: Results of sensitivity of daily cases input

Appendix C: Calibration Routines

This section describes the calibration routines used to set the key parameter values for each domain studied in this model. There were two calibration routines as described in the calibration section of this paper. In all cases the exact same calibration routine was used; the primary settings are described in Table 18, a few pages from here. Screenshots of the results from calibration process 1 are included as well. Note that in cases where each calibration run produced very similar payoff runs with different parameter values, the most reasonable set of parameters was selected and included in Table 17.

Table 17: Domain-specific information regarding process 1

Domain	Mean	Stdev	exponent	TURC	Calibration variable (model)	Calibration variable (data)
Airlines	-1.25	0.875	0.564	1000 (max)	effect of covid on airline passenger traffic	normalized demand
Restaurants	-0.656	0.892	0.486	404	calibration variable	us dinein revenue
Workplaces	-1.83	2.85	0.549	121	calibration variables (model) [work]	smoothed us mobility data [work]
Retail and Recreation	-1.91	1.80	0.647	73	calibration variables (model) [retail]	smoothed us mobility data [retail]
Grocery and Pharmacy	-5.06	3.04	0.587	31	calibration variables (model) [grocery]	smoothed us mobility data [grocery]
Transit Stations	-1.65	3.27	0.806	54	calibration variables (model)[trans]	smoothed us mobility data [trans]
Senior Housing	Not Considered at this stage due to the added model structure					

Method	additional starts	maxiter	init_step	tolerance
Powell	2	5000	1	0.00001

Payoff:	**airlines_po**
Action	minimize
Kind	Calibration
Element	Airlines.effect of covid on airline passenger traffic
Weight	1
Comparison Variable	Airlines.normalized demand
Comparison Run	-2
Comparison Type	Squared Error
Comparison Tolerance	0

Parameter:	Airlines.	Airlines.	Airlines.exponent	Airlines.time to update reference
min_value	-5	0	0	0
max_value	0	5	1	1000
scaling	1	1	1	0.001

	Airlines.	Airlines.	Airlines.exponent	Airlines.time to update reference	**airlines_po**
Starting at	-0.726	0.698	0.5	360	
This pass gave	-1.79546973173	1.25120068512	0.806650897625	1000(max)	132127.397404
Restarting at	-2.5	2.5	0.5	500	
This pass gave	-1.25551435593	0.874923090164	0.564065478572	1000(max)	132127.397401
Restarting at	-3.75	3.75	0.25	250	
This pass gave	-2.22583657311	1.55110435889	1(max)	1000(max)	132127.397409
After 86 runs	-1.25551435593	0.874923090164	0.564065478572	1000(max)	132127.397401

Starting optimization "restaurants_opt" at 2021-May-26 18:34:33

Method	additional starts	maxiter	init_step	tolerance
Powell	2	5000	0.1	0.00001

Payoff:	**restaurants_po**
Action	minimize
Kind	Calibration
Element	Restaurants.calibration variable
Weight	1
Comparison Variable	Restaurants.us dinein revenue
Comparison Run	-2
Comparison Type	Squared Error
Comparison Tolerance	0

Parameter:	Restaurants.	Restaurants.	Restaurants.exponent	Restaurants.time to update reference
min_value	-5	0	0	0
max_value	0	5	1	1000
scaling	1	1	1	0.001

	Restaurants.	Restaurants.	Restaurants.exponent	Restaurants.time to update reference	**restaurants_po**
Starting at	-0.626	0.93	0.5	360	
This pass gave	-0.655780856331	0.891534329743	0.486360755588	403.570902973	11586419.9492
Restarting at	-2.5	2.5	0.5	500	
This pass gave	-1.34836581775	1.83307347061	0.999994921309	403.585516342	11586419.9492
Restarting at	-3.75	3.75	0.25	250	
This pass gave	-1.15309531124	1.56752857302	0.855126471747	403.623776086	11586419.9492
After 323 runs	-0.655782509155	0.89152875031	0.486356905338	403.577519906	11586419.9492

Method	additional starts	init_step	maxiter	tolerance
Powell	2	1	1000	0.00001

Payoff:	**workplaces_po**
Action	minimize
Kind	Calibration
Element	Mobility.calibration variables (model)[work]
Weight	1
Comparison Variable	Mobility.smoothed us workplaces
Comparison Run	-2
Comparison Type	Squared Error
Comparison Tolerance	0

Parameter:	Mobility.[work]	Mobility.[work]	Mobility.time to update reference[work]	Mobility.exponent[work]
min_value	-5	0	0	0
max_value	0	5	1000	1
scaling	1	1	0.001	1

	Mobility.[work]	Mobility.[work]	Mobility.time to update reference[work]	Mobility.exponent[work]	**workplaces_po**
Starting at	-2.24	2.99	873.229118047	1	
This pass gave	-2.0449354334	3.20329343961	121.952826572	0.615125500202	1.07986866458
Restarting at	-2.5	2.5	500	0.5	
This pass gave	-1.8252349857	2.85900530887	121.990168849	0.54898453062	1.07986867318
Restarting at	-3.75	3.75	250	0.25	
This pass gave	-3.01402566162	4.72134296825	121.948412834	0.906642524475	1.07986866501
After 239 runs	-2.04492790755	3.20328888786	121.94926271	0.615128653314	1.07986866458

Method	additional starts	maxiter	init_step	tolerance
Powell	2	1000	1	0.00001

Payoff:	**retail_po**
Action	minimize
Kind	Calibration
Element	Mobility.calibration variables (model)[retail]
Weight	1
Comparison Variable	Mobility.smoothed us retail and recreation
Comparison Run	-2
Comparison Type	Squared Error
Comparison Tolerance	0

Parameter:	Mobility.[retail]	Mobility.[retail]	Mobility.time to update reference[retail]	Mobility.exponent[retail]
min_value	-5	0	0	0
max_value	0	5	1000	1
scaling	1	1	0.001	1

	Mobility.[retail]	Mobility.[retail]	Mobility.time to update reference[retail]	Mobility.exponent[retail]	**retail_po**
Starting at	-2.37	1.79	360	0.5	
This pass gave	-1.91534219706	1.80295240684	72.8749301971	0.645598993401	3.4536552538
Restarting at	-2.5	2.5	500	0.5	
This pass gave	-2.52388289804	2.37580985302	72.8746013001	0.850694487508	3.45365525611
Restarting at	-3.75	3.75	250	0.25	
This pass gave	-2.96677789615	2.79272187919	72.8735885017	1(max)	3.45365524902
After 279 runs	-2.96677789615	2.79272187919	72.8735885017	1(max)	3.45365524902

Method	additional starts	init_step	maxiter	tolerance
Powell	2	1	1000	0.00001

Payoff:	**grocery_po**
Action	minimize
Kind	Calibration
Element	Mobility.calibration variables (model)[grocery]
Weight	1
Comparison Variable	Mobility.smoothed us grocery and pharmacy
Comparison Run	-2
Comparison Type	Squared Error
Comparison Tolerance	0

Parameter:	Mobility.[grocery]	Mobility.[grocery]	Mobility.exponent[grocery]	Mobility.time to update reference[grocery]
min_value	-10	0	0	1
max_value	0	5	1	1000
scaling	1	1	1	0.001

	Mobility.[grocery]	Mobility.[grocery]	Mobility.exponent[grocery]	Mobility.time to update reference[grocery]	**grocery_po**
Starting at	-4.73856804233	2.844850887	0.315232532286	71.3722680107	
This pass gave	-4.92955555464	2.9658807541	0.573182084464	30.9342784017	31725.1902465
Restarting at	-5	2.5	0.5	500.5	
This pass gave	-5.05692911086	3.04254658141	0.587666195764	30.9621437077	31725.1908837
Restarting at	-7.5	3.75	0.25	250.75	
This pass gave	-7.59465881721	4.56933154136	0.883082915257	30.9358023529	31725.1894862
After 252 runs	-7.5946652706	4.56933307009	0.883090399612	30.9357688041	31725.1894862

Finishing optimization at 2021-Jun-02 19:45:53

Method	additional starts	init_step	maxiter	tolerance
Powell	2	0.01	1000	0.00001

Payoff:	**transit_opt**
Action	minimize
Kind	Calibration
Element	Mobility.calibration variables (model)[trans]
Weight	1
Comparison Variable	Mobility.smoothed us transit stations
Comparison Run	-2
Comparison Type	Squared Error
Comparison Tolerance	0

Parameter:	Mobility.[trans]	Mobility.[trans]	Mobility.exponent[trans]	Mobility.time to update reference[trans]
min_value	-5	0	0	0
max_value	0	5	1	1000
scaling	1	1	1	0.001

	Mobility.[trans]	Mobility.[trans]	Mobility.exponent[trans]	Mobility.time to update reference[trans]	**transit_opt**
Starting at	-2	2.99	0.5	360	
This pass gave	-1.64797836927	3.2748320092	0.805612124896	54.019187504	3.20899025985
Restarting at	-2.5	2.5	0.5	500	
This pass gave	-1.92065343454	3.81668369518	0.938903148637	54.0200379032	3.20899025996
Restarting at	-3.75	3.75	0.25	250	
This pass gave	-1.98376244225	3.94208965548	0.969742109438	54.0203889656	3.20899026016
After 288 runs	-1.64797836927	3.2748320092	0.805612124896	54.019187504	3.20899025985

In each calibration of process 2, the same variables (<mean> and <stdev>) were selected to be subject to the calibration routine. A summary of those two variables is below in Table 19. These variables, after reviewing the theoretical basis for the model structure as well as after confirming via sensitivity analysis are considered to be the two key variables capable of meaningfully affecting the behavior of the model. They were tested within the ranges listed below and the summary results of the calibration are given in Table 19.

Table 18: Calibration process 2 settings:

Setting	Selection
Payoff	[payoff]
Action	minimize
Kind	Calibration
Element	[output variable of module]
Weight	1
Comparison Variable	[imported data]
Comparison Run	Current Run
Comparison Type	Squared Error
Comparison Tolerance	0
Additional Runs	2
Method	Powell
Initial Step	1
Max Iterations	1000
Tolerance	.00001

Table 19: Domain-specific information regarding calibration process 2.

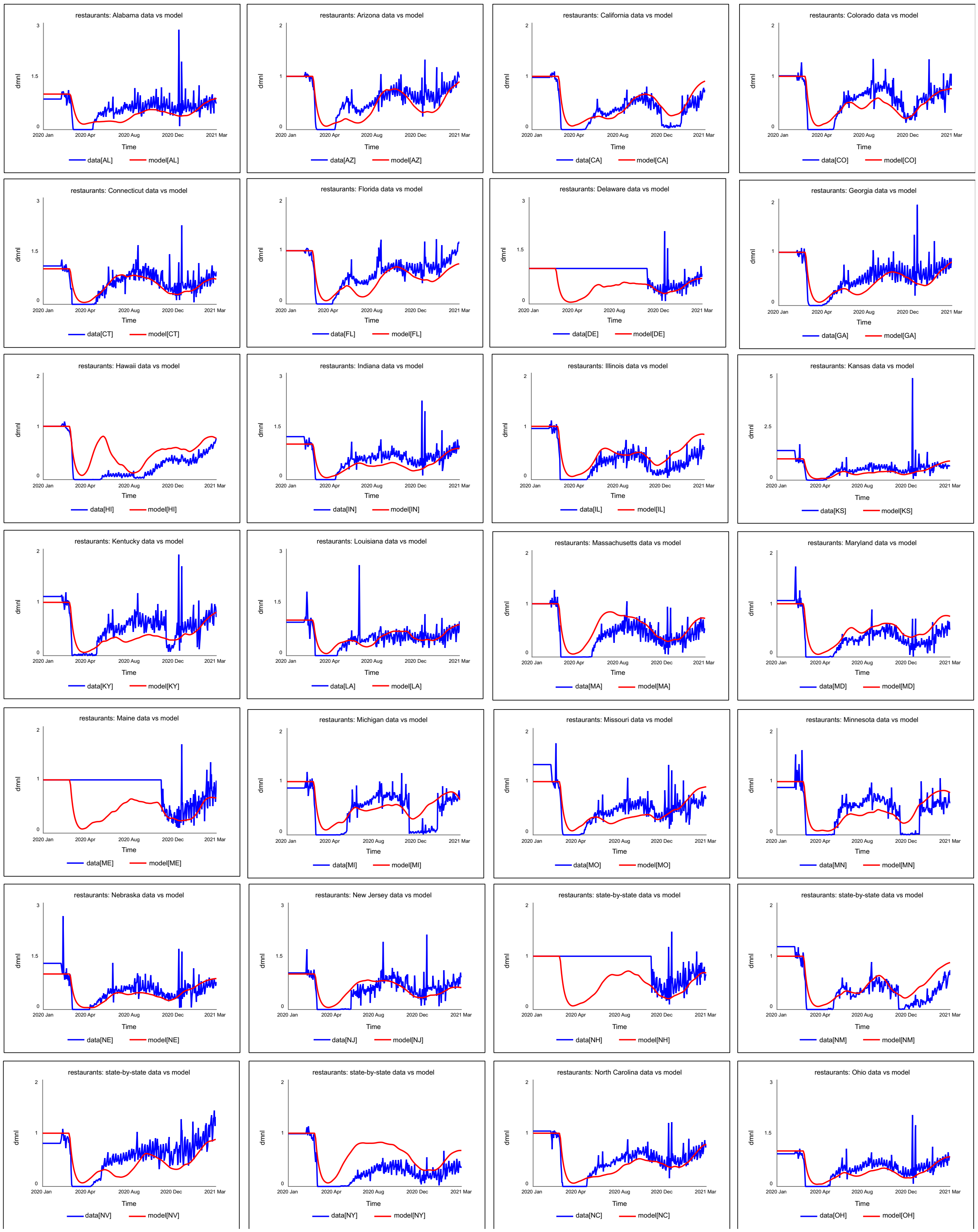
Domain	Mean	Stdev	Calibration variable (model)	Calibration variable (data)	Calibration Period
Airlines	-0.726	0.698	effect of covid on airline passenger traffic	normalized demand	0-500
Restaurants*	-0.626	0.930	calibration variable	us dinein revenue	0-500
Workplaces	-2.24	2.99	calibration variables (model)[work]	smoothed us mobility data [work]	0-500
Retail and Recreation	-2.37	1.79	calibration variables (model)[retail]	smoothed us mobility data [retail]	0-500
Grocery and Pharmacy	-3.59	2.20	calibration variables (model)[grocery]	smoothed us mobility data [grocery]	0-500
Transit Stations	-2.00	2.99	calibration variables (model)[trans]	smoothed us mobility data [trans]	0-500

Senior Housing	-1.27	0.78	brookdale.brookdale occupancy	Brookdale historical	0-456

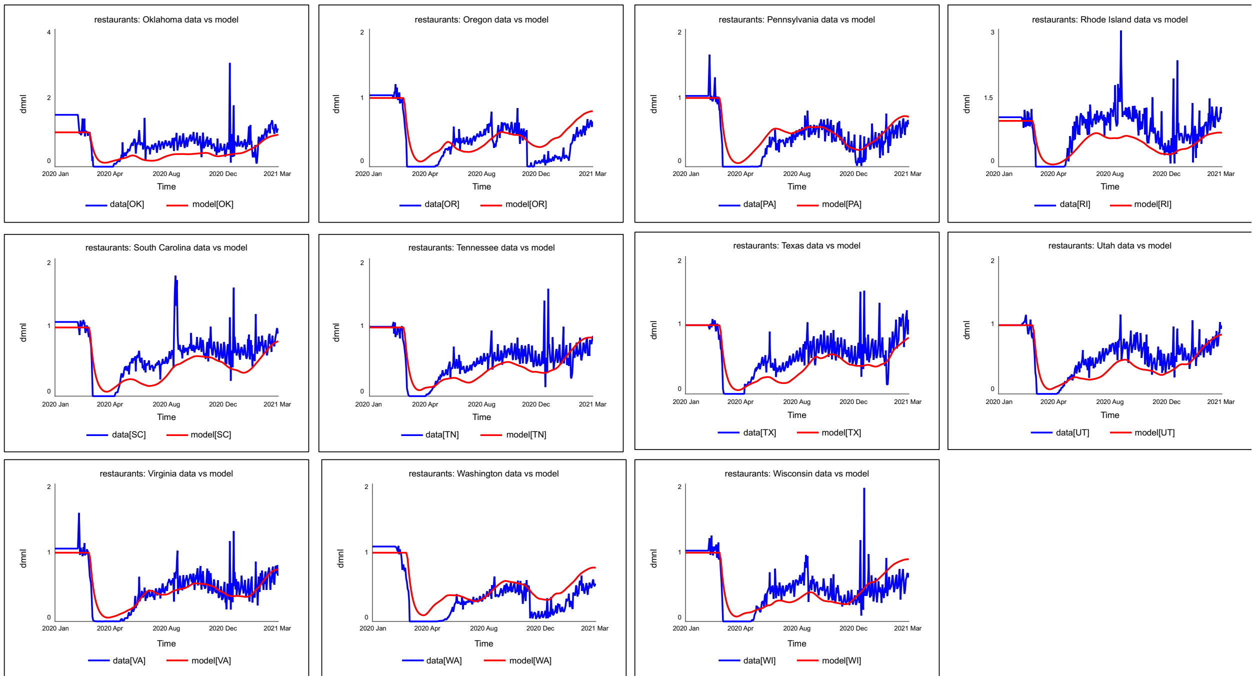
*A special calibration variable was used in the restaurants sector so that the period of full mandatory lockdown in most states from roughly mid-March to early-June was ignored.

Appendix D: State-by-State output graphs for restaurant and mobility domains.

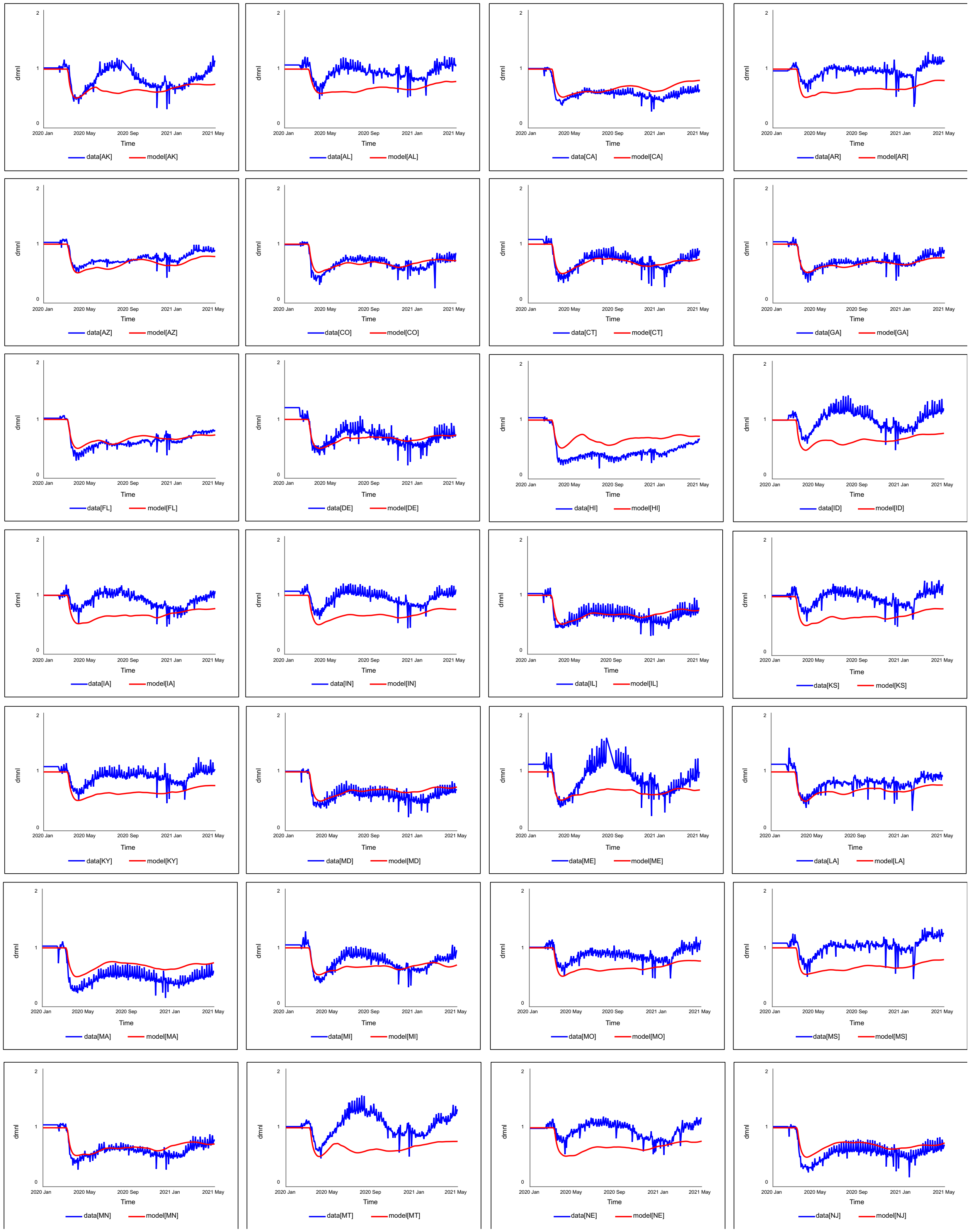
Restaurant results: state-by-state



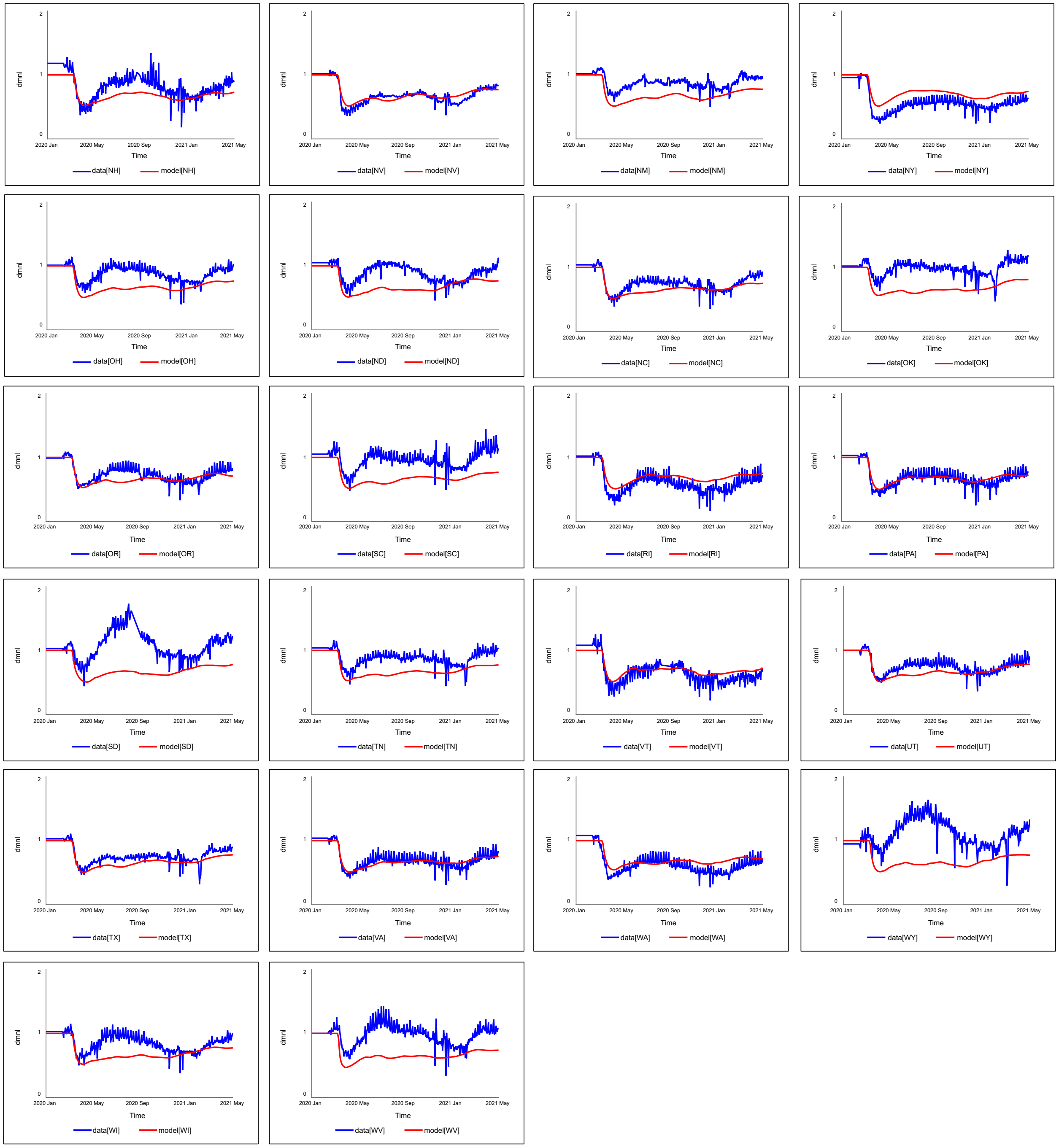
Restaurants, continued:



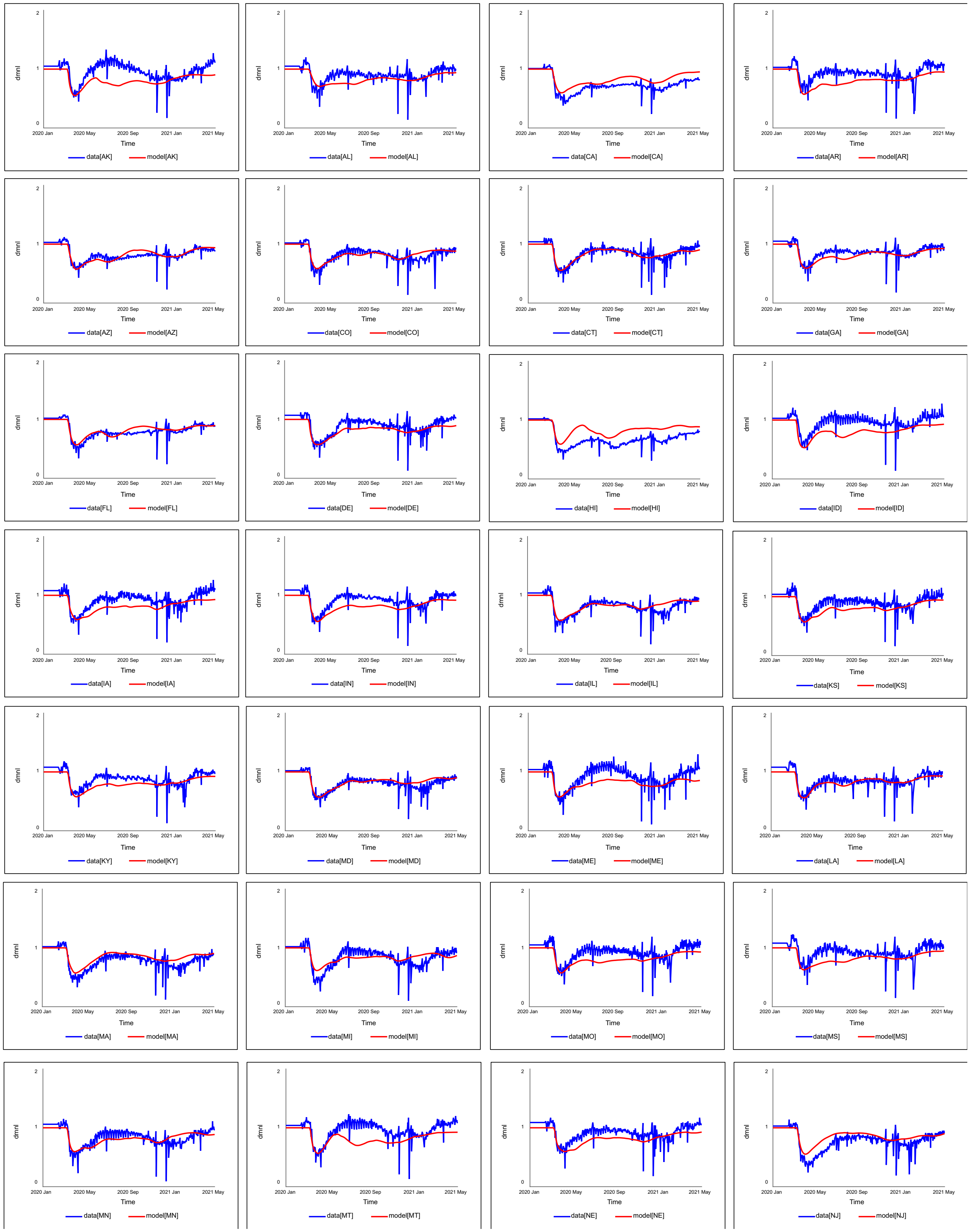
Transit Stations Mobility Results: state-by state



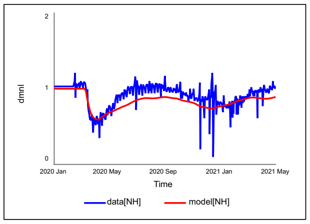
Transit Stations, continued:

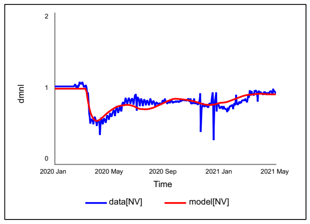


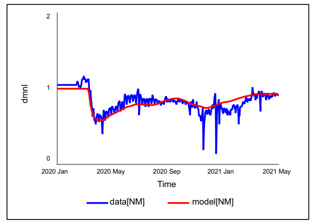
Retail and Recreation Mobility Results: state-by-state

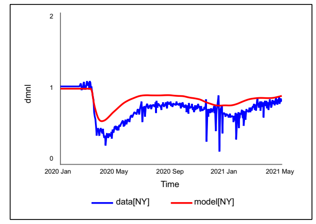


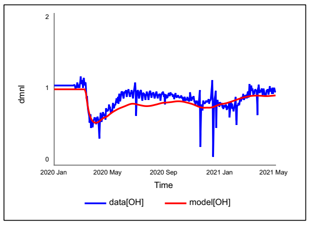
Retail and recreation, continued:

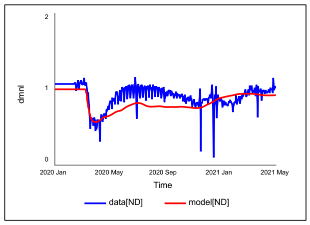


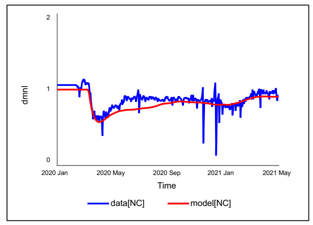


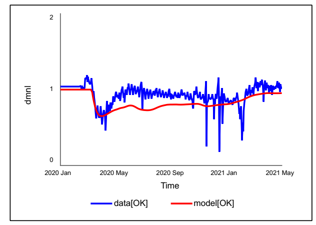


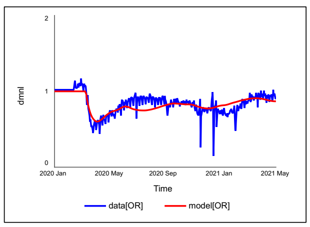


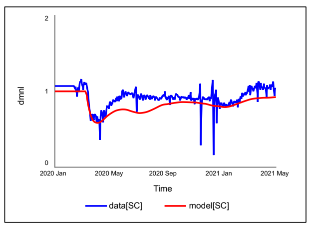


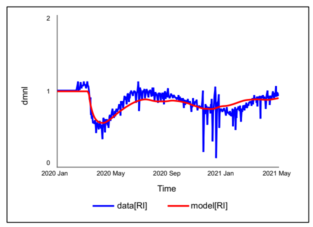


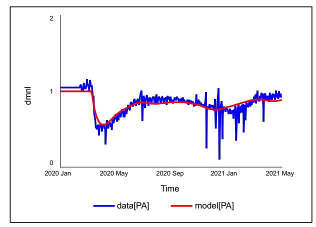


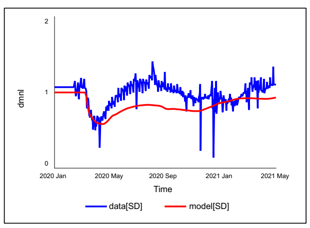


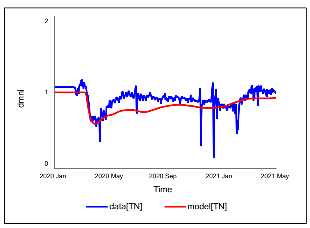


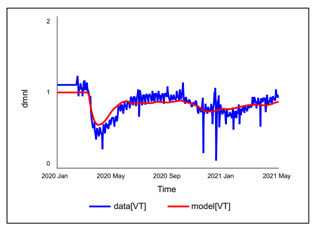


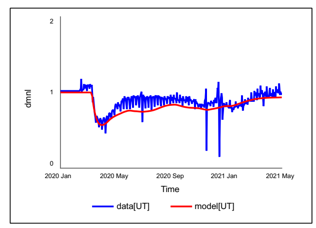


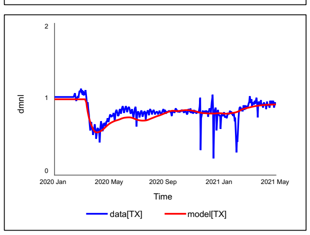


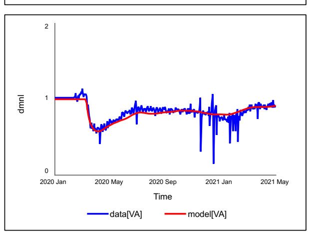


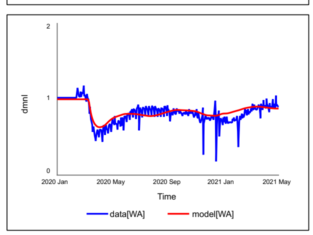


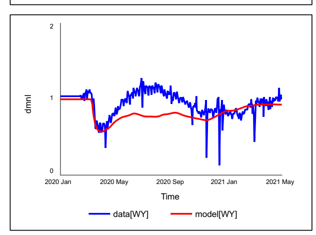


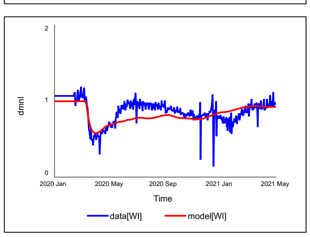


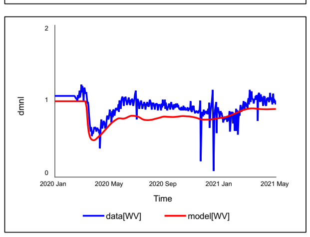




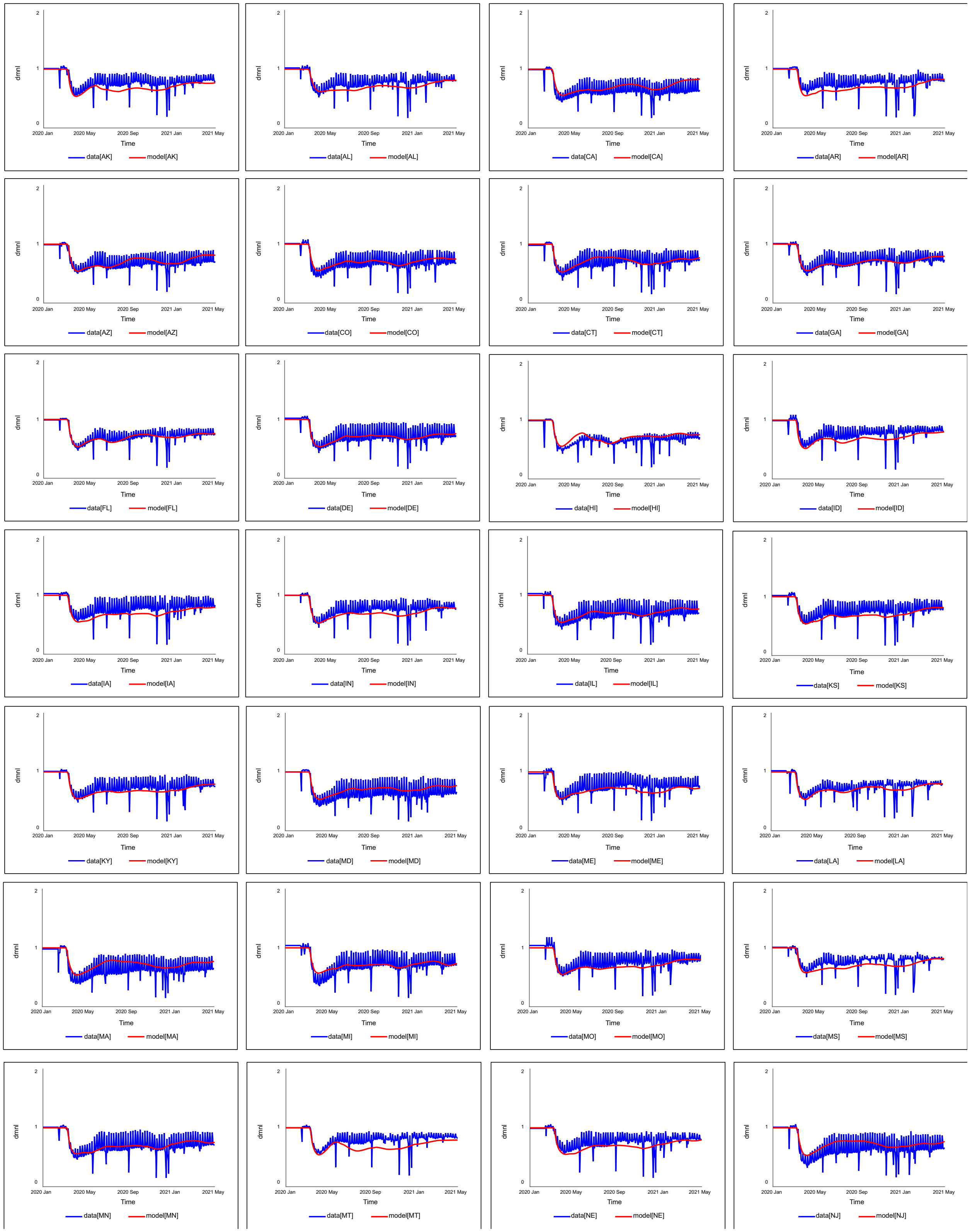




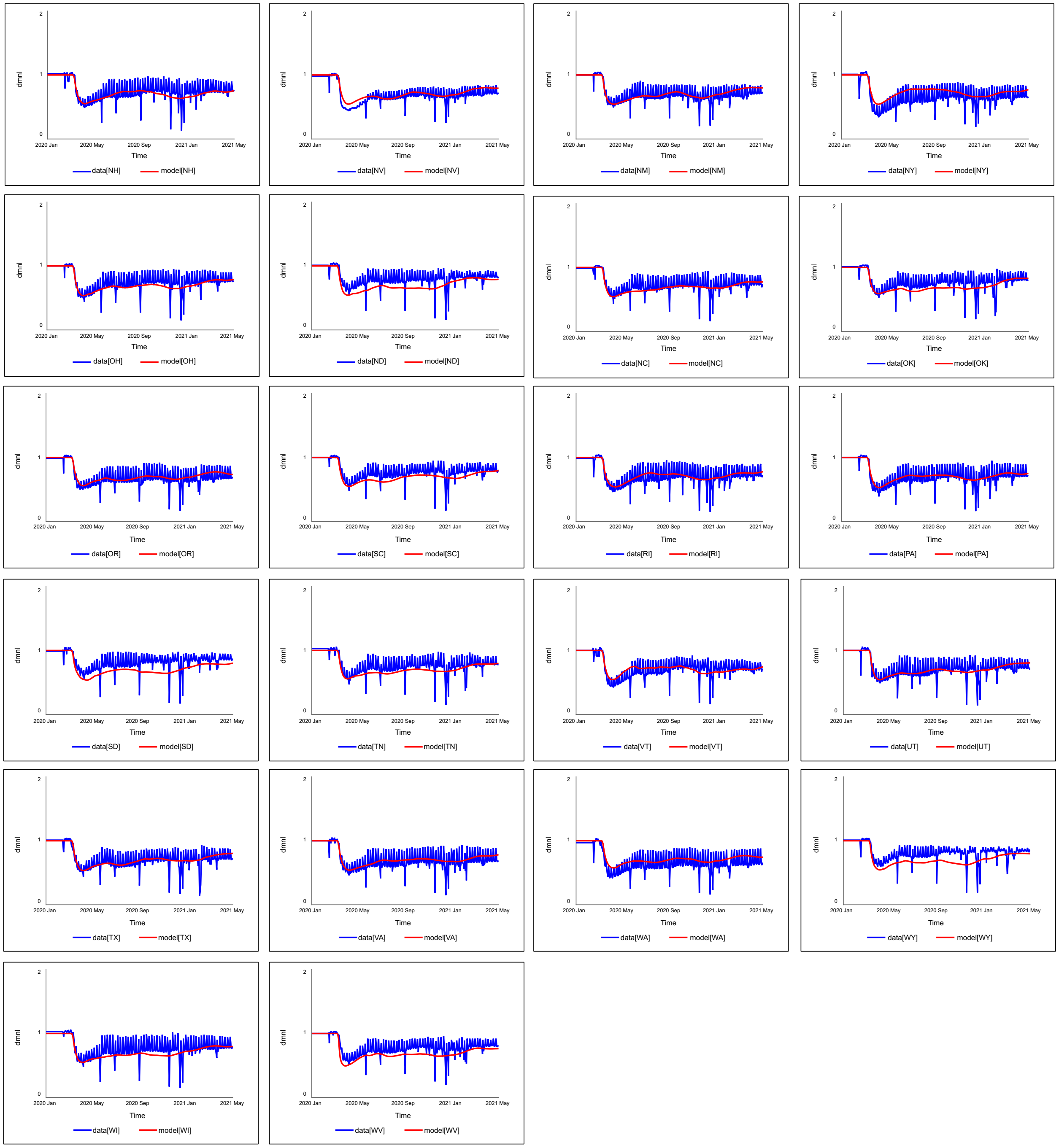




Workplace Mobility Results: state-by-state



Workplace results, continued:



Grocery and Pharmacy results: state-by-state

Grocery and Pharmacy results, continued: