A Social Impact based Model for Risk Assessment to Bolster Community Resilience During Crisis: A Covid Case Study

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Abstract

Functional systems to restore communities and areas which are under stress from a natural phenomenon such as disease or disaster are meant to target areas which have been affected by such a hazard in a timely process. The consequences of an unresponsive or ineffective system can have cascading effects towards other parts of the infrastructure-critical facility nexus. As a result, it can further hinder the ability of a community to recover. Current systems prioritize of needs during a time of distress but do not clearly indicate via quantitative analysis which approach is appropriate. To better improve a system's ability to manage the recovery of a community, we can observe historical data in tandem with social indexes to better understand how the combination of a hazard along with social connectivity information can indicate which areas under stress are at higher risk (higher vulnerability to hazardous impact). This study provides a simulated framework using spatiotemporal data to address these issues. The case study was performed on datasets from Illinois during the COVID-19 pandemic and provides insight into how vulnerability perceptions helped illuminate which areas needed assistance. Results show that areas which exhibited increased vulnerability (and as a result given aid) were able to recover quicker and stabilize migration.

1 Introduction

A community rests upon the shoulders of one another. During times of natural disaster areas that are densely populated are under immense pressure to continue sustaining supply chains, hospitals, and other critical infrastructure [28]. Enduring natural stressors of disease and disaster from a community is essential. Consequently, the preservation of critical infrastructure during tenuous times is just as necessary. A community's ability to support systems which support itself is indicative of the community's resilience. Likewise, the ability of a community to fail to support itself is indicative of a community's vulnerability. These indications assist decision-makers decide which areas are of particular interest when allocating resources to help mitigate the consequences of hazardous natural phenomena. As such, implementing a numerical and algorithmic approach to help a stakeholder allocate resources effectively to areas proportionate to their need while enduring a disaster would benefit the community's resilience and minimize vulnerabilities.

Furthermore, a form of natural disaster known as an epidemic is a cause for concern among the common populace. An epidemic is classified as an infectious disease that spreads quickly over a short amount of time. Due to the time-sensitive nature of an epidemic, it is pertinent for those with power to make decisions over others (stakeholders) to do so with a well-informed set of data in order to mitigate risk and maintain resilience in the community. This form of hazard among a community can be modeled in the form of an agent-based model [7] [11] [20]. Current literature has created various frameworks which handle the connections between community, stakeholder, and disaster [10] [3] [27]. To help model this in a time series fashion, during each decision point, there is a growth factor applied to each counties' population in addition to adjustments following the results of the disaster.

A good indication of an individuals vulnerability to a socially spread disease is their interconnectedness with their community and nearby communities [16]. In order to give the stakeholder agent a firm understanding of the communities vulnerability, we have used information from Meta's Data for Good social connectivity index. This index quantifies the connection of one county to another in the form of a complete graph. In this formation, each node represents a county and each edge represents a social connectivity index value. This is a bidirectional connection such that the connection from county A to county B shares the same value as the connection between county B to county A. By having a completed graph of all counties, we can discern which counties are more vulnerable than others by creating a new index based off of other information related to the disaster in action. An example of a social connection graph between arbitary counties A,B,C,D, and E are seen below.

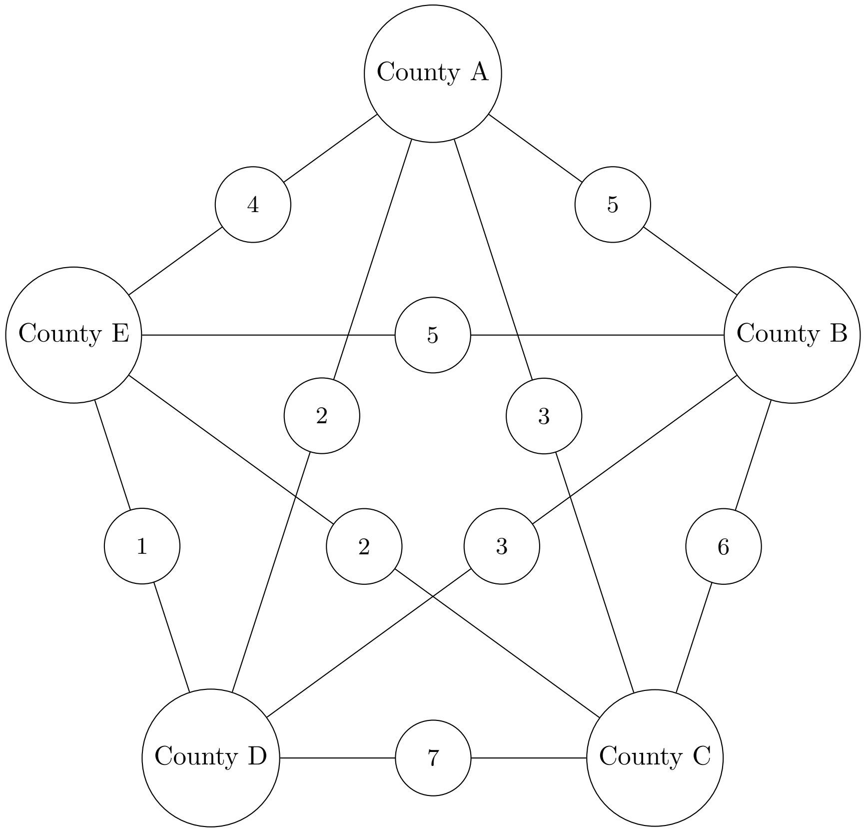

Figure 1: Example SCI connection between counties

This new index, referred to as the Vulnerability Index (VI) uses a classification of the severity of each disaster in each community. By establishing an indication of severity based on the ratio of the community affected versus the community not affected by the disaster, this provides key insight to a stakeholder agent responsible for levying aid to different communities across their jurisdiction. Communities who have a higher than average rate of inflicted population are at increased vulnerability and requires more immediate assistance from their acting government or stakeholder agents. To combine all of the connections between each county, a summarization of all connections based on their severity (highly impacted zones gaining priority) can be derived and then scaled by population. In the instance of a spreading epidemic, it is the consensus that denser populations are at a higher risk for further spread of the disease.

Beyond just having a socially connected nexus of counties classified by their risk, it helps to allow the population to have agency over their home county. Literature shows that migration patterns within an agent-based model are keen tools to provide meaningful information when performing analysis [17] [15] [12]. Moreover, migration can be used as a means to model active relocation during the simulation period to help create a more meaningful and gleaning framework [8] [23]. This methodology ensures a more dynamic and robust simulation environment which can provide meaningful insights. Utilizing migration within a model with many moving parts works best under an accurate quantification of the immigrating parties interest. For the application of modeling a natural disaster, using a metric to identify each counties risk can prove helpful to accurate represent migration patterns.

In the make of an agent-based model, the stakeholder agent requires a viable perception of how to make the most beneficial decision. Literature shows that risk perception can be an advantageous tool in the context of risk management systems [5] [26] [19]. More specifically, literature shows that the use of risk perception can be a useful tool for when performing risk analysis on epidemics such as COVID-19 [4] [6] [1]. This can be accomplished by creating a risk attitude which will change during the simulation period. In tandem, using a chance constraint in a risk assessments can be fruitful. Chance constraints are under utilized in risk assessment systems [29]. This method can prove as a useful metric for remedying complications caused by natural disasters.

Additionally, there is substantial supporting work which uses the implement of social cost [?] [21] [9]. Social cost can be modeled by having a willingness to pay (WTP). For this specific model, 3 critical facilities are assigned their own values of health, business, and retail facilities. Each county has its own individual count of critical facilities initialized and their social cost are calculated throughout the simulation period during each decision point.

2 Conceptual Model

This model proposes a social cost-based methodology to help order restoration tasks by need; consequently, resources are used optimally among the by stakeholders. The social cost was based upon such as medical, retail, or grocery facilities. These aspects are meant to represent the burden of the community when they overexert a particular service. During a time of crisis, hospitals beds could be occupied which lead to longer waiting times. Both retail and grocery facilities host a vulnerable supply line of food and merchandise to the public which can undergo additional stressors during a disaster. To numerically represent this cost, the willingness to pay (WTP) model will be used. WTP gives a quantitative value to help calculate the inconvenience of losing a critical service [22]. Using the WTP framework, a simulation and model were developed to evaluate the impact of a disease under different decision-making strategies. To summarize, the simulation encapsulates 3 different models of behavior for the stakeholder/government entity regarding risk (averse, neutral, and seeking) in aid decisions and the interactions between them. A case study was conducted to test the model and assess the effects of different aid decisions using data from a combination of sources Meta (Social Connectivity Index), USAFacts (Covid Deaths and Cases), Census (Socio-Economic) during a model of an epidemic in the state of Illinois.

Figure 2: Conceptual Model

The paper will develop as follows. To begin, a brief explanation of the interplay between the social connectedness and community vulnerability. Secondly, the social impact-based community restoration simulation modeling framework adopted in this study is described. Third, the specific case study and simulation experiments are explained in detail. Lastly, concluding remarks are given with limitations and future research directions.

3 Social Cost Quantifying Process

The literature surrounding the process of quantifying social impact due to disaster/disruption is diverse. The forms of disruptions can be a multitude of different forms such as reduced supply chains and reduced service (often caused by a over saturated critical facility (such as a hospital becoming strained during times of disease). Of the studies, many have created quantifiers to help numerically describe these disruptions as it relates to social cost [18] [2] [14].
The numerical equations do give a structures methodolgy for modeling the cost factors as they give a tangible cost factor which can be easily understood. However, in many cases they rely on data that may not exists nor is practical to obtain in a particular context. Using the WTP model provides a solution to this issue by communicating with an individual to determine how much they are willing to pay for a particular service or for goods. There are many studies which use this model to help estimate the WTP. One approach is to use the contingent valuation (CV) method to help approximate the WTP. This is done by asking the individual to give their WTP amount based off of a particular situation. Consequently, it should be understood that the WTP model does not directly correlate to the monetary value of a good or service, but instead is used to determine the amount of money an individual would be willing to pay to avoid the disruption of the service

4 Social Cost-Based Community Resilience Restoration Modeling Framework

Community resilience restoration has many social and technical components which must work in tandem with one another under an ever-changing environment. More specifically, this framework adopts an approach which uses agents which are able to interact with one another and each share their own responsibilities within the model. There are 3 (community, disaster, and government) agents broken down as follows:

4.1 Agent Breakdown

Community Agent

The model represents the community as a collection of the population in each county. This allows for the the computations (discussed later) to be optimized for the county's population to better encapsulate the behaviors of the community. As a result, the community holds agency over their own position in the model and may choose to migrate from their starting point based off of factors such as social cost and infection rates.

Disaster Agent

In this case study, we chose to perform a model of a COVID-adjacent outbreak. This was done by taking real spatial data from all counties within Illinois and incorporating infection rates. This agent affects the decision-making of the other two agents by creating a hindrance among the community via infection rates, increasing social costs, etc. By hindering the common life of the commmunity agent

Government Agent

The government agent acts as the stakeholder within the model to help to perform two key functions: analyze the current circumstance based off of infection rates and to also allot resources to help ease the strain of the disaster in each community based off of a predetermined budget. The model classifies the ability to receive help by 3 risk attitudes: averse, neutral and seeking. These will be discussed in more detail later on.

4.2 Abstraction of Disaster Agent

The Hazard Agent Class in our proposed agent-based model encompasses a diverse set of attributes crucial for effectively simulating various hazards, with a particular focus on biological risks. Initially, categorizing the type of hazard allows for differentiation between different phenomena, ranging from natural disasters like earthquakes and floods to biological outbreaks and technological accidents. Spatial extent is instrumental in defining the geographic reach and affected areas, a crucial factor for assessing the

Figure 3: Abstract Agent Based Model between Community, Disaster, and Government Agents

scope of impact. For instance, in our study, we considered multiple neighboring counties simultaneously affected by the hazard. Duration delineates the temporal span of the hazard, whether it unfolds suddenly or gradually. These attributes collectively provide the model with a solid foundation for comprehensive hazard simulation, facilitating exploration of their dynamics and interactions within complex systems. Depending on the probability distribution, specific counties may be associated with three severity levels: low, medium, and high. These are the baseline severity levels that we start the analysis by.

4.3 Abstraction of Community Agent

The Community Agent within our agent-based model serves as the representation of the population affected by hazards, encapsulating various socio-economic attributes. These attributes include the total population, employment rate, median income, economic consumption, and population growth, and level of social connectivity. The total population provides the fundamental measure of the affected community size. Employment rate delineates the workforce participation, influencing income stability and economic resilience. Median income reflects the economic status distribution within the population, crucial for understanding disparities and vulnerabilities. Economic consumption quantifies the monetary expenditure on goods and services, indicative of local economic activity and market dynamics. Population growth rate captures demographic trends, shaping future resource needs and infrastructure demands. By incorporating these attributes, the model can simulate the multifaceted impacts of hazards on different socio-economic strata, facilitating informed decision-making and policy interventions for mitigating vulnerabilities and fostering resilience within affected populations. Additionally, the level of social connectivity captures the interconnectedness of communities within the simulation.

This agent class also has several functions. The first function affiliated with the Community Agent class is the vulnerability index, which amalgamates the severity level of a county with its social connectedness attribute.

By aggregating the scaled Social Connectivity Index (SCI) [13] for each location based on varying levels of hazard severity (ranging from low to high) and scaling this sum by the county's population, we obtain an accurate predictor of true vulnerability for a community in a particular community. Consequently, this provides valuable insight into which counties are most vulnerable to the impact of the pandemic. Note that the vulnerability index will keep on updating at each decision interval.

The second function is migration function which depends on the Social Connectivity Index (SCI). By looking at all of the possible connections, the community agent is able to move between counties. Based off risk, we can allow community agents to investigate moving between different places to avoid possible COVID risk.

4.4 Abstraction of Government Agent

The Government agent class has attributes that include hazard perception, risk attitude, and budget available. The Government Agent Class within our agent-based model embodies the governing entities tasked with managing hazards and implementing mitigation strategies. Its attributes encompass key factors shaping governmental responses to hazards. Hazard perception denotes the government's assessment of hazard severity and likelihood, guiding decision-making processes. A risk attitude attribute is a variable attribute which may change from time-to-time period. Each government agent may start with three risk levels: The agent could be risk seeker, risk neutral, or risk averse. For example, if the agency was risk seeker at the previous decision point (i.e., assuming low vulnerability index) and observes that risk is lower than the minimum actual risk, then the agency's risk attitude would change to risk neutral at the next decision point. For a given decision point, an agency would become more risk seeking if the perceived vulnerability for the past decision horizon is greater than the observed actual vulnerability during the decision point. Likewise, the agency would become risk averse if the past vulnerability is lower than expected during the decision point.

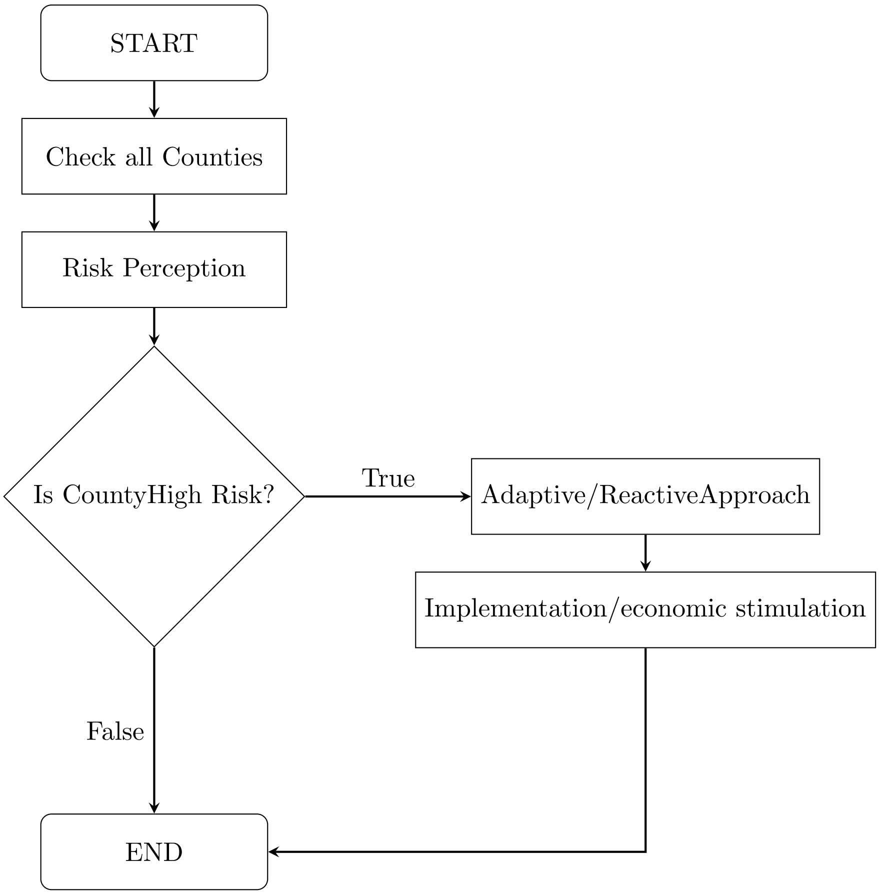

Figure 4: An abstract look at the decision making process of the government agent

4.5 Decision Intervals

The adaptation decision making process will use a method capturing periods to create decisions. This will take the desired timeframe, in this case, just a couple of years and divide them into subsets of weeks. These will have decision intervals ($ti + 1–ti$) realized by the difference between their decision points (ti). During these points, the government agent will be given a chance to reallocate funding to different areas based on factors such as covid risks and fatality rates. At the next interval, these values will be updated to reflect the current nature of the simulation as well as consider the risk attitude of the agent. This will iterate over the decision horizon until the end where decisions are tracked.

4.6 Risk Perception

The government agent will be responsible for performing a risk assessment for each county during each decision interval. To begin, their attitude will be neutral with the option to adjust following the initialization decision $t(0)$ towards risk seeking or risk neutral. Afterwards, they will observe both the positivity of each county versus the average positivity of all counties observed in addition to the vulnerability index of each county as it compares to the average vulnerability index of all counties observed. These risk attitudes will reflect the leniency towards spending in order to relieve the community via economic stimulus. More specifically, a risk averse perception would be more willing to spend money to stimulate the community versus a risk seeking perception which would be more frugal.

4.7 Case Study: Illinois COVID outbreak

This specific model was enacted on a case study of the state of Illinois spanning between the 3rd of March, 2020 until the 5th of May, 2023 with the goal to emulate the COVID-19 outbreak. This 3 year period has a decision interval bimonthly so that the wide breadth of information could be condensed intuitively to understand its effects over the timespan of this disease. This gives the model roughly 20 decision points in which it can modify the values of the agents, interact with one another and provide meaningful output at the end. In order to better understand the case study and approach of the model, let's begin by breaking down the algorithm.

4.8 Critical Facilities

Critical facilities are points of interest which are necessary during times of crisis. During an epidemic is it important to consider medical facilities and other businesses like retail and food which provide valuable resources to a community during a time of crisis.

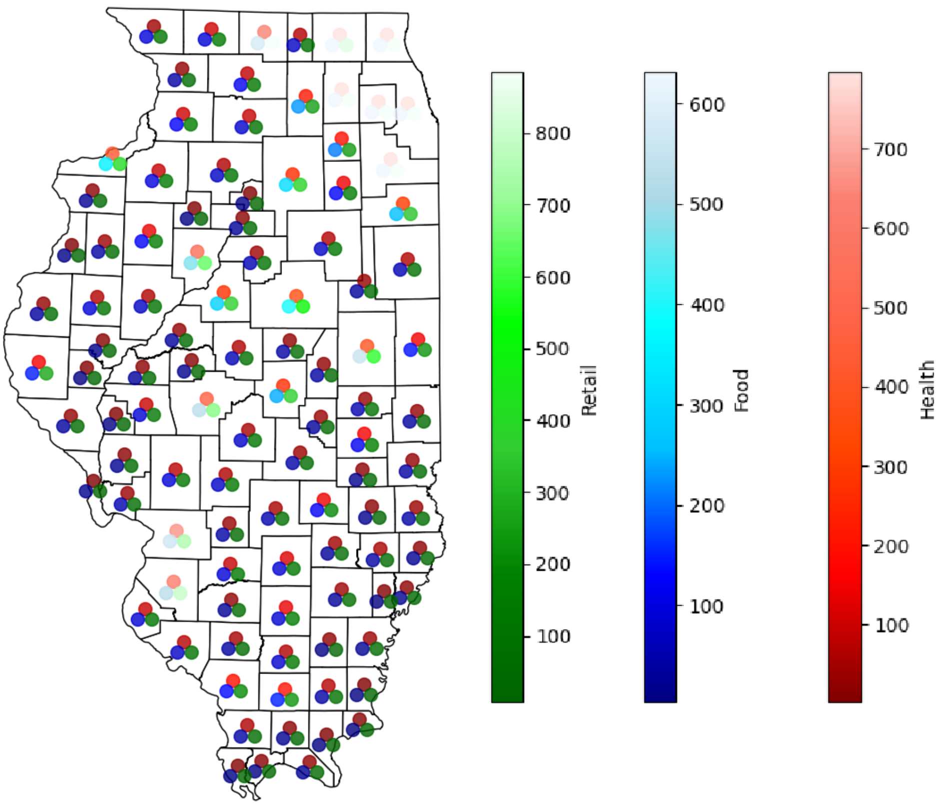

Figure 5: Dotted map corresponding to frequency of critical facilities adjusted for outliers in 95th percentile

4.9 Willingness to Pay

For each of the 3 critical facilities, they have an associated WTP value which is indicative of the numeric value cost for each minute during the simulation period. In order to derive an accurate social cost, one can multiply the number of facilities by their WTP value as well as the number of minutes in the simulation period.

Table 1: Willingness to Pay for Critical Facilities

Facility	**Tier**	**WTP**
Health	Tier 3	85
Retail	Tier 2	55
Food	Tier 2	40

4.10 Algorithm Part 1: Steps 1-4

The algorithm begins with an initial set of data to load in for values for the counties in addition to the time series data of the COVID-19 cases and deaths. Beyond the static initial data loaded in at the onset of the algorithm, we also load in the social connectivity index from Meta for each county in the form of a list that will be parsed to match the corresponding SCI value for each county when performing an intensive function such as migration or scaling the SCI after population changes (seen only after t(0)).

Algorithm 1: COVID-19 ABM – Part 1: Initialization and Steps 1–4

Data: Initial county data, SCI data, time series data for cases and deaths
Result: Simulation of population changes, vulnerability index, and economic impacts over time

Initialization: Initialize counties with population, economic, health, and Social Connectivity Index (SCI) data.
Main Simulation Loop (Part 1)
while *decision intervals remain* **do**
  foreach *county* **do**
    1. Population Updates:
      $newPopulation = (oldPopulation \times growthFactor) - deathsDuringDecisionPeriod$
    2. SCI Scaling:
    foreach *socialConnectionsInCounty* **do**
      $SCI = SCI \times (sourceCountyPopChange + sinkCountyPopChange + 1)$
    end
    3. Positivity Calculation:
      $positivity = \frac{COVIDCasesDuringPeriod}{newPopulation}$
      Determine mean positivity threshold for decisions.
    4. Vulnerability Index Calculation:
      $VI = \sum \left(\frac{lowPositivity + highPositivity}{lowPositivity} \right) \times population$
      Determine mean VI.
  end
end

4.11 Algorithm Part 2: Steps 5-7

The algorithm continues by allowing the community agent to migrate based on its source counties social connectivity and social cost as it compares to these same values in its connected counties. Once the community agents have moved about based on their preferences, the government agent is able to conduct a proper risk analysis with the new population metrics. In doing so, it will choose a risk attitude (averse, neutral, and seeking). Once this is complete, a series of economic equations will be calculated to better inform the model upon its next iteration. Finally, at the end of the algorithms iteration over the decision points, this information can be collected and processed as output data.

Algorithm 2: COVID-19 ABM – Part 2: Steps 5–7 and Output

```
Main Simulation Loop (Part 2)
while decision intervals remain do
    foreach county do
        5. Migration Calculation:
        foreach socialConnectionsInCounty do
            newPopulation =
            [(changeInPositivity+changeInSocialCost)*baseMigrationRate]*newPopulation
        end
            Update county demographics, population, and positivity data.
        6. Government Decision:
        aid = 1000
        if positivity < posititivityMean or VI < VIMean then
            riskAttitude = seeking
            chance = random(0.1, 0.3)*20
        end
        if positivity < posititivityMean and VI < VIMean then
            riskAttitude = averse
            chance = random(0.5, 0.7)*20
        end
        if averse attitude 3 times in a row then
            riskAttitude = neutral
            chance = random(0.3, 0.5)*20
        end
        chance times: infected pop gets max aid, uninfected gets 0.5*max aid
        (20-chance) times: total pop gets 0.2*max aid
        chance times: 1/2 businesses get max aid, other 1/2 gets 0.5*max aid (0.25 if risk
         seeking)
        (20-chance) times: businesses get 0.2*max aid
        aid at decision point = average of above
        7. Economic Equations:
            capability = newPopulation × (1 - unemploymentRate) × medianIncome
            demand = newPopulation × medianIncome × growthFactor
            sufficiency = (capability+businessAssist+populationAssist) / demand × 100
            socialCost =
          ∑(businessType × costOfOperationDuringDecisionPeriod) × aidReduction
    end
end
Output: Generate final results, including vulnerability indices and economic impacts.
```

4.12 Algorithm: Population Updates

Every decision interval must have a population update considering the effects of the previous state. For initialization, pre-obtained data from the Census are utilized [24] and are assigned a static growth factor to model a normal logistic growth of a community. For each period, the deaths are removed from the current population for each county[25]. This way, the populations are dynamic when performing SCI scaling. The formulat for population growth can be seen below.

$$\textit{newPopulation} = (\textit{oldPopulation} \times \textit{growthFactor}) - \textit{deathsDuringDecisionPeriod}$$

4.13 Algorithm: SCI Scaling

The social connectivity index (SCI) is a resource from Meta that helps to determine the inter-connectivity of a social nexus [13]. When the population of a county changes, so does its SCI as a consequence. In order to measure this, we take a percent change in the source and sink county populations, sum them and then multiply summation by its previous SCI value. This provides a bidirectional updated connection to be used later on. The formular for scaling SCI can be seen below.

$$SCI = SCI \times (sourceCountyPopChange + sinkCountyPopChange + 1)$$

4.14 Algorithm: Positivity Calculation

Very intuitively, each county needs to have a positive rate independent of its neighbor in order to indicate which regions are of particular risk or which areas may be considered less threatening. This can be done by dividing the new cases in the decision period by the population. The resulting quotient is the positivity rate. During this same step, the average positivity is determined to measure against for the government agent's risk assessment. The formula for calculating positivity can be seen below.

$$positivity = \frac{COVIDCasesDuringPeriod}{newPopulation}$$

4.15 Algorithm: Vulnerability Index Calculation

The vulnerability is calculated by addressing all of the possible connections between each county classifying them as SCI High (for higher than average positivity) or SCI Low (for lower than average positivity). For each SCI Low connection, the scaled SCI goes on the numerator and denominator. For each SCI high connection, the scaled SCI value goes on the numerator. This is done to give areas of higher than average positivity a larger value to effect vulnerability. Once this summation is calculated, it is scaled by the population of the source county to represent the inter-connectivity and population set being more vulnerable with higher populations. The formula for calculating VI is seen below.

$$VI = \sum \left(\frac{lowPositivity + highPositivity}{lowPositivity} \right) \times population$$

4.16 Algorithm: Migration

Migration is calculated by obtaining a normalized value of social cost and positivity then scaling that by a the base migration rate from each county. This is done to allow counties with higher social cost and higher COVID positivity to have a greater rate of migration than is alloted by their base migration value. Likewise, counties with lower comparative social cost and lower COVID positivity will have a lower rate of migration leading out of the county. The formula for calculating migration can be seen below.

$$newPopulation = [(changeInPositivity + changeInSocialCost) * baseMigrationRate] * newPopulation$$

4.17 Algorithm: Risk Attitude [Averse]

For the 3 risk attitudes, averse is the most liberal of the possible attitudes as it implements the most spending of the options. As a result, this can lead to lower migration rates, lower social costs, and a higher amount of people assisted. As it relates to the chance constraint, a random value between 0.5 and 0.7 is generated to help determine the number of people of the population which are assisted. This is the largest chance value given to any risk attitude.

4.18 Algorithm: Risk Attitude [Neutral]

The neutral risk attitude is the middle ground for the 3 risk attitudes as it provides a steady middle ground between risk seeking and risk averse. As it relates to the chance constraint, a random value between 0.3 and 0.5 is generated to help determine the number of people of the population which are assisted. This is a middle ground value between risk seeking and risk averse.

4.19 Algorithm: Risk Attitude [Seeking]

The final risk attitude implemented in risk seeking. This is the most frugal outlook as it utilizes restraint when dispursing funds. The consquences of this is that migration can be increased along with a higher social cost. Furthermore, this leaves the least amount of people assisted. As it relates to the chance constraint, a random value between 0.1 and 0.3 is generated to help determine the number of people of the population which are assisted. This the smallest chance value given to any risk attitude.

4.20 Algorithm: Economic Equations [Capability]

The capability of a county can be represented as its ability to provide economically during the simulation period. Consequently, this can be calculated by taking a county's population and multiplying it by the employment rate and the median income. This value provides an accurate representation of the economic capability of a county. The formula for calculating capability can be seen below.

$$\textit{capability} = \textit{newPopulation} \times \textit{(1 - unemploymentRate)} \times \textit{medianIncome}$$

4.21 Algorithm: Economic Equations [Demand]

The demand of a county can be represented by its necessary economic requirements during the simulation period. To model this, we have taken the population of the county scaled by their median income and then multiplied yet again by its growth factor used at the beginning of the decision period. This gives insight of what economic demand will be required. The formula for calculating demand can be seen below.

$$\textit{demand} = \textit{newPopulation} \times \textit{medianIncome} \times \textit{growthFactor}$$

4.22 Algorithm: Economic Equations [Sufficiency]

Another equation which is useful for economic insights is the sufficiency equation. This can be calculated by taking the capability (calculated earlier) in addition to the business assistance and population assistance provided by the government agent. This can then be divided by the demand and multiplied by 100 to give a value [0-100]. This is indicative of the county's ability to stimulate the economy during a time of crisis. The formula for calculating sufficiency can be seen below.

$$\textit{sufficiency} = \frac{capability + businessAssist + populationAssist}{demand} \times 100$$

4.23 Algorithm: Economic Equations [Social Cost]

Lastly, the final calculation in the algorithm is the social cost. This was briefly explained earlier, but will be done in more detail here. The calculation can be done by multiplying the business type (critical facility) by both the cost of the operation during the decision point and by aid reduction. Aid reduction here is a corresponding value based on the chance constraint. The formular for calculating social cost can be seen below.

$$socialCost = \sum (businessType \times costOfOperationDuringDecisionPeriod) \times aidReduction$$

5 Numerical Analysis - Results

As the model was simulated a series of tests were conducted in order to ensure the dynamic action of the interplay between the different components. By doing so, we are able to show which variables are able to directly or indirectly modify another. To begin, we have created a baseline data set of which everything else can be compared. This provides key insight into the base of the models mechanisms and how they work with one another. Additionally, we have aid variance testing which widens the gap for the chance constraint for each decision to be modified by $\pm 10\%$ such that the aid is more variable. In this same testing suite, we also run through a series of modifications to the aid package numerically by increasing and decreasing aid. Lastly, the final test runs a simple modification of migration rates wholisically across the model. To begin, here is the baseline data.

5.1 Baseline Data

The baseline.csv contains the model under normal conditions in which the risk attitude changes freely based on evaluation criteria of the vulnerability and positivity of each county. As a result, we can see a great fluctuation between the social cost as time periods progress. This is due to the model adjusting for each attitude giving a different amount of aid to each decision point. For example, we can see that there are periods in which the model shows a clear increase in social cost as a direct result of the risk attitude being shifted to seeking or neutral in which the aid given is reduced as compared to risk averse (where the most aid is given).

Date	Net Migration	VI Mean	Social Cost Mean	People Assisted Mean
3/23/2020	0	325,174	$8.43e+15$	40,937
5/22/2020	13,411	626,348	$7.80e+15$	43,769
7/21/2020	11,367	570,842	$8.03e+15$	42,139
9/19/2020	10,863	248,527	$9.00e+15$	36,648
11/18/2020	12,377	294,215	$8.63e+15$	38,849
1/17/2021	11,761	239,976	$8.18e+15$	41,159
3/18/2021	11,237	293,228	$8.75e+15$	37,555
5/17/2021	12,368	933,648	$8.89e+15$	37,231
7/16/2021	12,122	295,790	$8.98e+15$	36,374
9/14/2021	11,643	298,773	$8.41e+15$	39,535
11/13/2021	11,374	276,631	$8.54e+15$	38,065
1/12/2022	11,821	500,362	$8.13e+15$	43,612
3/13/2022	10,907	234,736	$8.47e+15$	40,414
5/12/2022	12,247	706,269	$8.43e+15$	39,915
7/11/2022	12,039	729,916	$8.33e+15$	39,751
9/9/2022	11,016	277,138	$8.93e+15$	37,135
11/8/2022	12,240	362,178	$8.38e+15$	38,583
1/7/2023	11,378	285,696	$8.55e+15$	37,331
3/8/2023	11,915	164,849	$8.42e+15$	37,504
5/7/2023	11,786	128,994	$8.40e+15$	37,919

Table 2: Baseline Output CSV

5.2 Risk Analysis

The following data sets are used only to modify the framework which is responsible for the decision making process. Specifically, the simulation was ran using a single risk attitude among different tests corresponding to each of the following attitudes: averse, neutral, and seeking.

5.3 Risk Averse Decision Making Analysis

The averse risk attitude provides a more secure method of assisting the public as more funds are dispersed. What can be observed as a result is that the migration rates for the risk averse attitude are smaller. This is because the residents within the migrating zone are more likely to be assisted and as a result are less likely to move out of their home region. What is relatively consistent among the different decision points is the vulnerability index since the infection rates of COVID-19 do not differ based on economic stimulation.

5.4 Risk Neutral Analysis

The risk neutral attitude represents a more balanced outline than that seen earlier with the risk averse and compared to risk seeking seen later. For this test, all decision attitudes were risk neutral to emphasize the effects of its aid package throughout the simulation period. More specifically, the neutral aid package discussed earlier with the chance constraints. Here we find that migration, social cost, and people assisted mean looks more like the baseline data compared to the risk averse data.

Date	Net Migration	VI Mean	Social Cost Mean	People Assisted Mean
3/23/2020	0	325,174	$7.19e+15$	48,863
5/22/2020	11,680	634,166	$7.25e+15$	48,881
7/21/2020	10,449	571,090	$7.12e+15$	49,727
9/19/2020	9,679	239,044	$7.60e+15$	47,638
11/18/2020	10,361	283,677	$7.48e+15$	49,332
1/17/2021	10,186	230,089	$7.03e+15$	51,862
3/18/2021	9,665	336,233	$7.55e+15$	47,968
5/17/2021	10,611	830,686	$7.38e+15$	48,745
7/16/2021	10,042	255,071	$7.29e+15$	48,522
9/14/2021	9,210	285,700	$7.06e+15$	51,121
11/13/2021	9,472	281,881	$7.52e+15$	48,701
1/12/2022	10,345	487,905	$7.13e+15$	52,732
3/13/2022	9,607	246,362	$7.18e+15$	51,004
5/12/2022	10,308	710,762	$6.99e+15$	51,128
7/11/2022	9,949	867,457	$7.19e+15$	49,768
9/9/2022	9,372	280,545	$7.10e+15$	51,112
11/8/2022	9,601	331,739	$7.37e+15$	49,357
1/7/2023	9,967	269,981	$7.06e+15$	50,596
3/8/2023	9,854	165,570	$7.41e+15$	48,838
5/7/2023	10,293	130,289	$7.24e+15$	49,329

Table 3: Risk Averse Output CSV

5.5 Risk Seeking Analysis

For risk seeking analysis, the least amount of aid is given during this simulation period. This is because the stakeholder agent is taking a more optimistic approach, believing that economic stimulation may not be as necessary. However, this does come with a cost. Specifically, the less aid given results in more migration cause by residents not feeling satisfied with their current place of residence. Additionally, this package gives the least amount of assistance towards social cost, so this is also a higher vlaue than was observed earlier. Lastly, we find that there are less people assisted using this risk attitude. This aligns with our assumption that this risk attitude would have a smaller aid package.

5.6 People Assisted Using Different Risk Attitudes

Here, one can observe the relationship between the different risk attitudes as it relates to the number of people who are assisted during the decision period. As one can expect, the risk averse attitude restricts the amount of people assisted whereas the risk seeking attitude provides the most people with funding.

5.7 Social Cost Using Different Risk Attitudes

Social cost spread across the different risk attitudes send a similar message to that of the number of people assisted. Specifically, the more funding leads to a lower burden on the community to keep critical facilities open. What occurs as a result is a higher social cost under risk seeking attitudes. This can lead to lower migration patterns as a result since migration depends on both social cost and positivity.

5.8 Migration Patterns Across Different Risk Attitudes

The migration at the initialization point all begins at 0 since there is no migration occuring at decision point 0. However, as we expected there are significantly less people who are migrating as a result of a risk averse attitude. This is because of the economic stimulation of the society relieving some of the burden of the social cost.

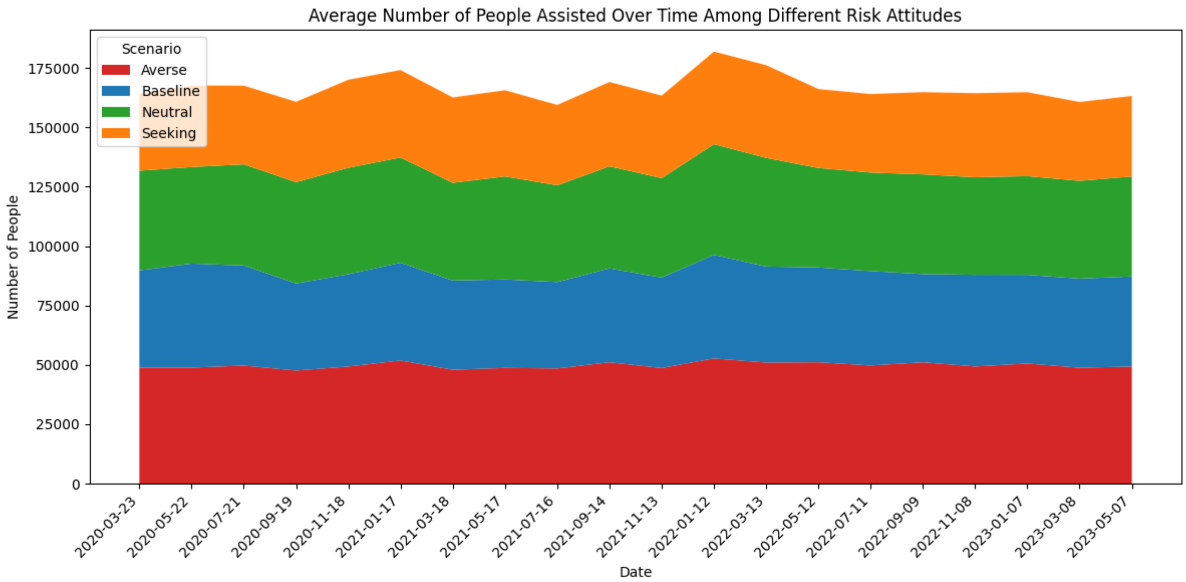

Figure 6: The average number of people assisted across different risk attitudes

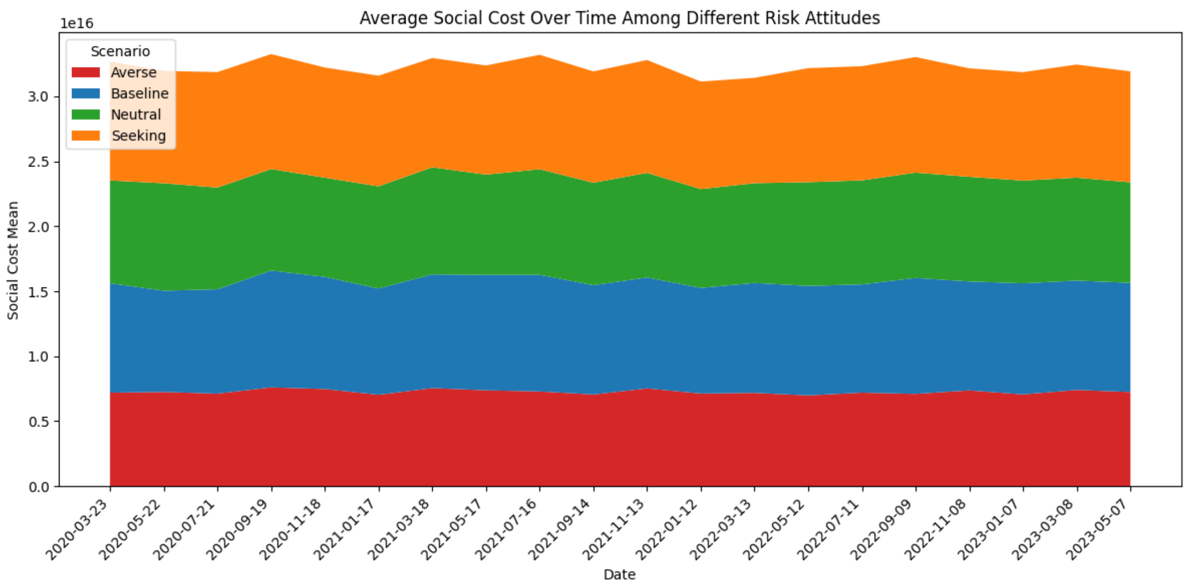

Figure 7: The average social cost across different risk attitudes

Date	Net Migration	VI Mean	Social Cost Mean	People Assisted Mean
3/23/2020	0	325,174	$7.91e+15$	41,956
5/22/2020	12,731	634,096	$8.27e+15$	40,666
7/21/2020	12,034	565,499	$7.83e+15$	42,568
9/19/2020	10,601	241,832	$7.81e+15$	42,632
11/18/2020	10,614	306,976	$7.64e+15$	44,805
1/17/2021	10,335	243,006	$7.87e+15$	44,291
3/18/2021	10,768	277,021	$8.24e+15$	41,126
5/17/2021	11,587	929,365	$7.72e+15$	43,363
7/16/2021	10,518	265,357	$8.13e+15$	40,709
9/14/2021	10,284	304,965	$7.89e+15$	42,945
11/13/2021	10,545	257,277	$8.05e+15$	41,839
1/12/2022	11,185	426,986	$7.61e+15$	46,582
3/13/2022	10,144	229,883	$7.68e+15$	45,733
5/12/2022	10,971	715,232	$7.98e+15$	41,859
7/11/2022	11,272	744,266	$8.01e+15$	41,447
9/9/2022	10,499	280,781	$8.10e+15$	41,951
11/8/2022	10,886	352,206	$8.06e+15$	41,063
1/7/2023	10,843	265,818	$7.90e+15$	41,532
3/8/2023	11,029	165,023	$7.92e+15$	41,143
5/7/2023	11,086	129,506	$7.74e+15$	42,051

Table 4: Risk Neutral Output CSV

5.9 Aid Variance Analysis

By manipulating the amount of aid given during the simulation period, we are able to glean information regarding its ability to assist individuals, how it effects migration, and its direct changes to social cost. For the next set of tests, we decided to have an increased chance constraint for all of the risk attitudes in addition to modifying the amount of aid for each output. Specifically, we take the normal constraint and modify it such that the bounds expand by a factor of 10 on each side. Therefore for risk neutral being [.30,.50] for the chance constraint, it instead becomes [.20,.60], this provides a wider possibility of stochastic elements to take place during the simulation period. In addition to the increased variance among the risk attitude's chance constraints, we also have modified the aid package 6 different ways. $\pm 20\%$, $\pm 15\%$, $\pm 10\%$. This allows for a static scale to be added to the aid which was 1000 previously. With a modifier of -0.2, it instead becomes 800 for max aid. Likewise for +.2 it becomes 1200 for max aid. This helps to reveal the effects of different aid packages during different simulation periods.

5.10 People Assisted Across Varying Amounts of Aid

As we increase the amount of aid given to a particular population, we find that more people are assisted with the extra funds. This is inline with our assumptions since an increased budget is able to adequately assist more people. However, it should be noted that since the risk attitude is within baseline parameters, then it does not change the amount of people assisted with greater variance. That is why the $+20\%$ shows the least amount of people assisted on average despite having more money to give away. The risk attitude has a greater weight in determining the number of people assisted.

5.11 Social Cost Across Varying Amounts of Aid

As the aid increases, we find that social cost decreases. This is because the facilities are stimulated with a higher degree of aid and the burden is not passed on to the average citizen.

5.12 Migration Patterns Across Varying Amounts of Aid

As aid increases, we can observe that migration will decrease. This is because residents who recieve aid are more likely to stay in their home county and not relocate during the simulation period. What else we can observe is that the lowest aid package seems to be the most responsive to varying degrees of migration, but as the aid increases, this volatility smooths over and decreases in regards to net migration over time.

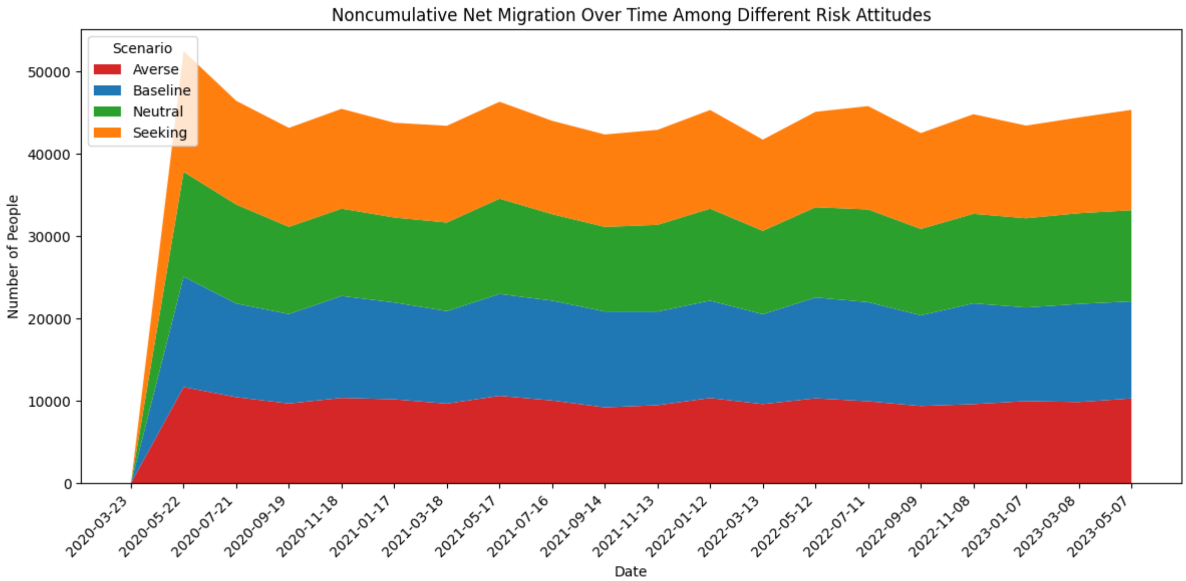

Figure 8: The average net migration across different risk attitudes

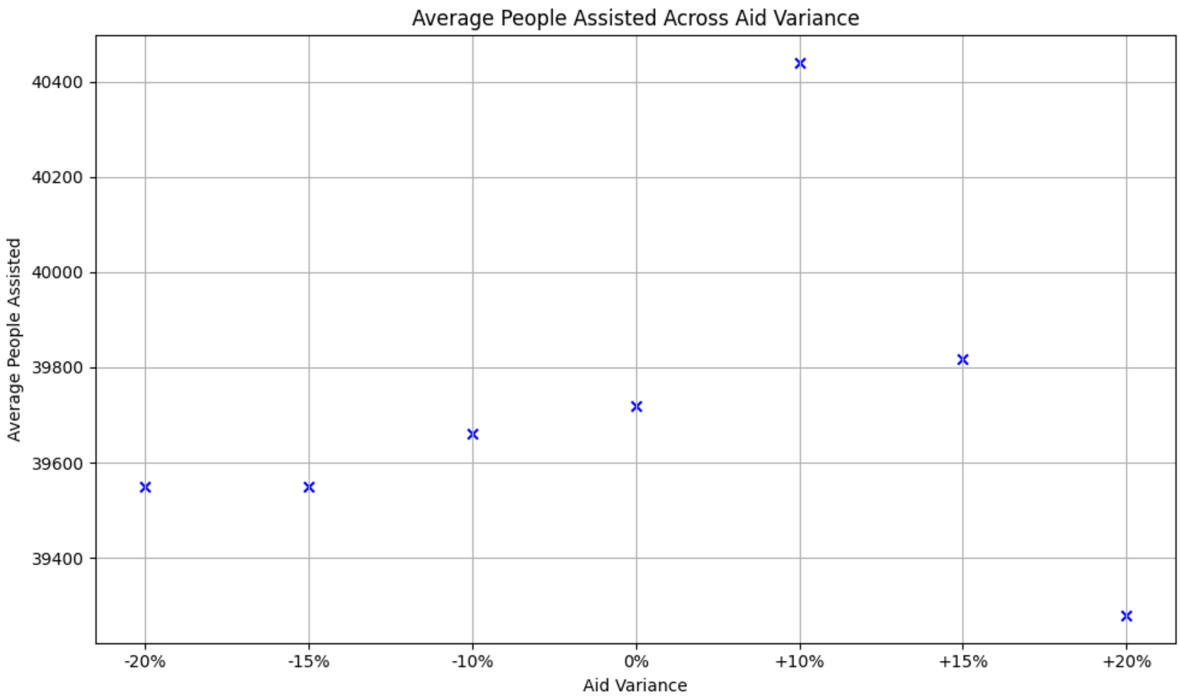

Figure 9: The average number of people assisted across varying aid packages displayed in a scatter plot

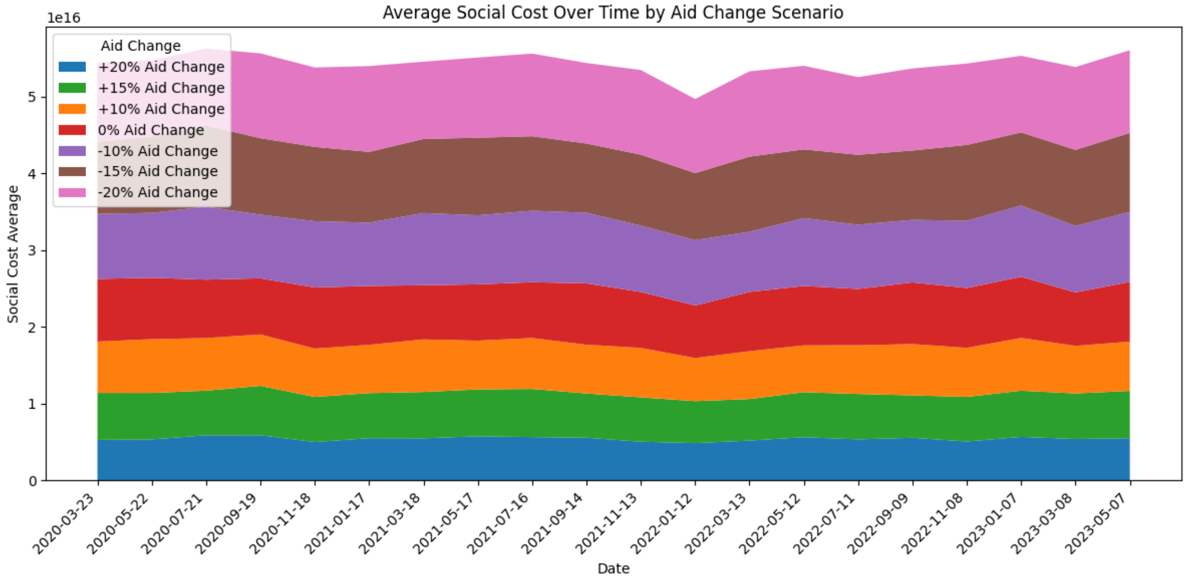

Figure 10: The average social cost across varying aid packages

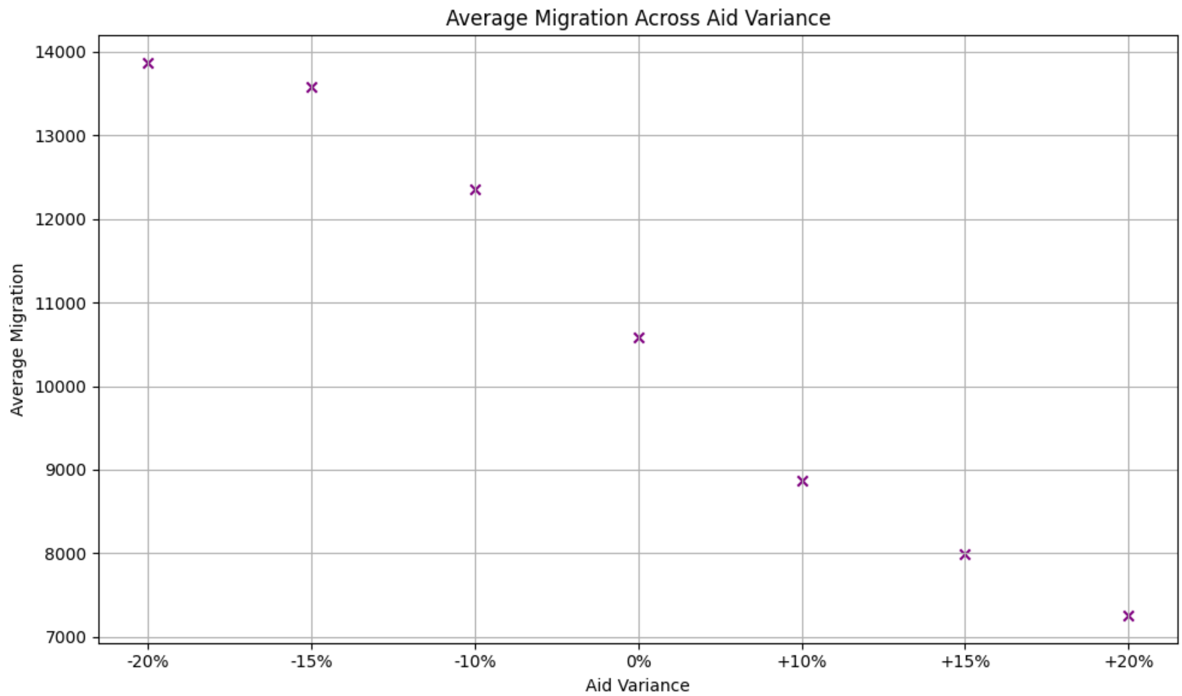

Figure 11: The average net migration across varying aid packages

Date	Net Migration	VI Mean	Social Cost Mean	People Assisted Mean
3/23/2020	0	325,174	$9.15e + 15$	32,294
5/22/2020	14,670	634,019	$8.65e + 15$	34,329
7/21/2020	12,595	579,927	$8.89e + 15$	33,140
9/19/2020	12,019	240,005	$8.85e + 15$	33,858
11/18/2020	12,126	332,082	$8.48e + 15$	37,058
1/17/2021	11,503	233,951	$8.52e + 15$	36,830
3/18/2021	11,746	349,765	$8.41e + 15$	35,958
5/17/2021	11,773	890,807	$8.40e + 15$	36,299
7/16/2021	11,339	249,976	$8.81e + 15$	33,853
9/14/2021	11,225	312,746	$8.57e + 15$	35,506
11/13/2021	11,531	275,849	$8.69e + 15$	34,774
1/12/2022	11,985	434,562	$8.28e + 15$	38,991
3/13/2022	11,078	235,045	$8.11e + 15$	39,034
5/12/2022	11,587	762,698	$8.78e + 15$	33,235
7/11/2022	12,548	816,499	$8.79e + 15$	33,077
9/9/2022	11,645	256,542	$8.90e + 15$	34,628
11/8/2022	12,097	334,903	$8.35e + 15$	35,406
1/7/2023	11,250	261,933	$8.35e + 15$	35,353
3/8/2023	11,632	164,139	$8.71e + 15$	33,215
5/7/2023	12,188	128,467	$8.54e + 15$	33,934

Table 5: Risk Seeking Output CSV

6 Discussion

The simulation of the agent-based model can categorize different factors during COVID-19 based upon their relationship with other factors. For example, it is reasonable to say that the greater number of people in a county will reflect a larger amount of covid cases . During the span of this project lots of data scraping was conducted from sources such as Meta's Data for Good, census information, and statewide information regarding COVID-19 case and death count as it relates to time [13] [24] [25]. This simulation is multi-faceted and considers many different parameters that interwork with one another to produce a comprehensive understanding of the economic impact of COVID-19 on a community.

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