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Simulation Modeling for Robust and Just Public Policy Decision-Making

Jack Mitcham

SIMULATION MODELING FOR ROBUST AND JUST PUBLIC POLICY DECISION-MAKING

A Dissertation Presented

by

JACK MITCHAM

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ABSTRACT

SIMULATION MODELING FOR ROBUST AND JUST PUBLIC POLICY DECISION-MAKING

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Public policy decision-making is challenging for several reasons. First, the outcomes of pulling a public policy lever are often deeply uncertain because of the complexity of the social and physical systems involved. Second, even if outcomes can be predicted, there are multiple points of view to consider, and the same outcome can be viewed anywhere from very positively to very negatively by different stakeholders. Because of this, public policy decisions should be both robust and just. Robustness helps with the uncertainty in outcomes and justice helps with differences in worldview. In this dissertation, I employ system dynamics and agent-based simulation modeling techniques to assist decision-making in two public policy contexts: COVID-19 non-pharmaceutical interventions and police funding. I also develop a framework in which both robustness and justice can be handled simultaneously in complex public policy problems.

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CHAPTER 1

INTRODUCTION

Public policy decisions are made under conditions of complexity stemming from many sources. The first is the “impossible” challenge of aggregating group preferences (under certain axioms, as per Arrow 2012). A related challenge is finding solutions that are just. Even if a group preference could be aggregated, such that 99% of the population agreed to a course of action, it might still be a bad idea. To wit, a policy supported by 99% of people in which the remaining 1% are enslaved is repugnant.

A separate challenge involves the complexity of the systems involved themselves. The results of enacting a particular policy might involve both physical and socioeconomic systems whose potential outcomes may span orders of magnitude. This is described by Lempert (2002) as “deep uncertainty.” Yet, despite this deep uncertainty in which unknowable futures are evaluated with an impossible set of preferences, decisions still have to be made.

Analyzing public policy problems from a decision analysis perspective in which the problem is laid out, alternatives are developed, outcomes are generated, tradeoffs are evaluated, and a decision is made (the so-called “rationalist approach,” see Bardach & Patashnik 2019) has been heavily criticized as unrealistic and inadequate (e.g., Braybrooke

& Lindblom 1970, Fischer 1998, Kingdon 2011, Stone 2012), in part due to the challenges listed above.

In this dissertation, I present three papers that aim to make the rationalist, decision-analytic approach to public policy more capable of handling the concerns of deeply uncertain outcomes and competing views as to how to value those outcomes. The aim of all three papers is to simultaneously handle issues of robustness and justice and all three involve simulation modeling as a methodology. Simulation modeling is a useful tool to handle the nonlinear interactions found in complex systems such as society.

Chapter 2 is a modified version of Mitcham & Keisler (2022). In that chapter, we explore decision-making in the early stages of a pandemic using COVID-19 as an example. We use a system dynamics model to generate pandemic outcomes with robust sensitivity analysis to generate a wide range of outcomes, and then evaluate each of those outcomes by multiple "worldviews" incorporating views of life, liberty, and the economy. A dashboard is presented in which a decision-maker could explore the ramifications of using different worldviews to view a wide range of potential outcomes.

Chapter 3 was inspired by the Black Lives Matter protests that occurred over the summer of 2020. This chapter explores under what conditions reallocating police funding to social spending may increase or decrease crime using the concepts of "hardship" and "legitimacy" as lenses. An agent-based model is used to capture the spatial phenomena and the heterogeneous nature of the population.

Chapter 4 introduces a decision-making framework that simultaneously addresses issues of robustness and justice in deeply uncertain public policy decisions in a way that is easy to understand. It provides a way to unify the "maximin" principle in social justice theory (Rawls 1971, 1974) with the "maximin" decision rule from multi-criteria decision analysis.

Taken together, these three papers demonstrate an approach to public-policy decision-making that embraces the complexity of the challenges. Rather than trying to maximize an average outcome for an average stakeholder, it looks for solutions that minimize the variability both among diverse stakeholders and among deeply uncertain outcomes. A decision alternative that performs acceptably well for every stakeholder no matter in which way the uncertainty in outcomes is resolved can be said to be both robust and just.

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CHAPTER 2

MULTI-ATTRIBUTE COVID-19 POLICY EVALUATION UNDER DEEP UNCERTAINTY

2.1 Introduction

The 2019 novel coronavirus, SARS-CoV-2 (which causes COVID-19) continues to spread in the face of countermeasures such as closing businesses and schools, banning large gatherings, limiting travel, and mandating masks. Many governments are facing cries from their citizens to relax or end the countermeasures for the sake of the economy. Phrases such as “the cure shouldn’t be worse than the disease” have been used both in US media and by the President of the United States to insist that damage to the economy from social distancing measures could be more costly than COVID-19 itself.

This implies a tradeoff between economic health and physical health, for which there exists ample literature. However, this literature is not being cited in the political sphere when pundits and politicians debate about whether or not to “re-open the economy.”

On one hand, there are people who are convinced that the economic damage is worse than the lives lost to COVID-19, and on the other hand, there are people who are averse to putting a price on lives at all. Neither side appears to be citing a dollar amount they put on each life, or each year of life lost.

Furthermore, there are groups of people who are protesting the countermeasures against COVID-19 in the name of "freedom." Signs at "anti-lockdown" protests read "Freedom is Essential" and "Land of the Free" among other things. (Gabbatt 2020) This demonstrates there is a third piece to the equation: a hedonic element in which people weigh their personal liberty against both economic well-being and health risks.

The challenge, then, is not only to formulate a utility function for decision-makers to use when evaluating strategies to stop a pandemic but also how to apply such a utility function when the underlying values differ from person to person.

To address this challenge, we will synthesize several methods. First, we create a multi-attribute utility function that incorporates the values of life, liberty, and the economy. Then, we outline plausible worldviews, representing different weights on that utility function. Next, we model the pandemic and mitigation strategies using an SEIR system dynamics model and perform global sensitivity analysis to generate a large range of scenarios, analyzing the differences between the strategies to gain insight into what works under what conditions. Last, we use the Robust Decision Making (Lempert 2019) framework to find mitigation strategies that are robust not only against characteristics of the pandemic but also robust against differing worldviews.

2.2 Literature Review

We shall use several well-established techniques which manifest in some unique ways and combine in an interesting fashion. We describe these here very briefly and provide some links to the extant work in these techniques.

2.2.1 Deep uncertainty and the robust decision-making framework

The impact of COVID-19 can be characterized by "deep uncertainty." As defined by the Decision Making Under Deep Uncertainty Society, deep uncertainty exists when:

> *"...parties to a decision do not know, or cannot agree on, the system model that relates action to consequences, the probability distributions to place over the inputs to these models, which consequences to consider and their relative importance."* *(Decision Making Under Deep Uncertainty Society, 2015)*

COVID-19 meets all of those criteria. There are many epidemiological models which can be used to predict pandemics, including mathematical models and agent-based models, and they don't necessarily give the same results. (Connell et al., 2009) The parameters of those models are almost completely unknown at the very start of the pandemic, which is when some policy decisions need to be made. And lastly, there is disagreement about the relative importance of the consequences, which is the main focus of this paper.

When faced with deep uncertainty, robust methods can be used to generate insights for the decision-maker (Keith & Ahner 2021). Robust methods are applied over a wide range of situations to stress test and refine decisions by comparing alternatives under different extreme assumptions about factors whose exact values are not easily ascertained (e.g. Jang 2019, Wei et al. 2013, Mild et al 2015). Rather than trying to optimize a decision for some "most likely" scenario, robust methods can be used to investigate which decisions provide a satisfactory outcome across a wide range of scenarios.

One such robust analytical framework to handle decision-making under deep uncertainty is Robust Decision Making (RDM) (Lempert 2019) (Fig. 2.1). Rather than trying to come up with assumptions and creating a predictive model, RDM focuses on examining a large range of possibilities using exploratory modeling (Bankes 1993), and global sensitivity analysis (Wagner 1995) to illustrate strengths and weaknesses in policy decisions.

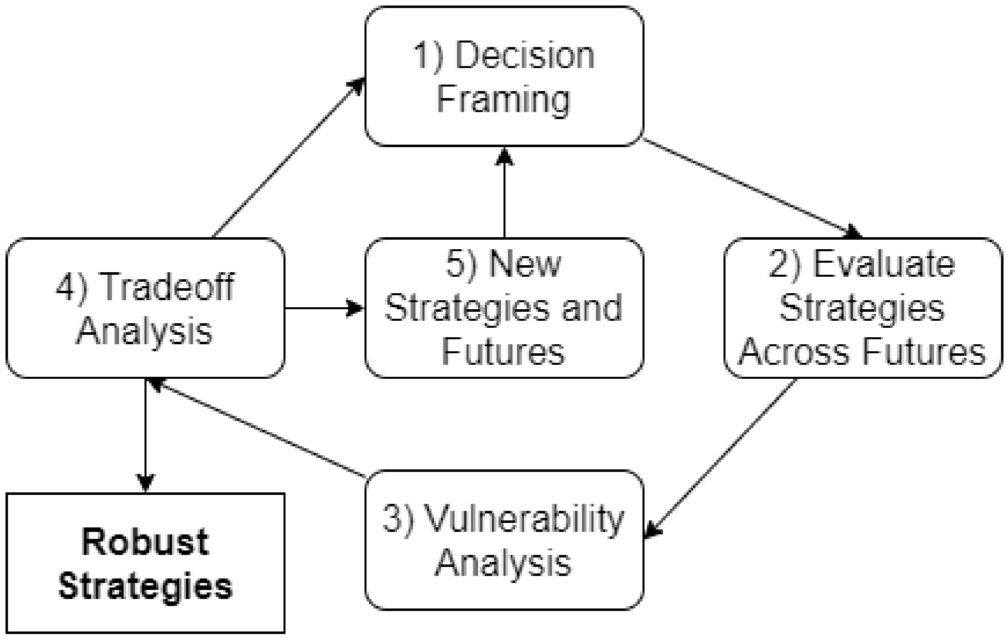


Fig. 2.1 *The RDM process*

There are five steps to RDM:

1. Decision Framing
2. Evaluate strategies across futures
3. Vulnerability analysis
4. Tradeoff analysis
5. New Futures and Strategies

The main thrust of this paper is step 4, tradeoff analysis, which is detailed more in the next section. Additionally, we are not only evaluating the strategy across futures (step 2), but also across different worldviews, leading to strategies that are robust against variations in both.

2.2.2 Multi-criteria decision analysis

Multi-criteria decision analysis (MCDA) (Belton & Stewart 2002) is a technique that can help decision-makers decide between alternatives when there are multiple criteria to take into consideration. Multi-attribute Utility Theory (MAUT) (Keeney & Raiffa 1976) holds that one can create a utility function in which each criterion is listed and weighted in order of importance. The result is a composite measure of different criteria that can be used to measure each alternative. This is useful when the criteria being evaluated are not all on the same scale. For instance, comparing the tradeoff between economic outcomes, hedonic value of liberty, and health outcomes, as we're doing here**.** Public policy alternatives often lie on a Pareto frontier in which one option is best on one criterion and another option is best in a different criterion. This method can be used to help differentiate between options on the Pareto frontier by selecting the alternative with the highest utility value.

This method works best when there is a unitary decision-maker that can set the weights of the utility function. In the case of governments, there generally isn't such a unitary decision-maker. A government that wishes to uphold democratic ideals will look to represent the interests and viewpoints of all of its citizens to the best of its ability, even when there are disagreements. Nevertheless, MCDA and MAUT can be used as a way to explore differences in individual viewpoints to aid in public policy decision-making.

MAUT is generally concerned with maximizing utility under uncertainty, but this is not the most robust measure (Rosenhead et al. 1972). Another measure, regret (Savage, 1951), is often used, especially when using the RDM framework (Groves & Lempert 2007). Regret is the difference between the utilities of two different outcomes. While utility is to be maximized, regret is to be minimized. One common way to use regret is to minimize the maximum regret, also known as "minimax regret". Minimax regret is useful when facing large "tail risk", (Anthoff & Tol 2014) which is common when facing deep uncertainty. It is plausible to have a strategy that is not usually preferred in most cases but is often second-best, and rarely has a large regret value.

2.2.3 Epidemiological modeling

As we are using COVID-19 as a case study, an epidemiological model will be necessary to evaluate strategies across futures and worldviews. We use a compartmental model known as SEIR (Susceptible - Exposed - Infected - Removed)(Li & Muldowney 1995). The SEIR model is often used for diseases for which there is a time gap between being exposed to a virus and being infected by it, as well as a group who are removed (either through recovery and immunity or through death) at the end. Both of these appear to apply to COVID-19. (Lauer et al. 2020). There are models which are even more detailed than the basic SEIR model used here. RAND Corp, for example, has several extensions to the basic SEIR model in their COVID-19 decision support tool. (Vardavas et al. 2021). These extended models can provide better predictions in suitable situations, where needed data are available. But in a decision context, such refinements must be balanced against the richer connections to alternatives and utility they require, and they may be of secondary importance for questions about where stakeholder values are likely to be in conflict or in harmony.

Looking ahead, in section 2.3 we propose a way to integrate the three approaches. In section 2.4 we develop a utility function. In section 2.5, we develop and implement an SEIR model for COVID-19 as a System Dynamics model in Vensim. and populate the integrated model by developing assumptions about values or range epidemiological parameters, economic parameters, policies, and utility functions. This model will be used as a "scenario generator" to perform exploratory analysis. Parameters for each run of the model will be generated through Monte Carlo sampling, and we will evaluate the output of each sample using the utility function developed in section 2.4 across many runs of the model.

2.3 Theory development

The goal of this paper is to assist with public policy decisions featuring deep uncertainty with regard to outcomes and value disagreements about how to interpret those outcomes. To achieve this aim, we combine several commonly-used OR methods into a novel modeling framework. One such method is quantitative modeling. Here, we use the aforementioned SEIR model. Another method is Monte Carlo sampling of a quantitative model of a system with large parametric uncertainty. A good example of an application of this method is Anthoff & Tol (2014). In that paper, the authors use an existing climate model and perform a Monte Carlo simulation of the parameters. They convert all of the outcomes (a statistical life lost, a square kilometer of wetland lost, and so on) to a dollar value, and analyze the results. We diverge in this paper in that we don't use a single value to convert the outcomes to dollars, which leads to another OR method: multi-criteria decision making. We explicitly build a utility function to interpret the output of the simulation. Rather than giving the terms of the utility function a single value, we look at different plausible values for those terms. This adds a second layer to the interpretation of the results. Not only do we look at a large range of possible scenarios and try to pick a strategy that is robust against a large range of them, but we also view the results through the lens of differing worldviews to pick a strategy that is robust against those worldview differences. Ideally, this will lead to a strategy that is not only good for society in the face of deep uncertainty but will also be easier to implement because it is robust against differences in personal values.

The notion of “worldview robustness” was introduced by Lempert & Turner (2020) who used an idealized lake pollution model in a semi-prescriptive fashion. In that paper, they started with worldviews and determined what strategies to employ to balance the tradeoff between economic output and lake pollution based on what those worldviews prefer. Here, we instead start with strategies and consider how each worldview would interpret the results. By applying this idea in a real-life example with real-world parameters, we also illustrate some of its benefits and challenges.

Figure 2.2 is an illustration of the full research framework.

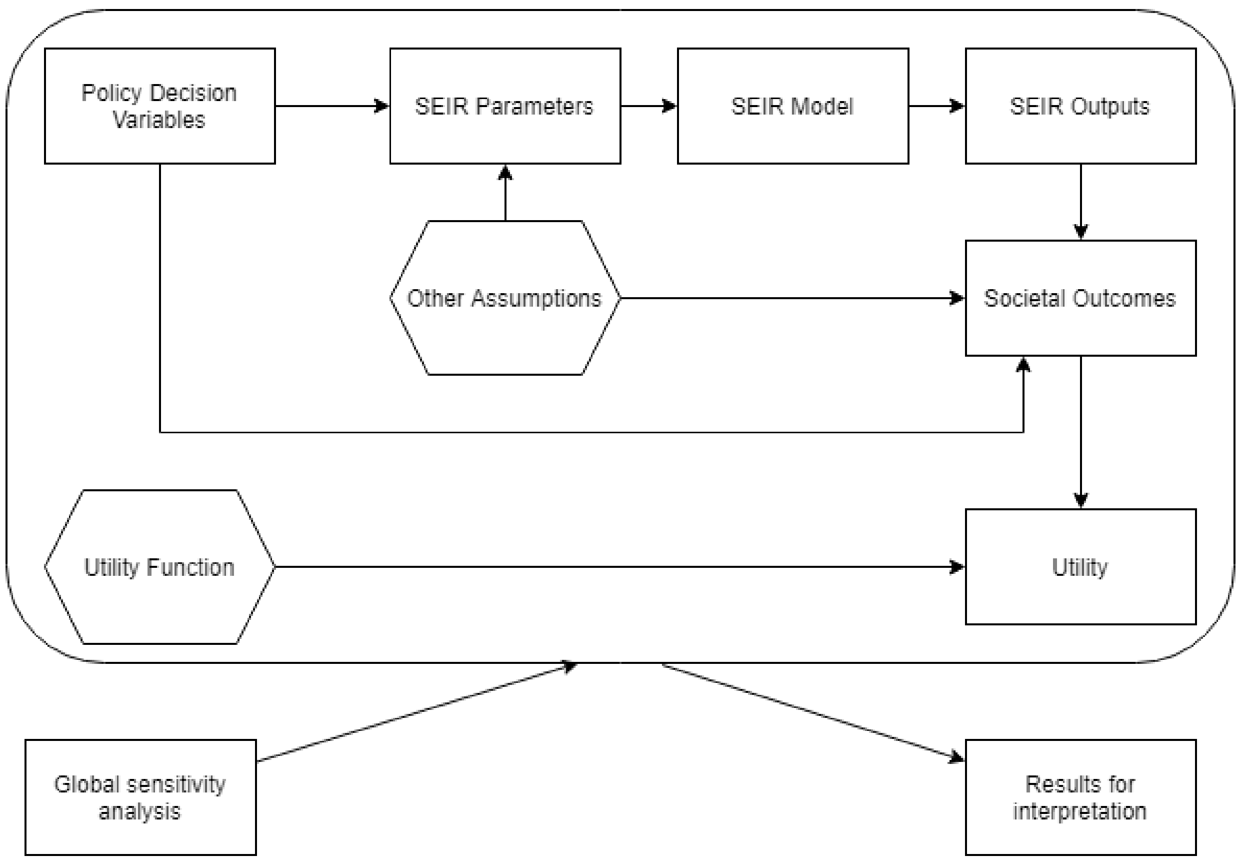


Fig. 2.2 *Research framework. Outputs from an SEIR model are interpreted through a utility function, and then global sensitivity analysis is used to generate insights for decision-makers.*

The top portion represents the quantitative model developed in section 2.5. The Policy Decision Variables directly impact both the SEIR parameters and the societal outcomes. For example, the policy decision variable related to mandatory mask-wearing will influence the relevant parameter in the model as well as have the societal outcome of people being required to wear masks. Other assumptions also impact those two concepts, for instance, the number of hospital beds available. The SEIR parameters are then used to run the model, and the outputs from that model describe the portion of societal outcomes related to the disease spread.

Those SEIR outputs are interpreted through the lens of the utility function we develop in section 2.4.

That entire process is repeated multiple times by randomly varying the parameters to perform global sensitivity analysis, and analyzing the results of the sensitivity analysis, to determine the impact of the policy decisions on the overall utility across different worldviews.

2.4 Utility Function

To interpret the results of the model through differing worldviews, we must first build a utility function with plausible ranges on the weights of each term. A utility function should contain terms representing the considerations that drive an individual's preferences over different outcomes. Given the cacophonous public discourse as well as the deep uncertainty, just defining clear measures and a coherent way of combining them is a challenge. However, our stated purpose is to understand the implications of value differences in the context of potential COVID-19 policies, rather than selecting or recommending a single such policy. Hence, we develop a form for the utility to be used that maps preferences relating to the main arguments about policies involving some sort of restrictions. For analyzing similar questions about a richer set of policies and responses, a more complex utility function could be developed.

2.4.1 Utility Parameters

The proposed utility function has three fundamental objectives: life value, economic value, and hedonic value of liberty. In principle, we could have included any number of other decision criteria. Stone (2012) lists 5 policymaking goals: Equity, Efficiency, Liberty, Welfare, and Security. Here, efficiency is represented by economic value, and life value is a type of security. We explicitly include a liberty term. Outside of our scope, but also interesting would be terms for welfare and equity, which could be useful to include in an extension of the model with a more granular analysis of policy impacts on individuals (as would be appropriate for a prescriptive model guiding policy-makers on what to do). Such analysis would also require more granular epidemiological and economic models. Here, we do not distinguish the potentially differential impacts of the pandemic and its solutions across socioeconomic, racial, or gender lines.

2.4.1.1 Life

One of the important tradeoffs we have to face is the tradeoff between life and the economy. This is perhaps the most controversial part of the utility. Value is placed on life-years routinely in medical settings as well as public policy settings. There are many approaches to put a monetary value on life. Each of these approaches leads to a range of valuations. The tradeoff between life and money depends both on what measure is used and one's personal values.

One method to place a monetary value on life is the Value of a Statistical Life (VSL) (Viscusi & Aldy 2003) in which the cost of a government policy is weighed against the statistical lives it saves. This is largely based on a "willingness to pay" metric. In other words, how much are people willing to pay to reduce their risk of mortality? The US Department of Transportation uses a VSL measure, which uses a value of $9.4m per statistical life when making decisions. They use a range of $5.4m - $13.4m for sensitivity analysis. (US Department of Transportation, 2016)

Using a "statistical life" valuation makes sense when the lives being saved or lost have the same statistical parameters as the population. However, when a disease like COVID-19 has a nonuniform impact on different segments of the population, VSL is not necessarily the best measure.

Keeney (1990, 1994) turns the VSL around. Instead of putting a dollar value on lives, he asks how many statistical deaths would a reduction of wealth cause. Poverty leads to increased mortality, he argues, so, therefore, increasing taxes to pay for a government program to save lives will increase poverty which can cost lives. In this way, instead of comparing dollars to dollars, we can compare lives to lives. This avoids some of the controversy of putting a value on lives. In the 1990 study, he estimates that a fatality might be induced by an economic cost of $3m to $7.5m in 1980 dollars. In the 1994 study, Keeney estimates that the number is in the range of $5m to $50m in 1990 dollars. (Keeney, 1990, 1994) Updating the values from Keeney (1990) to 2020 dollars gives us a range of $9.4m to $23.5m. The wider range from Keeney (1994) in 2020 dollars is $9.9m to $99m. As with the VSL approach, this counts all lives the same, regardless of age, disability, or any other factor. Another way to calculate this value is to look at the years lost. After all, everybody dies. What is actually lost are the years of life between when someone died from a particular cause, and when they otherwise would have died in the absence of that cause.

This is common in medical literature, where they use the concept of the QALY, or Quality-Adjusted Life-year (Zeckhauser & Shepard, 1976). This measure looks at how many years of life are gained by a particular medical intervention adjusted for the quality of those years. For instance, a year of life on a ventilator will be adjusted downwards when compared to a year of perfectly healthy life. This sort of calculation is used when determining how to allocate limited medical resources.

Typical values per QALY are in the range of $100,000 to $150,000, with sensitivity analysis values recommended by Neumann et al. ranging from $50,000 to $200,000. (Neumann et al., 2014)

If we assume an average life has 40 QALYs left (to put it on par with the "statistical life" saved in the VSL) that provides a range of $2m to $8m per life. The lower bound on this range is probably too low as argued in Neumann et al. The upper bound is in the same neighborhood as middle-ground estimates of both the VSL method and Keeney's method of estimating deaths from economic costs.

A common criticism of QALYs is that each year of life should not be adjusted for quality of life (as defined by health economists). The Institute for Clinical and Economic Review (ICER) uses a measure called Equal Value Life-year Gained, or evLYG, in addition to the QALY to determine the effectiveness of interventions. (ICER n.d.) For the most part, this is not different enough from the QALY to make a difference in our analysis. For COVID-19, the difference between life-years lost and QALYs lost is about 20% according to the Centre for Health Economics in London. (Briggs 2020) But in any case, the QALY is an upper bound of how much a year of life can be valued, in that one QALY is one life-year lived in good health.

A last point is that regardless of the number of life-years lost or saved, the manner of death matters. When someone is murdered, we as a society do not base the punishment on the number of life-years the victim had left. Thus, we can assume that society additionally places some fixed value on each life saved, regardless of the number of life-years the person had left. To model this, the life portion of the utility function is of the form:

$V_D X_D + V_{LY} X_{LY} X_D$

Where:

V_D, V_{LY} are the values placed on each death due to COVID-19 and the value of each life-year lost due to COVID-19 respectively.

X_D, X_{LY} are the number of deaths due to COVID-19 and the average number of life-years lost per death, respectively.

It would be feasible to only put a value on one or the other. For example, one could value each life lost at a fixed number, regardless of how many years of life the person would have otherwise had. On the other hand, one could only consider the number of life-years lost, valuing each life lost at $0 by itself.

To bound the parameters V_D and V_{LY}, we consider a little bit wider of a range than most of the literature. This is to allow for the differences between ways to discount life-years lost and to capture a wide range of reasonable positions of valuing not only life-year but the relative importance of the economy.

V_D should be bounded between \$0 and \$25m. The latter value is just above the upper range from Keeney 1990, and roughly double the Department of Transportation's \$13.4m upper bound for sensitivity analysis.

V_{LY} should be bounded between \$50,000 and \$500,000. The lower bound is a valuation of the QALY that Neumann et al. (2014) called "curiously resilient" as they argue it should be updated. The upper bound is far above most measures and is near the upper bound of Keeney (1990).

Table 2.1: Different values for life

Source	Value of life (2020 USD)	Value per year (2020 USD)
Neumann et al. lower bound (QALY)	2,160,000	**54,000**
Neumann et al. upper bound (QALY)	13,000,000	**325,000**
DoT lower bound (VSL)	**5,400,000**	135,000
DoT upper bound (VSL)	**13,400,000**	335,000
Keeney 1990 lower bound	**9,400,000**	235,000
Keeney 1990 upper bound	**23,500,000**	587,500
Keeney 1994 lower bound	**9,900,000**	247,500
Keeney 1994 upper bound	**99,000,000**	2,475,000

Note: Upper and lower bounds for valuing life. Bold numbers indicate the value given in the literature expressed in 2020 dollars. Non-bold values are derived by assuming there are 40 life-years lost per statistical life lost.

Additionally, the sum of $V_D + 40V_{LY}$ should not be higher than \$30m, to avoid double-counting of life-years (40 being an estimate of the average number of life-years lost in a Value of a Statistical Life calculation). This gives a wide range of plausible values for life in terms of economic value to examine.

2.4.1.2 Liberty

People place a value on their comforts and liberties. Philosophers at least as far back as Jeremy Bentham and John Stuart Mill talk about hedonistic utilitarianism. Economists seek to measure this with a Willingness to Pay (WTP) measure (e.g., Potoglou 2010, Viscusi & Zeckhauser 2003). Many responses to COVID-19 restrict the liberties of the members of society, and this needs to be accounted for in the utility function.

Rather than pick a particular range of values from WTP estimates, we will just use reasonable upper and lower bounds. A year of having one's freedoms completely restricted is certainly not worth less than losing a year from one's life, so a natural upper bound is the value per life-year, V_{LY}. There exist cases in medical literature in which an outcome can be worse than death, however, we can reasonably stipulate that being isolated at home is not one of those situations. A natural lower bound on this value is \$0. So, if V_H is the hedonic value of losing a year of liberty, then

$0 \le V_H \le V_{LY}$

In general, the restrictions placed to mitigate the spread of COVID-19 will be less than a total restriction of freedoms. The "strength" of the restrictions, X_R, can be represented by a constructed scale from 0 to 1, depending on the specifics of the policies being proposed, where a 0 means no restrictions, and a 1 is equivalent to having all of your liberties completely curtailed.

The last two factors to consider are the length of time these restrictions are in place and the number of people impacted by the restrictions. These can be represented by X_{RT} and

X_{RP}, where X_{RT} is in fractional years, and X_{RP} is the number of people. Then, the total hedonic part of the utility function is:

$V_H X_R X_{RT} X_{RP}$

This will capture the hedonic cost to society caused by the restrictions on liberty.

2.4.1.3 Economy

Valuing the loss to the economy is not as straightforward as it seems. A first-order approximation of economic damage is a decrease in GDP from what we otherwise would expect. There are multiple issues with only looking at GDP, however. Some of which include:

1. **Value of life measures don't generally refer to GDP.** When the Department of Transportation looks at VSL, they are looking at government expenditures. When Keeney looks at the cost of regulations, he's not explicitly looking at GDP, but rather the wealth of the population. QALYs are generally valued against expenditures from a specific limited budget. None of these cases is a comparison to an increase or decrease in GDP.
2. **GDP doesn't take into consideration inequality.** It's not difficult to envision a scenario in which GDP drops by redistributing wealth, leaving the majority of people better off. Conversely, it is feasible to come up with a situation where GDP increases, but more people die from poverty due to a redistribution of wealth to the wealthiest individual in society.
3. **Government expenditures are part of GDP.** This means that the government could go into debt and increase spending to offset a drop in personal income and business

investment. This would mask the real economic costs occurring due to COVID-19 mitigation strategies.

4. **The broken window fallacy.** The broken window fallacy states that if a shopkeeper has his window broken, it is a boon to the economy, since the glazier gets more business, boosting GDP, who will then, in turn, spend more money, further increasing GDP, and so on. This ignores opportunity costs. Likewise, increased business selling masks may look like a boon to the GDP, but it still represents an economic cost that should be taken into account.

So rather than looking at a specific measure like GDP, we're considering "economic costs" similar to what is seen in (Meltzer et al., 1999). Note that this does not pass the "clairvoyant test," (Morgan et al., 1990) since there is no number that a hypothetical clairvoyant could look at and say whether or not our prediction would come to pass. In fact, there is no prediction being made at all. Predictions are an anathema to exploratory modeling. Rather, we use the "Bridgeman test" as used in Cooke (2012), which states, "Every term in a model must have operational meaning, that is, the modeler should say how, with sufficient means and license, the term would be measured." So, while a clairvoyant wouldn't be able to give an exact numerical quantity of economic dollars lost, we would be able to come up with a way to measure each individual piece of the puzzle given the resources to do so. Another thing worth noting is that economic impact is really just a proxy for other outcomes. When people have more money, they have both improved health outcomes and more access to necessities and pleasures.

Furthermore, economic value is not an independent measure. Both the hedonic value of liberty and life value are measured in terms of units of economic value. If, for example, one wanted to downplay the importance of a loss in economic value, this would be equivalent to increasing the weights of life and hedonic values. Conversely, a low value for life and liberty is equivalent to placing a greater importance on economic value. This is a key reason the value of life spans such a large range.

The loss in economic value is the base unit for which the other measures are defined, and can be represented by X_E. This consists of a few components. There are direct costs due to the illness (e.g. the cost of doctor's treatments), indirect costs due to the illness (e.g. missing time at work), and costs due to mitigation strategies (e.g. forcing a business to close or reduce services). We give equal weight to each sub-attribute. For example, we are indifferent to whether someone misses a day of work because they're sick, or misses a day of work because of an imposed quarantine, at least for the economic part of the utility. The difference between the two would show up in the hedonic value of liberty, not the economic value.

Lastly, we do not include the economic cost of death since that is already counted in the value of life piece of the utility function. Many of the valuations of life-years are related to economic productivity, and we do not disaggregate the economic value of life from the noneconomic value of life. In other words, if someone misses a day of work because they're ill, that counts as an economic cost. If someone misses work because they died from the illness, that counts as a life cost.

2.4.2 Total utility function

Combining the above pieces gives us the utility function:

$$-(X_D(V_D + V_{LY}X_{LY}) + V_H X_R X_{RT} X_{RP} + X_E)$$

In general, we want to maximize utility. All of the above pieces of the utility function were costs, so higher numbers are worse. Thus, we need a negative sign in front of the sum of the above pieces to the utility function so that we are correctly maximizing utility.

Lastly, we are assuming a linear utility function. That is, we value losing 1,000 lives as exactly half as bad as losing 2,000 lives. This does not necessarily hold in the extreme, as second-order effects take place. For an absurd example, we would value losing every human being on the planet as infinitely worse than losing only half. But short of a catastrophe of that size, a linear utility function should suffice from a societal perspective. We also assume that the terms are independent, which isn't necessarily accurate. For example, we assume that the value of a life remains constant even when the economy is damaged. Anthoff & Tol (2014) uses a VSL of 200 times the annual per capita income, for example. If the pandemic, the countermeasures to prevent the pandemic, or both lower the annual per capita income, that could plausibly change the VSL. We ignore this interaction for simplicity and because it is likely a small effect.

2.4.3 Utility function worldviews

One challenge to decision-making is determining the relative preference between multiple value criteria. These preferences can be combined into "worldviews," which describe a coherent way of interpreting the world. (Churchman 1968). For example, the value of lives, the hedonic value of liberty, and the value of economic prosperity are largely a matter of preference, and differing worldviews will put different weights on each. Robust Decision Making can be used to find a set of policies that are not only robust against the scenarios generated by the epidemiological model, but also robust against different worldviews.

With life and liberty utility expressed in terms of units of economic utility, we have 4 feasible extremes of the utility function, which we have grouped into worldviews.

2.4.3.1 Maximum life

The “Maximum life” utility function places the largest value on life and the minimum value of liberty. Someone with this worldview would prefer to save as many lives and life-years as possible, without regard for personal liberty. The economy is an intermediate concern. This roughly corresponds to an orthodox liberal view in the United States.

2.4.3.2 Maximum liberty

In contrast, “Maximum liberty” places the lowest feasible value on life, and sets the value of liberty to its maximum value (which in this case is the same as the value of life). This corresponds to a person who sees being told to wear a mask as an untenable overreach by the government. The economy is a secondary concern. A motto of such a person might be “give me liberty or give me death.”

2.4.3.3 Maximum economy

“Maximum economy” is functionally the same as minimizing the value of life and liberty. Someone who wants to maximize the economy would want to limit the deaths due to the virus since those deaths would hurt the economy. They would support measures to limit freedoms (like forcing people to wear masks or extensive monitoring for contact tracing) as long as it means businesses can stay open. This roughly corresponds to an orthodox conservative view in the United States.

2.4.3.4 Minimum economy

Lastly, the "Minimum economy" worldview means placing the highest possible values on both life and liberty. As in the "Maximum liberty" worldview, this sets the value of a year of liberty equal to the value of a year of life. The difference is the value of life is maximized, and therefore losses to the economy are less impactful. A person who holds this view might want to close businesses but keep parks and beaches open, or want to fund a vaccine but make it optional.

2.4.3.5 Others

In general, people will not be at one of the four extremes. Rather, they will exist somewhere in the middle. Anyone's preferences could be described by a linear combination of the four worldviews. Therefore, by evaluating scenarios against the above "extreme" worldviews, we can establish upper and lower bounds on the utility.

2.4.4 Decision Frame

In order to use the utility function to analyze the results of the simulation model, we need to set a decision frame. For this example, the decision frame is a decision-maker in the state of Massachusetts at the beginning of the COVID-19 pandemic, before most of the properties of the disease were known. We chose Massachusetts because COVID-19 mitigation decisions were largely made at the state level, and we choose the beginning of the pandemic because that's both when uncertainty was the greatest and when some of the most critical decisions had to be made.

Looking at this from the societal level, we invoke Rawls' Veil of Ignorance (Rawls, 1971) to aggregate individual preferences. For instance, one young, healthy person may find their liberty to not wear a mask as worth more than the lives of a thousand strangers. But

Rawls' Veil of Ignorance states that decisions should be made as if no one knows whether or not they'll be the one to be affected adversely by the consequences. A young healthy person making a decision about a mask mandate, for example, should make the decision from behind a veil of ignorance, such that they don't know if they're going to be in the high-risk category. In this spirit (though cognizant of its limitations), we are able to compare the value of one person's life with the value of someone else's liberty.

2.5. Integrated RDM Model

The RDM model consists of three parts: an epidemiological model, an economic model, and a liberty model. The relationships are illustrated in figure 2.3. The Epidemiological model is used as a "scenario generator" to create a wide range of plausible outcomes, which are combined with the outputs of the Economic and Liberty models and interpreted through a utility function. Sections 2.5.1, 2.5.2, and 2.5.3 will develop the Epidemiological, Economic, and Liberty models respectively.

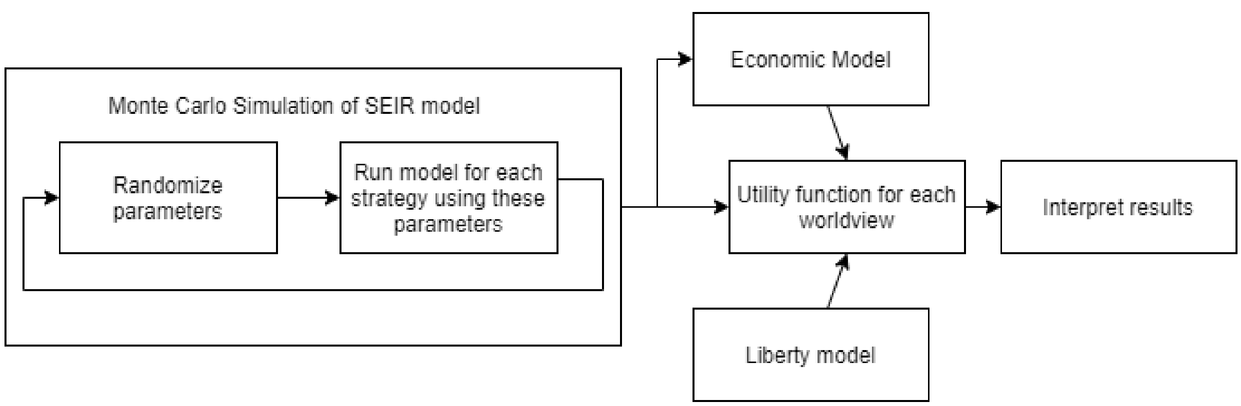


Fig. 2.3 *The integrated epidemiological, economic, and liberty model.*

2.5.1 Epidemiological model

For the epidemiological model, we have to consider both the characteristics of the disease and the policy levers that can be used to influence the rate of spread. The impact of policies will be summarized in terms of their direct impact on the effectiveness of masking and isolation measures. In 2.5.1.1, we describe the disease model, which includes parameters for the direct policy impacts. In 2.5.1.2, we define a set of mitigation strategies to be analyzed.

For the sake of simplicity and clarity, we consider static strategies. A better but more involved method might be to use adaptive dynamic strategies, which turn on or shut off depending on dynamically evolving conditions. The use of the utility function to evaluate adaptive strategies is the same as for the static strategies, and that is what we want to highlight here.

2.5.1.1 SEIR model

To model the disease, we use a System Dynamics model, based largely on the Community Coronavirus Model version 8 by Tom Fiddaman. (Fiddaman, 2020). It is an SEIR compartmental model implemented in Vensim. Figure 2.4 shows the structure of the model. Several changes were made to Fiddaman's model to add policy levers that can be modeled. In particular, "mask effectiveness" and "social distancing and lockdown effectiveness" were added. One lever, isolation effectiveness, was already in place in the original model.

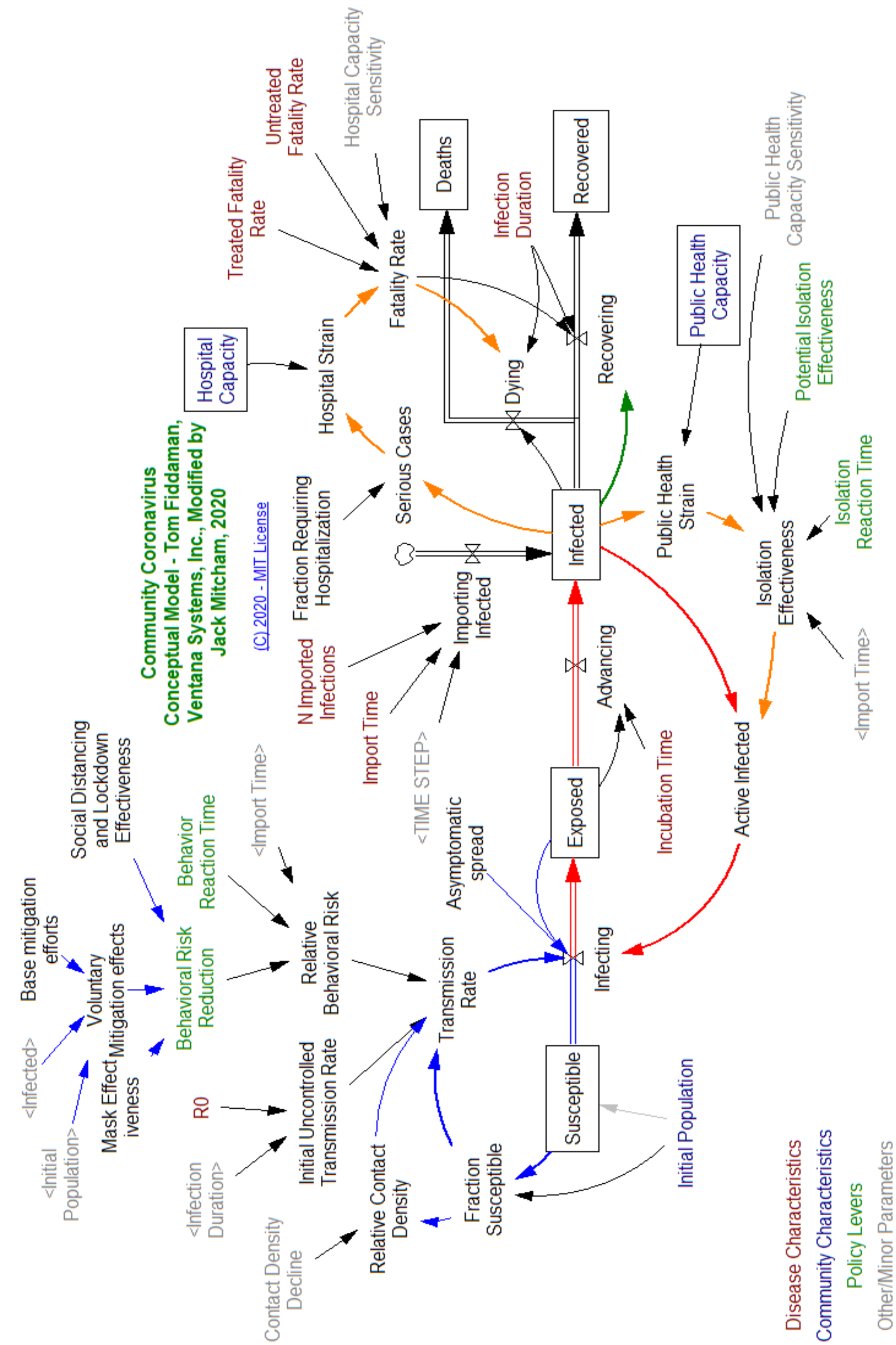


Fig. 2.4 *COVID-19 System Dynamics model in Vensim*

Table 2.2: Disease parameters used in the Monte Carlo simulations

Parameter	Range	Description	Source or Rationale
R0	1.4-6.5	Basic Reproductive Number	Liu et al. 2020
Treated Fatality Rate	0.001-0.02	Fatality rate among those who received treatment	Range spanning a factor of 20, roughly in line with Influenza infection fatality rates (Wong et al. 2013)
Untreated Fatality Rate	2-6*(Treated Fatality Rate)	Fatality rate among those who were not treated	Assumption that deaths are 2 to 6 times worse if treatment is unavailable.
Incubation Time	4-8	Average time (in days) for an exposed person to become infected	Lauer et al. 2020
Duration	7-21	Average time (in days) for an infected person to be removed	Assumption based on early recommendations of a 2-week quarantine
Hospitalization Rate	5-10*(Treated Fatality Rate)	Rate at which infected people need to be hospitalized	Assumption that between 10-20% of those needing to be hospitalized will die
Life-years lost per death	10-25	Number of life-years lost per death	Assumes older people die more than younger people

Note: Each run drew a value for each parameter from a random uniform distribution

Table 2.3: Strategy parameters used in the Monte Carlo simulations

Parameter	Range	Description	Source or Rationale
Mask Effectiveness	0.15-0.65	Effectiveness of a mask mandate to lower the infectiousness	Assumption, considering both reduction in spread due to mask-wearing and effectiveness of the mandate itself.
Base Mitigation	0.33-0.67	Maximum effectiveness of the community's ability to lower infectiousness on its own	Assumption, roughly based on Google mobility data
Light Lockdown Effectiveness	0.1-0.25	Effectiveness of a light lockdown to lower the infectiousness	Assumption
Heavy Lockdown Effectiveness	0.4-0.6	Effectiveness of a heavy lockdown to lower the infectiousness	Assumption
Base isolation effectiveness	0.4-0.6	Maximum effectiveness of self-quarantine of infected individuals	Assumption
Central Quarantine effectiveness	0.9-0.95	Maximum effectiveness of centrally quarantining infected individuals	Assumption that a complete quarantine would be close to 100% effective but not quite.

Note: Each run drew a value for each parameter from a random uniform distribution

Table 2.4: Fixed parameters and initial conditions

Parameter	Value	Description	Source
Initial Population	6,700,000	Estimated population of Massachusetts in 2020	Renski & Strate, 2013
Asymptomatic Spread	0.5	Fraction of Exposed people which contribute to spreading the virus	Assumption
Hospital Capacity	4849	Hospital beds available to COVID patients in Massachusetts	IHME
Public Health Capacity	100,000	Maximum number of infected people the health system of Massachusetts can accommodate for tracing and isolation	Assumption
Contact Density Decline	0	Decline in contacts as the infection penetrates less-connected portions of the social network	Simplifying assumption. Results were insensitive to modest changes in this parameter
Imported Infections	100	Number of infections in the initial population to start	Initial condition

The version of the SEIR model implemented includes a number of parameters, some specific to the COVID context. These are listed in tables 2.2 (disease parameters) and 2.3 (strategy parameters) below with a brief description of each parameter's role in the model. Table 2.4 lists the fixed parameters and initial conditions. The tables also give the ranges of potential values we assumed for the simulation. Again, with the RDM model being used for informing the decision process, the ranges are intended to be plausible estimates and are themselves based only on limited background. Sources or rationales for the assumed ranges are offered in the last column of the tables. The policy levers and strategy parameters outlined in table 2.3 will be defined in more detail in section 2.5.1.2.

The search for robust strategies requires exploration of the range of possibilities rather than probabilistic risk analysis. With 11 parameters, a large number of runs is required to explore the entire parameter space. An alternative to Monte Carlo simulation would be to discretize the parameter distributions and exhaustively calculate results for every combination of the minimum, midpoint, and maximum parameter values. However, this would require 3^{11}, or 177,147 runs, and would grow by a factor of three for any other parameter that might be included, and would miss what happens with intermediate parameter values between the minimum and midpoint or midpoint and maximum. Thus, the random inputs in Tables 2.2 and 2.3 are simply drawn from a random uniform distribution, while other subtle considerations are not explicitly modeled as uncertain parameters. For instance, the asymptomatic spread parameter in Fiddaman's original model was assumed to be zero. Here, we assume it to be 0.5 (meaning 50% of asymptomatic people contribute to the spread) but do not vary the number in the Monte Carlo simulation. In Fiddaman's original model, he included a seasonality term, which we do not include here since we are looking at a full year and assume the seasonal variance will balance out.

Simulation settings: To sample the possibility space, we use a Monte Carlo simulation with two loops. The "outer loop" iterates 100,000 times with a random sampling of the parameters. Within each iteration, there is an "inner loop" of the 5 strategies, each using the same values for the parameters. This leads to a total of 500,000 data points. This was done in Python using the PySD library (The PySD Cookbook — PySD-Cookbook 0.1.0 Documentation n.d.) to control the Vensim model.

The model simulates one full year of the pandemic. It used a time step of 0.25 (i.e., 6 hours), and thus ran for 1,460 time steps. Each strategy was held constant throughout each run of the simulation.

2.5.1.2 Policy levers and strategies

The model includes three policy levers, Mask (yes or no), Lockdown (none, light, heavy), and Quarantine (yes or no), that could be combined to form a strategy. There are 12 such combinations, but to start we're only considering 5 of them, in order of increasing severity. We use this as a starting point that will help us identify new strategies later. Modeling all 12 at the start would increase the computation time and make analysis more difficult and cluttered.

- **Base**: Do nothing and let the disease run its course. Let society self-regulate the response.
- **Masks**: Mandate mask-wearing by the entire population, but take no other mitigation measures.
- **Light Lockdown**: In addition to mandatory mask-wearing, also shut down large gatherings, and encourage social distancing.
- **Heavy Lockdown**: In addition to everything in Light Lockdown, also close non-essential businesses.
- **Central Quarantine**: In addition to everything in Heavy Lockdown, also centrally quarantine infected individuals, rather than sending them home to recover.

Table 2.5: Strategy table

		Policy levers		
		Mask	Lockdown	Quarantine
Strategies	Base	No	None	No
	Masks	Yes	None	No
	Light	Yes	Light	No
	Heavy	Yes	Heavy	No
	Quarantine	Yes	Heavy	Yes

The differences between the strategies are as follows:

- **Base**: Mask effectiveness of 0, isolation effectiveness is between 0.4 and 0.6, lockdown effectiveness is 0
- **Masks**: Mask effectiveness is between 0.15 and 0.65, isolation effectiveness same as Base, lockdown effectiveness is 0.
- **Light Lockdown:** Mask effectiveness and isolation effectiveness same as Masks, lockdown effectiveness between 0.1-0.25
- **Heavy Lockdown:** Mask effectiveness and isolation effectiveness same as Light Lockdown, lockdown effectiveness between 0.4-0.6
- **Central Quarantine:** Mask effectiveness and lockdown effectiveness same as Heavy Lockdown, isolation effectiveness between 0.9 and 0.95

2.5.2 Economic model

As with the epidemiological model, the economic model is intentionally simple for purposes of tractability in particular during the integration of the different elements of the RDM model.

Below, we define the economic cost terms used and describe the assumptions used in the model and their rationales. We consider both direct and indirect economic costs due to illness and the costs related to the strategies to mitigate the illness. This is similar to Meltzer et al. (1999) which compared the cost of a flu vaccine (which is a cost of mitigation) to the economic cost of pandemic flu.

2.5.2.1 Direct costs of illness

The direct cost of COVID-19 arises from medical treatment. For those that don't need to be hospitalized, we estimate the direct cost to be $200, per Meltzer's study (*ibid*.) which found the average cost for outpatient treatment, including prescription drugs, for influenza was $140 in 1999 dollars.

For those that are hospitalized, the cost is much higher, and we estimate this to be $75,000. This is roughly in line with a report from FairHealth which put the cost at $73,300 (FairHealth 2020).

Sensitivity analysis showed that there was not a big difference in the results if those numbers were modestly higher or lower, and here the numbers are unlikely to be orders of magnitude different.

2.5.2.2 Indirect costs of illness

The only indirect cost of illness we consider is lost productivity at work. We estimate average production per person to be around the same amount as average wages. In fact, production is higher than wages, but this is balanced out by the fact that some affected people are not employed.

The average daily wage in Massachusetts (which is our decision frame) is estimated to be about $250 a day. The US Bureau of Labor Statistics shows the mean hourly wage in

Massachusetts as of May 2019 was $31.58 per hour, which leads to a daily wage of $252.64 assuming an 8-hour workday.

We do not consider any differential impact on who gets sick and has to miss work. It may be the case that certain low-wage employees, like fast-food workers and grocery store cashiers, might be more exposed to the virus and thus more likely to get sick than people who can work from home, like software developers. Instead, we let sensitivity analysis handle this. Increasing or decreasing the value by a factor of three has little impact on the analysis.

2.5.2.3 Cost of mitigation

Each mitigation strategy has a different cost associated with it. In each case, we provide an option on the Tableau dashboard to perform real-time sensitivity analysis on these parameters.

Base: The "no mitigation" strategy will have indirect costs associated with it, mainly in that people will modify their behavior to reduce their risk of getting sick even without a government response. We consider this to be true in every mitigation situation and treat it as a baseline. Thus, the costs of the other strategy should be considered a departure from this baseline, and not an absolute cost.

Masks: This is the strategy in which the only thing the government does is mandate mask-wearing. Everything stays open otherwise. In this case, the only economic cost is the cost of the masks per person. We estimate this to be $50, e.g., 200 disposable masks per person at $0.25 per mask. The results are insensitive to large changes in this value either up or down.

Light Lockdown: With this strategy, masks are also required, but also, large gatherings are prohibited, and some social distancing is enforced. To estimate the overall economic impact, we're using a percentage of state GDP as a baseline. Even though GDP has myriad problems as a measure of economic impact, it at least sets the correct scale. So if, for example, we assume an economic cost of 10% of GDP, we don't mean that GDP will necessarily drop by 10% of what it otherwise would be. Rather, we assume that when the direct and indirect economic costs are added up, they will sum to a value that is 10% of GDP. We don't assume an absolute cost of a light lockdown. Rather, we set the impact to be on the order of 10% for the year, and conduct sensitivity analysis from this baseline.

Heavy Lockdown: Heavy Lockdown is the strategy in which bars and restaurants are curbside pickup only, most indoor businesses are closed, and so on. Similar to Light Lockdown above, we do not estimate a single economic cost, but rather check it against a range of plausible inputs. We assume the cost will be on the order of 20% of the state GDP.

Central Quarantine: This strategy has all of the heavy lockdown restrictions, but instead of infected people going home to infect their families, they are centrally quarantined in a facility. The cost of this would be the same as Heavy Lockdown, plus the cost of quarantining each individual. We consider a range of possible quarantine costs across an order of magnitude, from \$200 to \$2000 per person per day of infection for a length of time equal to the duration of the infection, with a baseline assumption of \$500. For comparison, the cost of quarantining an Ebola patient in 2014 was estimated to be \$1,000. (Hyman 2014), and that included police protection and meals.

2.5.3 Liberty cost model

The last piece of the model is valuing liberty. We've established that the maximum value society can place on a year of one's liberty is the value of a year of life. This maximum value should correspond to the difference between the situation where when liberty is maximally curtailed (within our range of consideration) vs. when it is not curtailed at all. But what percentage of that maximum is it when one has to, for example, wear a mask when leaving the house, or cannot eat in a restaurant? A study after the fact could use a Willingness-To-Accept measure to see how much money people would be willing to accept to live under the lockdown restrictions, but in the absence of such data, we again make assumptions and test them with sensitivity analysis.

For masks, the policy is somewhat straightforward, and in some ways, the liberty impact is easier to estimate. For light and heavy lockdowns, the policies are a bit more nebulous. These strategies are highly simplified for the purpose of demonstrating the utility function. Thus, we estimate the percentage impact on liberty as a direct consequence of the strategy, which is included in the overall model results.

2.5.3.1 Masks

When wearing a mask, one can do almost anything one could do without a mask. It is a minimal infringement on liberty. Here, we consider mandatory mask-wearing to be a restriction on liberty of 2% of the maximum value. If a person valued a year of life to be worth $500,000, this would put the liberty cost of wearing a mask at $10,000. If we interpret that as a “willingness-to-accept” measure, it is a reasonable number. Results are insensitive to minor changes in this value.

2.5.3.2 Light Lockdown

Here, we assume that only shutting down large gatherings and enforcing some social distancing is a 10% restriction on liberty. As with masks, one can still do almost anything.

2.5.3.3 Heavy Lockdown

We assume that a heavy lockdown, in which bars and restaurants are take-out only, movie theaters are closed, and so on, is a much bigger restriction on liberty than in the light lockdown scenario. We assume that such a lockdown accounts for 50% of the maximum liberty value.

2.5.3.4 Central Quarantine

We assume that individuals who are centrally quarantined experience a 100% loss of liberty.

2.6. Results

The data from the simulation was loaded into Tableau for visualization. This was done to create a dashboard where the parameters could be adjusted to see instant updates in the visualization. This would allow a decision team to answer "what if" questions in real-time. The dashboard was uploaded to Tableau Public and can be found here: https://public.tableau.com/profile/jack.mitcham#!/vizhome/CovidProject_15976817050220/UtilityDashboard

This decision support tool has several filters and parameter sliders to aid in sensitivity analysis. A screenshot of the tool is shown in figure 2.13 (in the appendix).

Before analyzing the results, we should take a moment and review the manner in which the results will be analyzed. We are interested in several questions:

- What is the spread of utility results for each strategy
- Which strategy was preferred for each scenario
- How each strategy performs compared to the "best" strategy

Then, each of the above will be checked against each worldview. We are looking for robustness not only across scenarios but also across worldviews.

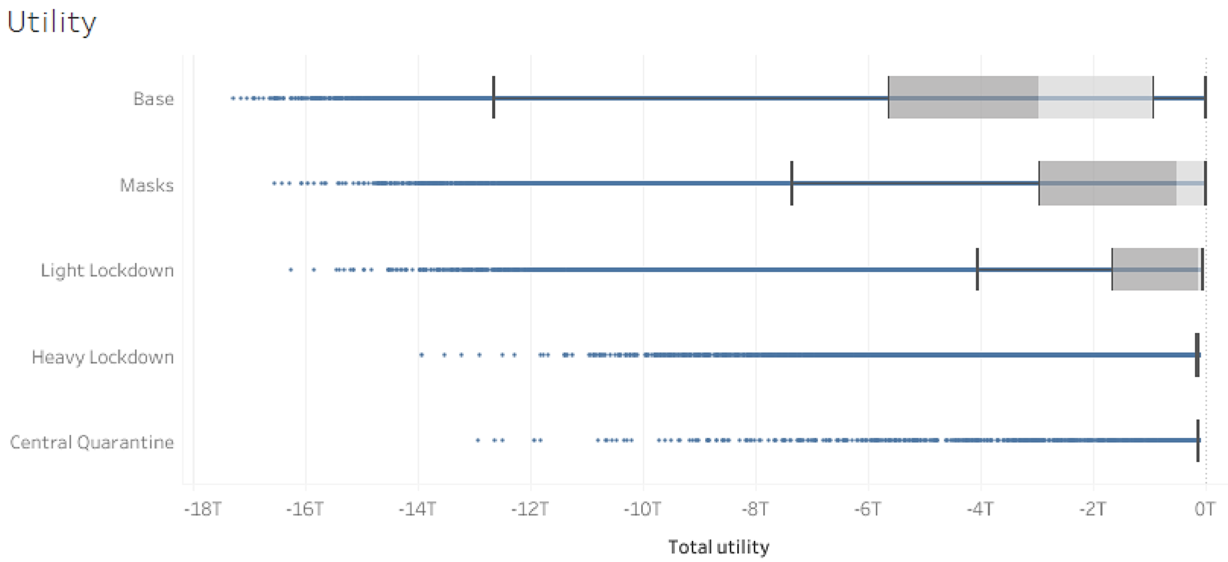
We include both utility and regret in the results. (Figs. 2.5-2.12) In order to provide decision-makers with qualitative insights using the quantitative model, the entire distribution of results is presented rather than relying solely on summary statistics.

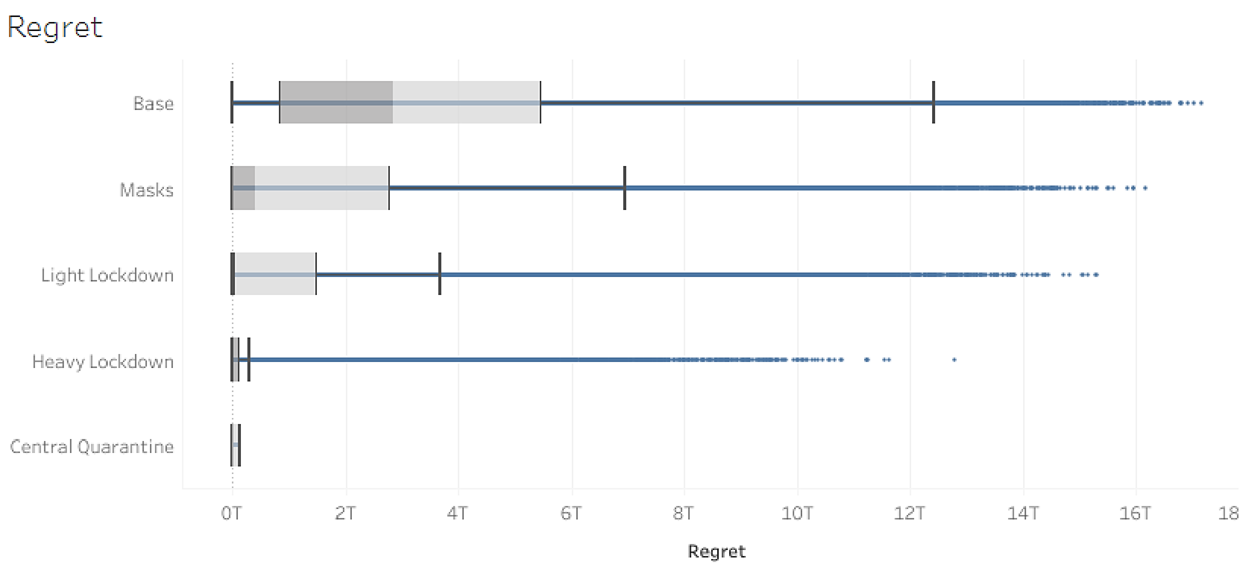
2.6.1 Results by Worldview

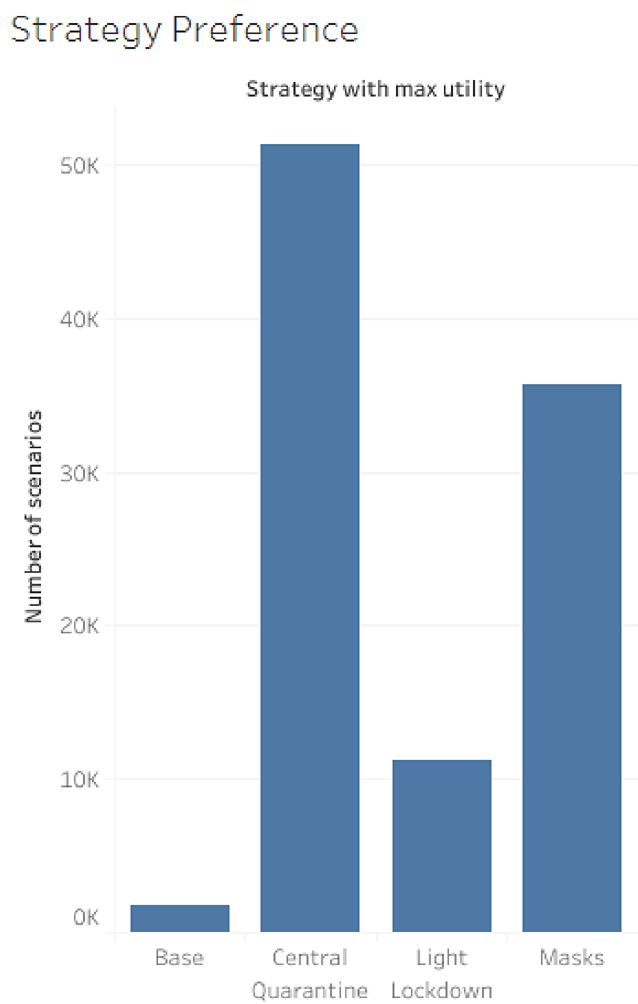
What follows are the results of applying the four worldviews (Maximum Life, Maximum Liberty, Maximum Economy, and Minimum Economy) to the output of the scenarios. Furthermore, two versions of "Maximum Life" and "Minimum Economy" are presented, which shows the impact of valuing lives over life-years or vice versa.
Care should be taken not to interpret a strategy being preferred in a certain number of scenarios as a probability that the strategy will be preferred in real life. All it means is that a strategy is preferred in a larger volume of parameter space in this particular model. It says nothing about the likelihood of those parameters being correct in the real world.

2.6.1.1 Maximum Life

The following are the results with life maximized such that the value of each life lost is $10,000,000, and the value of each life-year lost is $500,000.


Utility
Base
Masks
Light Lockdown
Heavy Lockdown
Central Quarantine
-18T
-16T
-14T
-12T
-10T
-8T
-6T
-4T
-2T
0T
Total utility


Regret
Base
Masks
Light Lockdown
Heavy Lockdown
Central Quarantine
0T
2T
4T
6T
8T
10T
12T
14T
16T
18
Regret

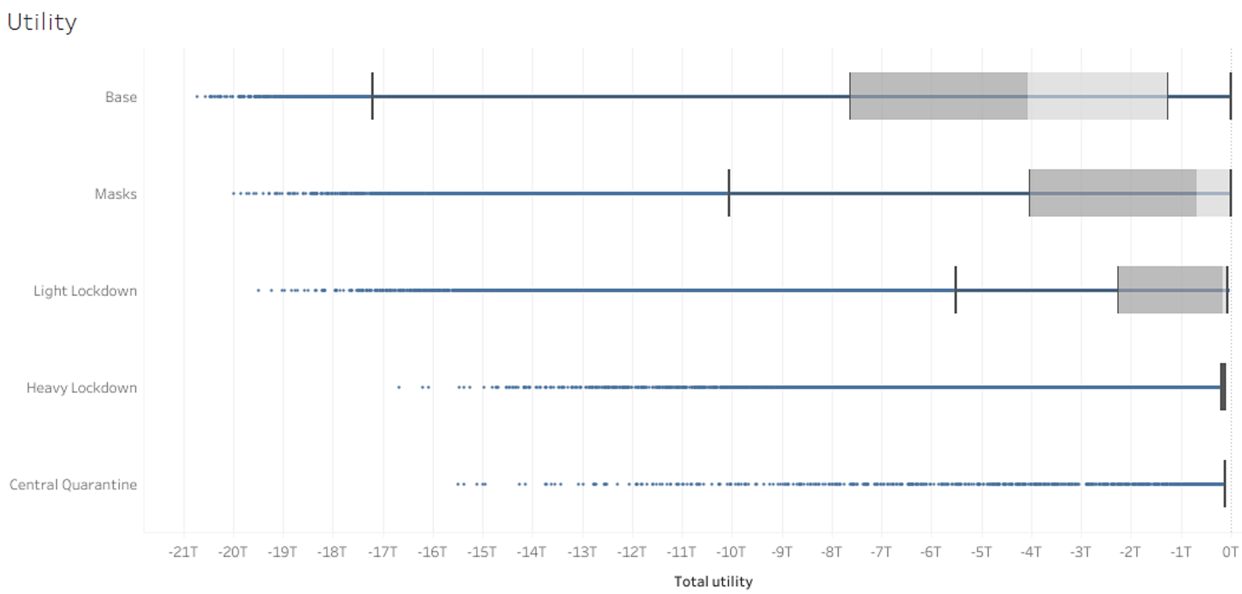


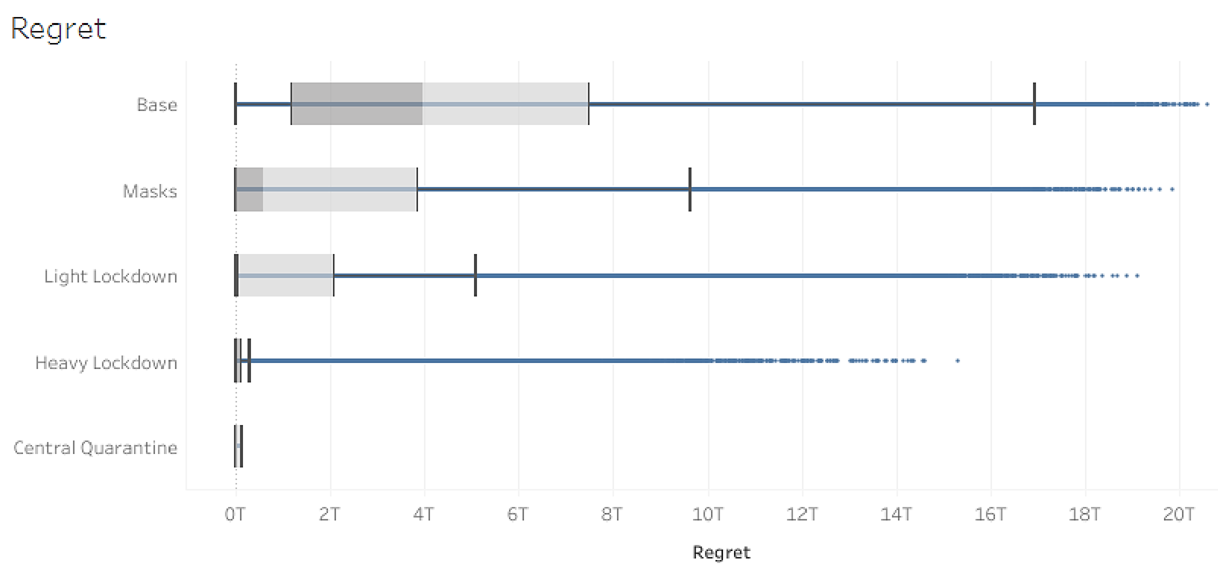
Utility measures

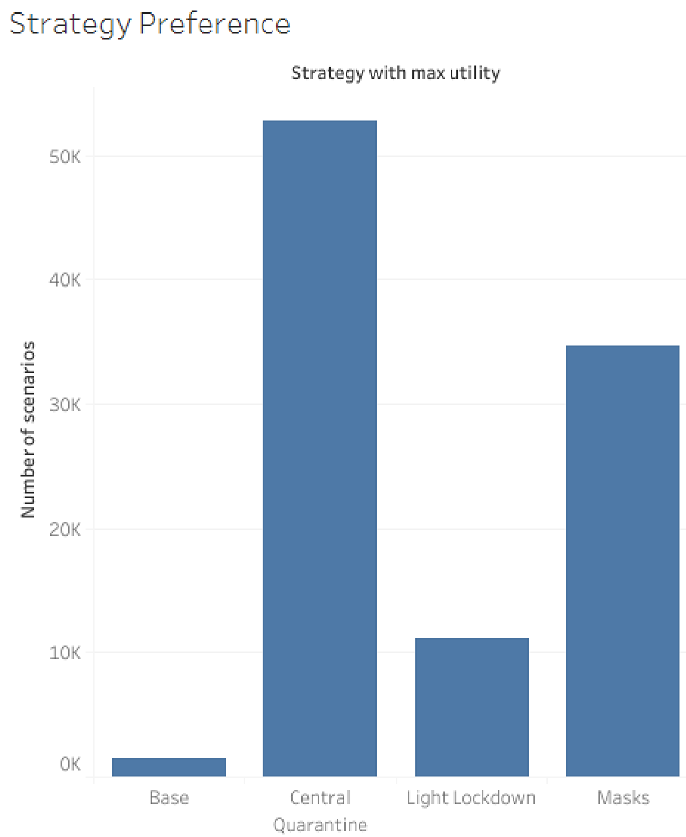
	Max. Regret	Avg. Total Utility	Min. Total Utility
Base	17,167,000,000,000	-3,643,000,000,000	-17,289,000,000,000
Central Qua..	120,000,000,000	-141,000,000,000	-12,940,000,000,000
Heavy Lock..	12,784,000,000,000	-362,000,000,000	-13,933,000,000,000
Light Lockd..	15,313,000,000,000	-1,312,000,000,000	-16,259,000,000,000
Masks	16,169,000,000,000	-1,849,000,000,000	-16,558,000,000,000

Fig. 2.5 *Utility, Regret, and Strategy Preferences for the Maximum Life worldview, maximizing the value of Life-years*

Next are the same graphs with the value per life-year at $200,000, but the value per life lost at $22,000,000.


Utility
Base
Masks
Light Lockdown
Heavy Lockdown
Central Quarantine
-21T -20T -19T -18T -17T -16T -15T -14T -13T -12T -11T -10T -9T -8T -7T -6T -5T -4T -3T -2T -1T 0T
Total utility


Regret
Base
Masks
Light Lockdown
Heavy Lockdown
Central Quarantine
0T 2T 4T 6T 8T 10T 12T 14T 16T 18T 20T
Regret



Utility measures

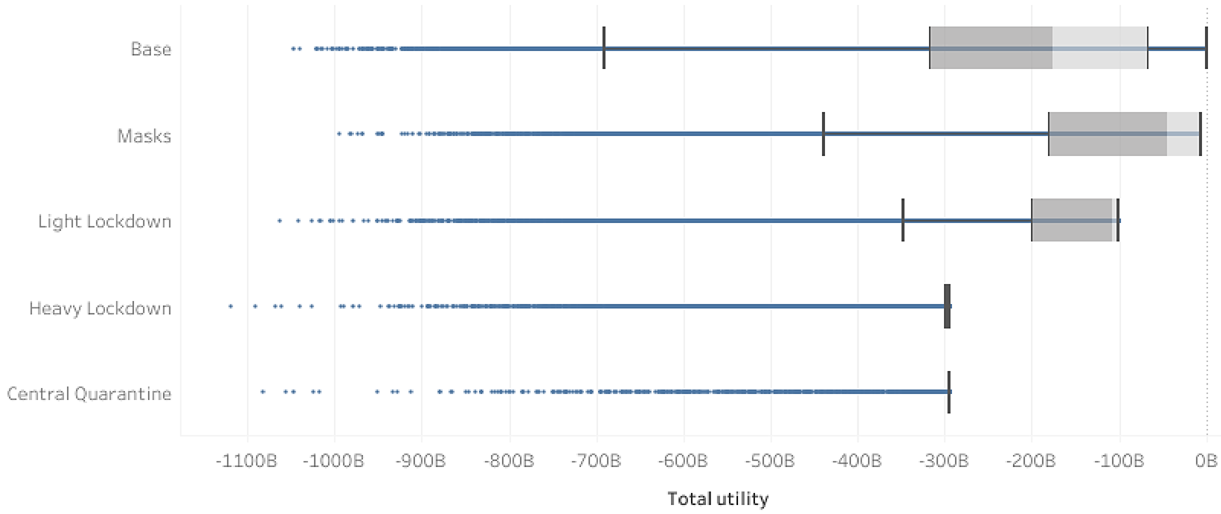
	Max. Regret	Avg. Total Utility	Min. Total Utility
Base	20,608,000,000,000	-4,942,000,000,000	-20,730,000,000,000
Central Qua..	120,000,000,000	-149,000,000,000	-15,488,000,000,000
Heavy Lock..	15,330,000,000,000	-448,000,000,000	-16,684,000,000,000
Light Lockd..	19,116,000,000,000	-1,758,000,000,000	-19,486,000,000,000
Masks	19,869,000,000,000	-2,508,000,000,000	-19,991,000,000,000

Fig. 2.6 *Utility, Regret, and Strategy Preferences for the Maximum Life worldview, maximizing the value of Lives*

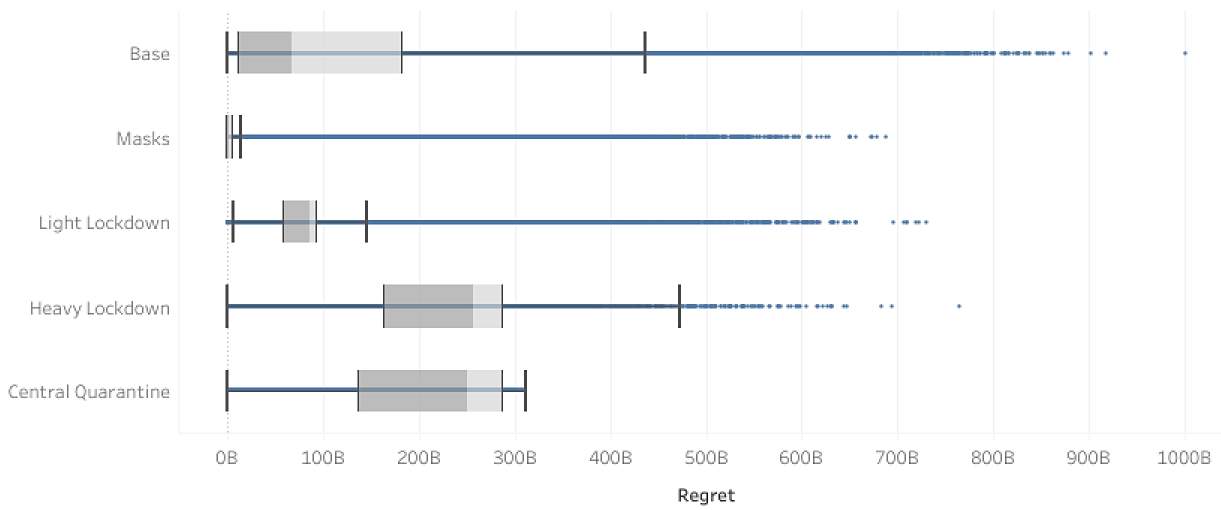
2.6.1.2 Maximum Liberty

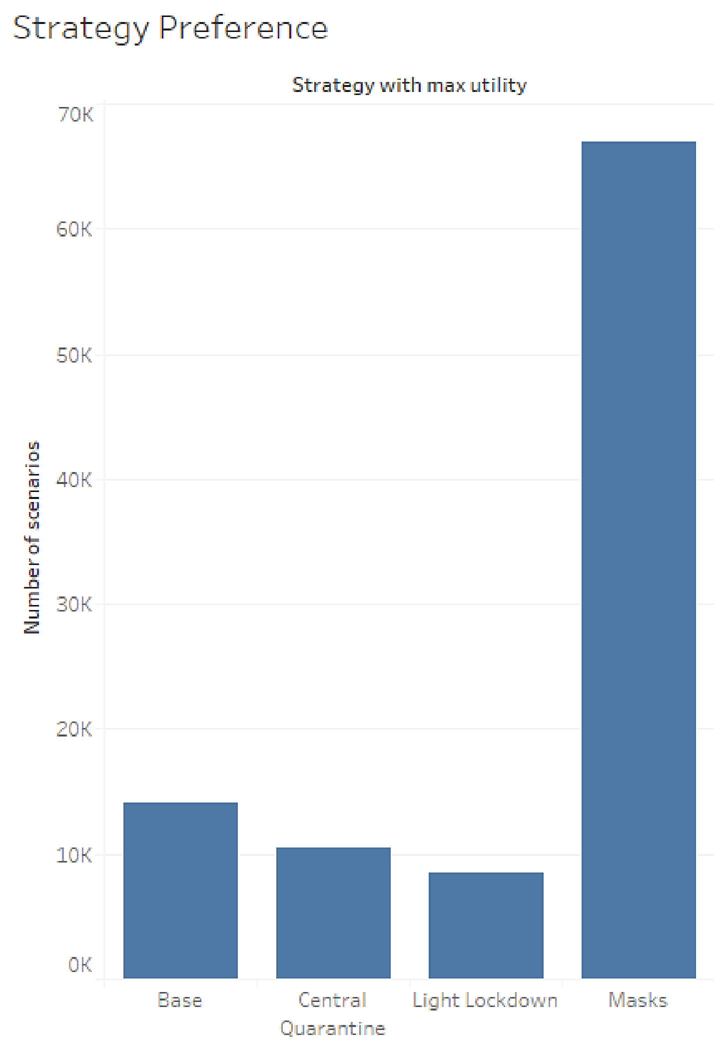
The Maximum Liberty worldview sets the value of each life-year lost at $50,000, the value of each life at $0, and the value of a year of liberty also at $50,000.

Utility



Regret





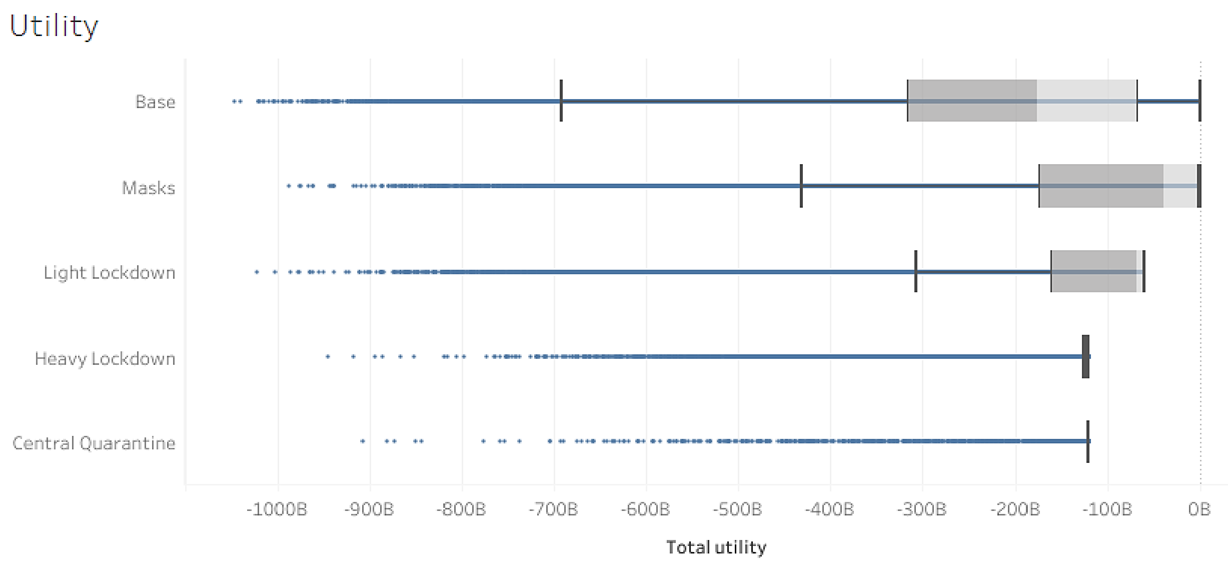
Utility measures

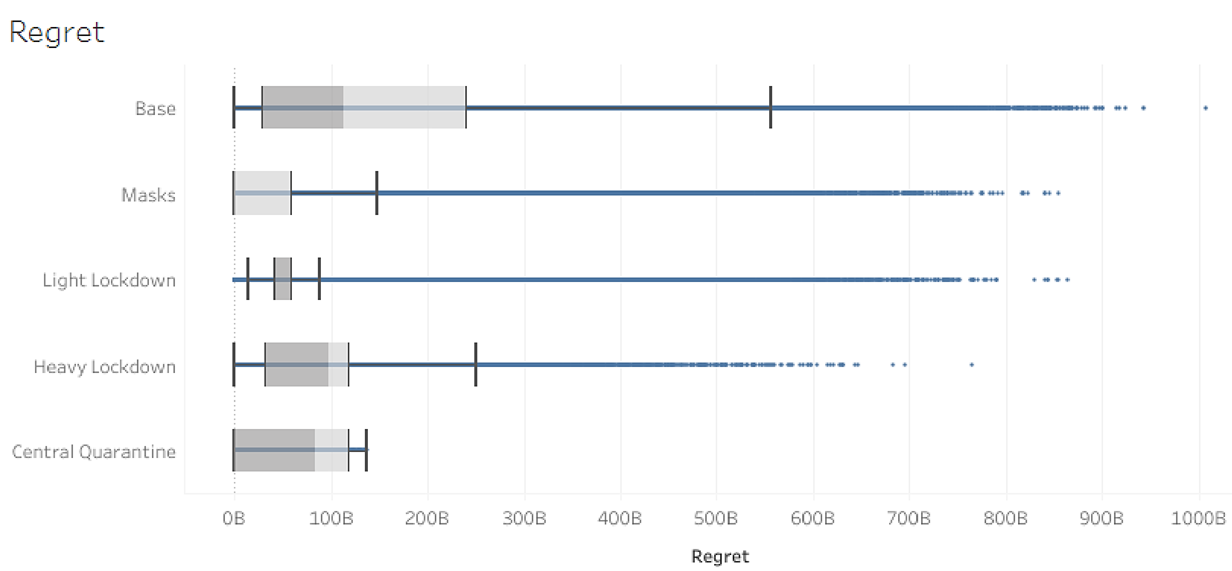
	Max. Regret	Avg. Total Utility	Min. Total Utility
Base	1,001,000,000,000	-211,000,000,000	-1,046,000,000,000
Central Quarantine	311,000,000,000	-296,000,000,000	-1,081,000,000,000
Heavy Lockdown	765,000,000,000	-309,000,000,000	-1,119,000,000,000
Light Lockdown	730,000,000,000	-174,000,000,000	-1,062,000,000,000
Masks	688,000,000,000	-115,000,000,000	-994,000,000,000

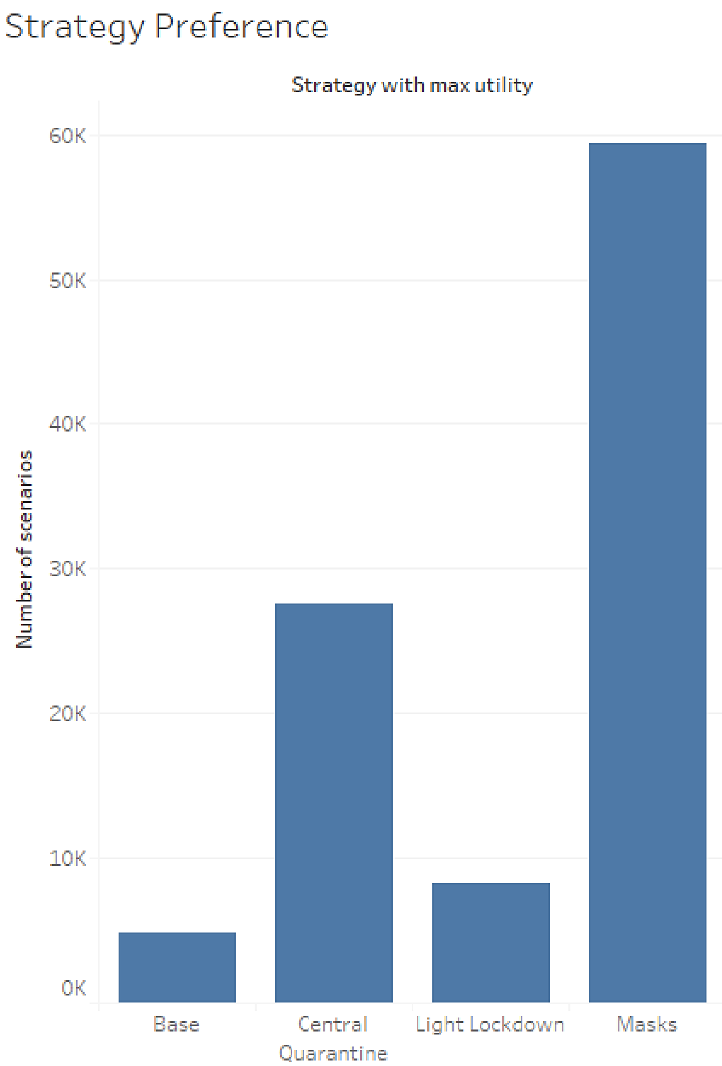
Fig. 2.7 *Utility, Regret, and Strategy Preferences for the Maximum Liberty worldview*

2.6.1.3 Maximum Economy

The Maximum Economy worldview sets the value of life to the minimum value of $50,000 per life-year, $0 per life, and the hedonic value of liberty at $0. Thus, impacts on the economy are the greatest driver.







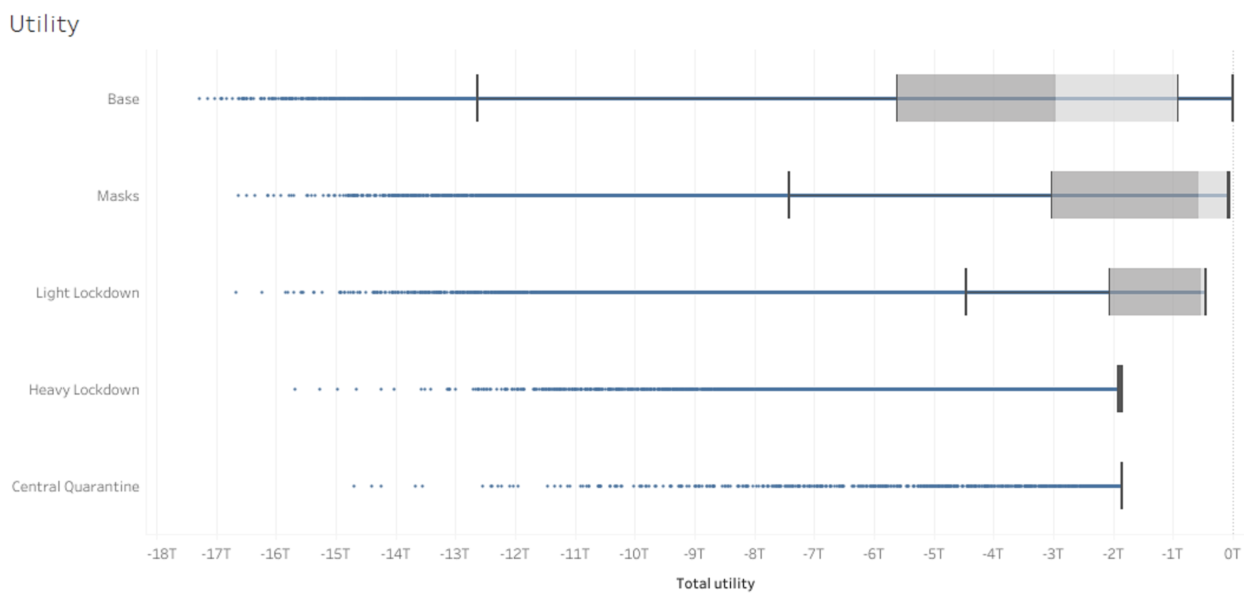
Utility measures

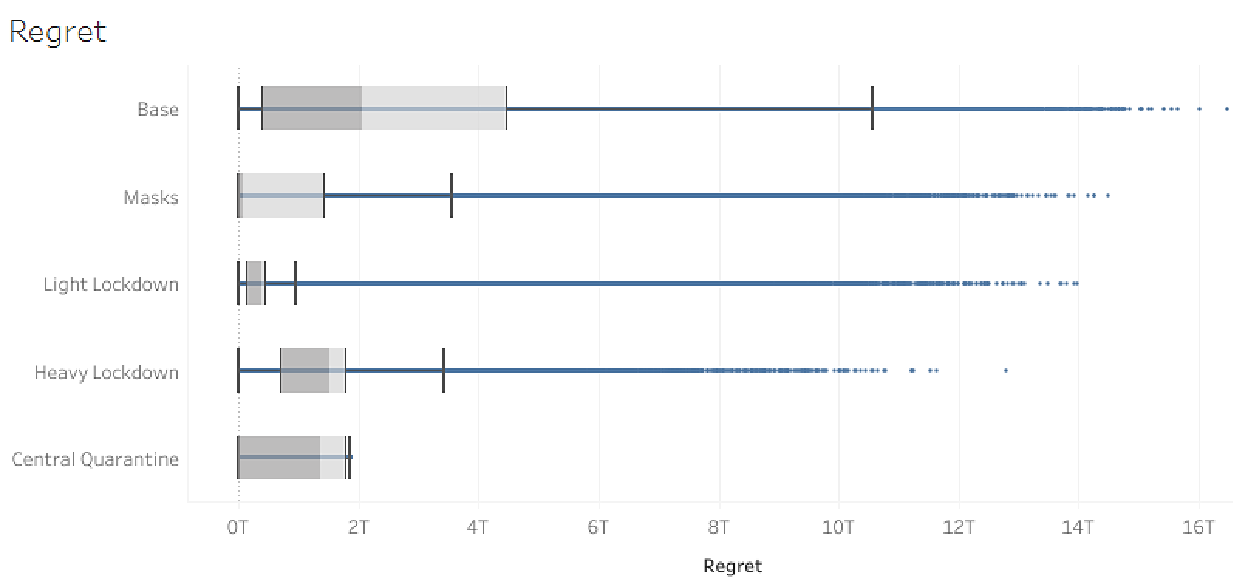
	Max. Regret	Avg. Total Utility	Min. Total Utility
Base	1,008,000,000,000	-211,000,000,000	-1,046,000,000,000
Central Quarantine	137,000,000,000	-122,000,000,000	-907,000,000,000
Heavy Lockdown	765,000,000,000	-135,000,000,000	-945,000,000,000
Light Lockdown	864,000,000,000	-134,000,000,000	-1,022,000,000,000
Masks	856,000,000,000	-108,000,000,000	-987,000,000,000

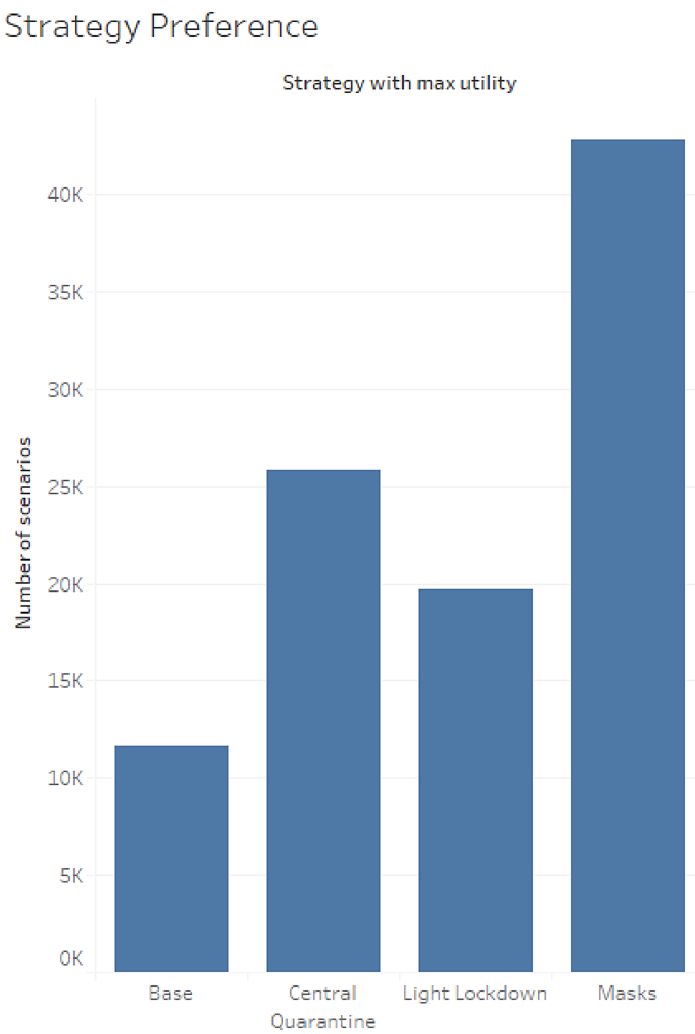
Fig. 2.8 *Utility, Regret, and Strategy Preferences for the Maximum Economy worldview*

2.6.1.4 Minimum Economy

The minimum economy worldview maximizes both Life and Liberty values. First, we look at the results when both the value of each life-year and the hedonic value of liberty are maximized at $500,000, and the value of each life is $10,000,000.







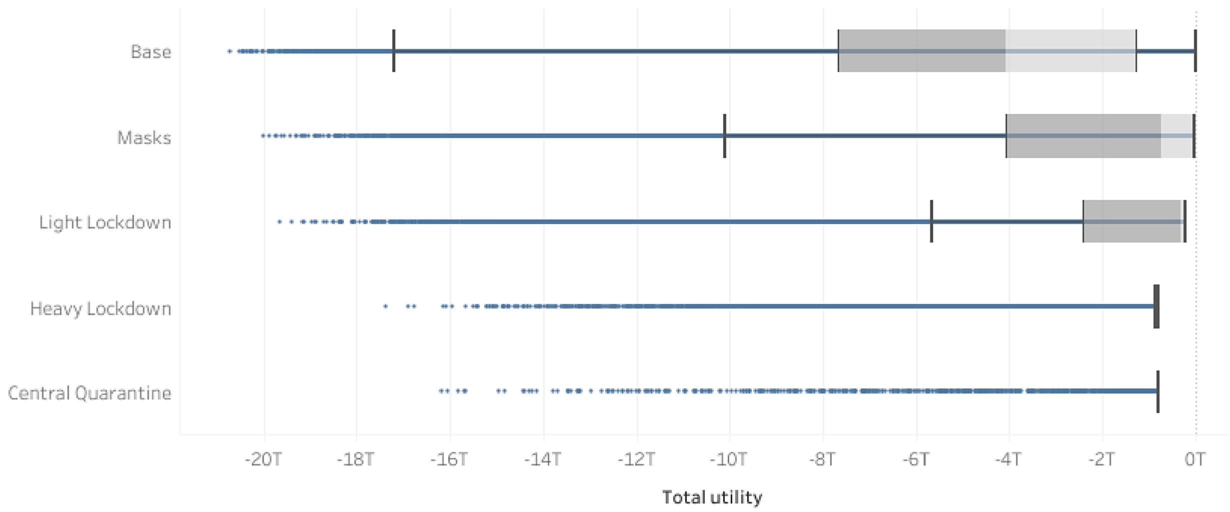
Utility measures

	Max. Regret	Avg. Total Utility	Min. Total Utility
Base	16,490,000,000,000	-3,643,000,000,000	-17,289,000,000,000
Central Quarantine	1,862,000,000,000	-1,883,000,000,000	-14,688,000,000,000
Heavy Lockdown	12,784,000,000,000	-2,104,000,000,000	-15,675,000,000,000
Light Lockdown	13,973,000,000,000	-1,714,000,000,000	-16,661,000,000,000
Masks	14,494,000,000,000	-1,916,000,000,000	-16,625,000,000,000

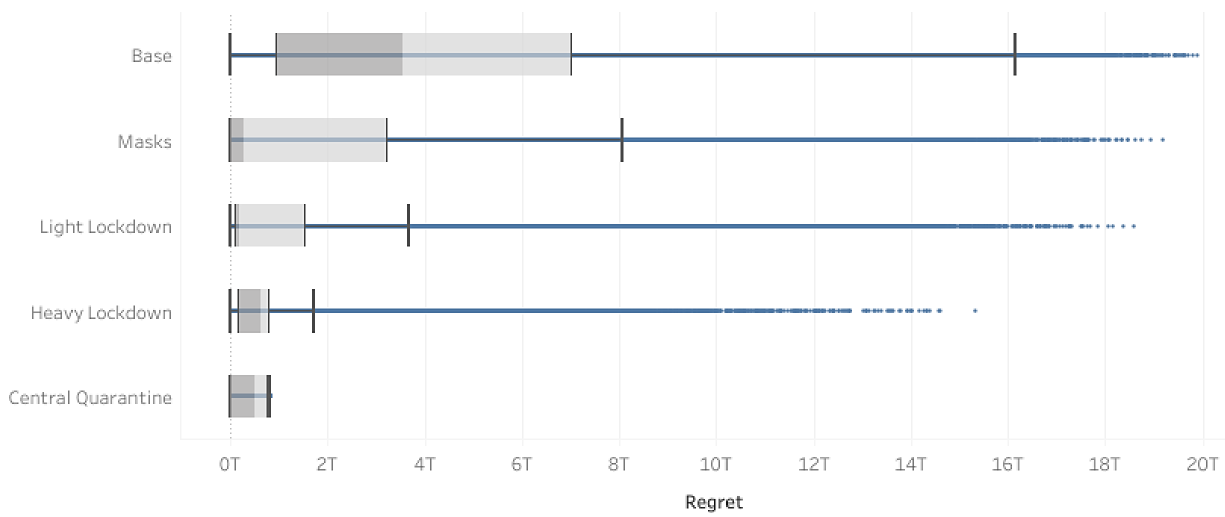
Fig. 2.9 *Utility, Regret, and Strategy Preferences for the Minimum Economy worldview, maximizing the value of Life-years*

Next, we look at the worldview when the value of each life is $22,000,000 and the value of each life-year and the hedonic value of liberty is $200,000.

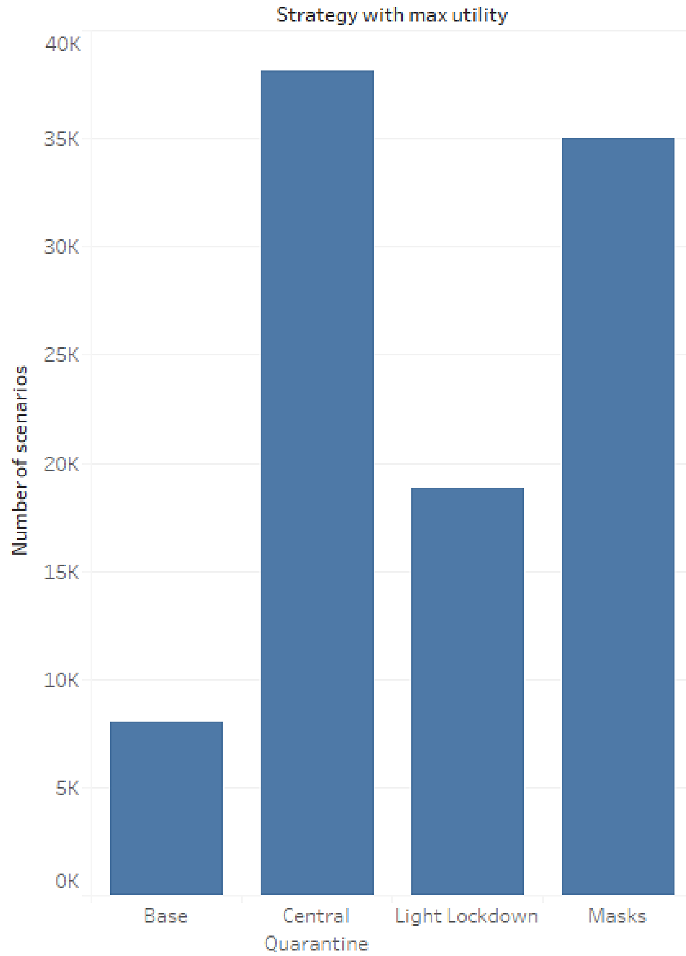
Utility



Regret



Strategy Preference



Utility measures

	Max. Regret	Avg. Total Utility	Min. Total Utility
Base	19,911,000,000,000	-4,942,000,000,000	-20,730,000,000,000
Central Quarantine	817,000,000,000	-846,000,000,000	-16,188,000,000,000
Heavy Lockdown	15,330,000,000,000	-1,145,000,000,000	-17,381,000,000,000
Light Lockdown	18,580,000,000,000	-1,919,000,000,000	-19,647,000,000,000
Masks	19,199,000,000,000	-2,535,000,000,000	-20,018,000,000,000

Fig. 2.10 *Utility, Regret, and Strategy Preferences for the Minimum Economy worldview, maximizing the value of Lives*

2.6.2 Results by Strategy

Next, we take the above information and analyze each strategy. Under what conditions does each strategy make sense for each utility function?

2.6.2.1 Base

The “base” strategy in which the government lets the disease take its course is almost never correct. For this to be correct, we should be very sure that the R0 of COVID-19 is less than 2, and even then, most worldviews would prefer masks in a large percentage of the scenarios. The base strategy has a long tail of bad outcomes that are in the plausible range, even if we limit scenarios to those with an R0 under 2 (see figure 2.11).

Even for the “maximum liberty” worldview, which almost always prefers the base strategy over mandatory mask-wearing, the regret for the mask strategy is never large, while doing nothing is a much riskier strategy, even when R0 is under 1.98 as above.

For the other worldviews, the preference for other strategies is even stronger. Doing nothing is a very risky strategy in this model.

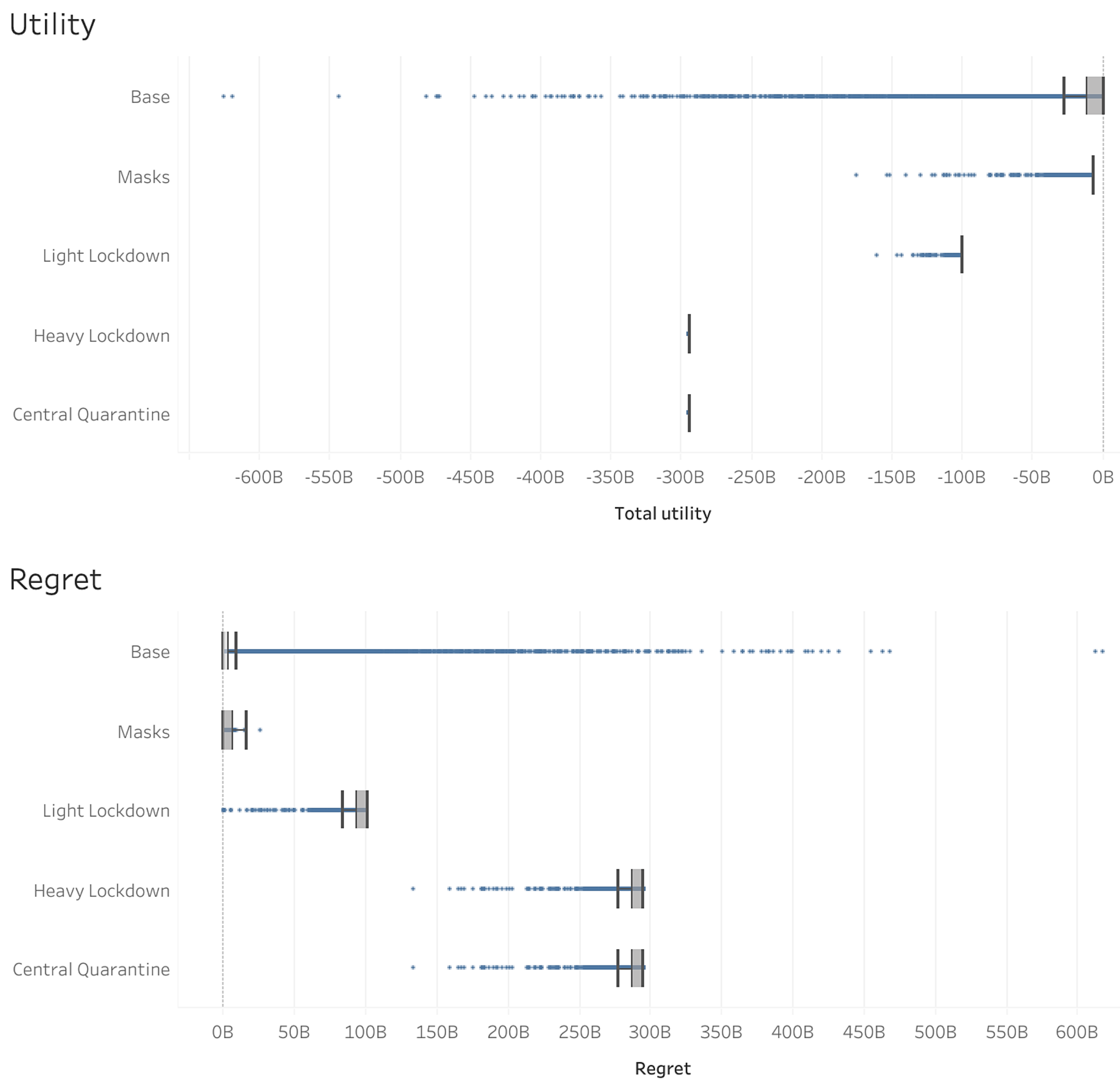
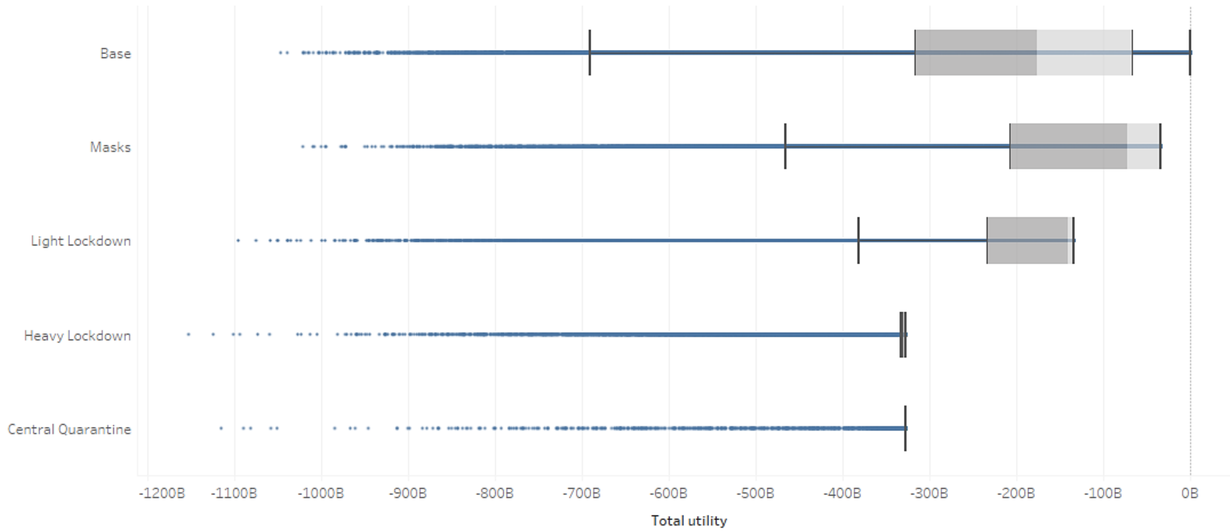


Fig. 2.11 *Utility for maximum liberty worldview with R0 between 1.4 and 1.98*

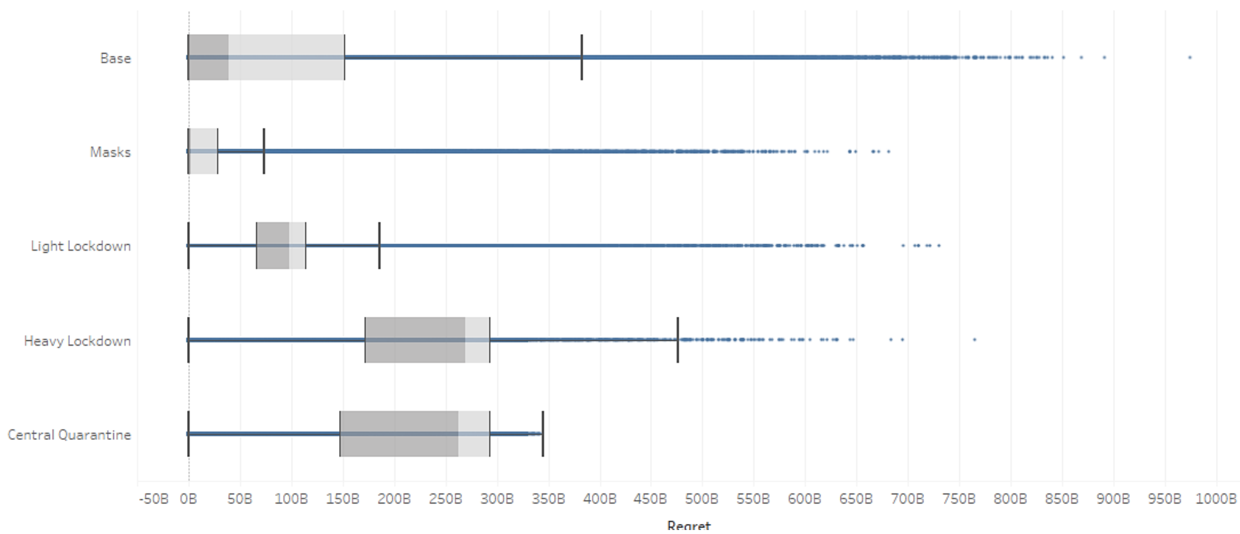
2.6.2.2 Masks

The mask strategy tends to perform well with every worldview. Interestingly, the Maximum Liberty worldview seems to like masks the best, since it represents such a small infringement on liberty while still saving lives. Even if we assume that a mask mandate is a 10% infringement on liberty, the strategy is still generally preferred to doing nothing.

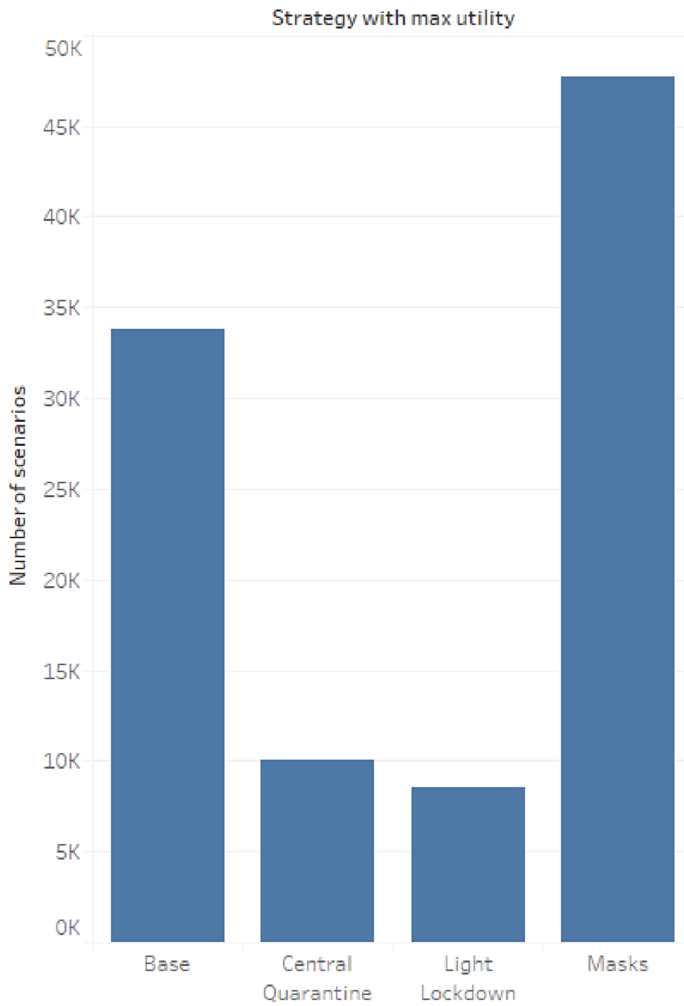
Utility



Regret



Strategy Preference



Utility measures

	Max. Regret	Avg. Total Utility	Min. Total Utility
Base	975,000,000,000	-211,000,000,000	-1,046,000,000,000
Central Quarantine	338,000,000,000	-323,000,000,000	-1,108,000,000,000
Heavy Lockdown	765,000,000,000	-336,000,000,000	-1,146,000,000,000
Light Lockdown	730,000,000,000	-201,000,000,000	-1,089,000,000,000
Masks	688,000,000,000	-142,000,000,000	-1,021,000,000,000

Fig. 2.12 *Utility, Regret, and Strategy Preferences for the Maximum Liberty worldview maximizing the value of Liberty, assuming that a mask mandate is a 10% infringement on liberty.*

2.6.2.3 Light Lockdown

The strategy of having a light lockdown is not generally preferred by any worldview assuming an economic impact of 10% of GDP. In fact, it's not preferred by any worldview with any value for economic impact greater than 0.

The general trend is that if the virus is on the lower end of severity, the Mask strategy is preferred. If the virus is severe enough, the Central Quarantine strategy is preferred. The Light Lockdown strategy is only preferred in a thin slice of the parameter space, where the virus is bad, but not too bad. And exactly where that slice is changed depending on which worldview is looking at it.

2.6.2.4 Heavy Lockdown

The Heavy Lockdown strategy is almost completely dominated by the Central Quarantine strategy. Heavy Lockdown is virtually never the preferred strategy. Even if we make Central Quarantine as unattractive as possible by increasing the cost per patient per day to $2,000 a day, Heavy Lockdown is virtually never preferred.

2.6.2.5 Central Quarantine

The Central Quarantine strategy is particularly interesting, because the maximum regret across all scenarios and worldviews is very low, and it provides low variance in outcomes. The economic and liberty costs of a heavy lockdown plus centrally quarantining patients are largely fixed, regardless of the properties of the virus. So, when the virus is particularly bad, Central Quarantine is seen as the best option across all worldviews, but when the virus is not bad (i.e., when you "guess wrong"), the utility cost associated with the strategy is capped.

This is the opposite case for the Base scenario, in which no countermeasures are taken. If you "guess right" and the virus isn't bad, there isn't a big utility loss, but the potential downside is almost unbounded.

The Maximum Life worldview is particularly happy to use this strategy, while the Maximum Liberty worldview rarely prefers it.

These results are not very sensitive to the Heavy Lockdown economic cost. The Maximum Life worldview still is very often happy with the Central Quarantine strategy even if it ends up having a much larger economic impact than 20% of GDP, while the Maximum Liberty worldview is unhappy with it even if the economic impact is a bit lower than 20%.

2.6.3 Life-years vs Lives

We also included the sensitivity analysis on valuing Life-years more highly than Lives. When maximizing the value of life and minimizing the hedonic value of liberty, the distinction largely didn't matter. The ordering of the strategies didn't change in any way. However, when using the Minimum Economy worldview, in which both life value and the hedonic value of liberty are maximized, there was a difference. When maximizing the value of each life, and limiting the value of each life-year, we're also limiting the maximum hedonic value of liberty. In this case, the value of life dominates, and the preferences look more like the Maximum Life worldview than the Maximum Liberty worldview.

2.7. Discussion

We find that in this model, the Mask strategy seems to have the most support across all worldviews. However, the Mask strategy still has a long tail of bad scenarios in which a mask mandate alone wasn't enough. The Central Quarantine strategy also had a lot of support across most worldviews in many scenarios, and in every case had the lowest maximum regret. This is because the majority of the utility loss comes from the lockdown itself, regardless of the parameters of the disease. The worst-case scenario when implementing the Central Quarantine strategy is far better than the worst-case scenario when using the mask mandate-only strategy. No worldview preferred the Light Lockdown strategy in much of the parameter space. There seemed to be a thin slice of parameter space for which all four worldviews preferred the Light Lockdown strategy, but that particular slice was different for each worldview. On the other hand, no worldview routinely had Light Lockdown as the worst strategy; it was usually on the lower end of the regret measure.

There are some counterintuitive results here. For example, we find that the Liberty Maximizing worldview would often prefer a light lockdown or a mask mandate over doing nothing. This is because there is a minimum value they can assign to lives and life-years. Under many sets of parameters, the life cost of doing nothing is much higher than the liberty cost of masks or a light lockdown, even if they minimize the life cost and maximize the liberty cost. This is an interesting result because there has been a widespread backlash against mask mandates. (McKelvey, 2020) However, many of the people who oppose mask mandates also believe that COVID-19 is not particularly deadly or as infectious, or that mask effectiveness is very low, or even 0. In those cases, if you limit the parameters to where COVID-19 is less dangerous than the seasonal flu and mask effectiveness is very low, the Maximum Liberty worldview prefers the strategy of doing nothing in almost every case.

This also relates to what some are calling the “Paradox of Preparation.” Dr. James Hamblin said: “if shutdowns and social distancing work perfectly and are extremely effective it will seem in retrospect like they were totally unnecessary overreactions.” (Hamblin, 2020). So, some of the professed support for the “do nothing” strategy can be attributed to people seeing the observed rate of spread in the face of countermeasures and mistaking that for the rate of spread in absence of those countermeasures. Additionally, this initial decision is being made at the very beginning of the pandemic when there is deep uncertainty about the parameters of the disease. In the real world, we're only reacting to one realization of the course of the pandemic out of the countless possible futures which could have occurred that needed to be accounted for in the decision-making process.

All of the above is only for the first run of the model. Robust decision-making takes place in a cycle, in which information from one run of the model can help develop new strategies to explore (step 5 of fig. 2.1). This is similar to the Hybrid Strategies approach in Decision Analysis, first described as part of Kusnic & Owen's (1992), "Unifying Vision process."

In this case, we note that the Central Quarantine strategy completely dominated the Heavy Lockdown strategy, in which the only difference was the isolation effectiveness. We might consider whether or not the isolation strategy could also be applied to the mask mandate strategy. Thus, keeping everything open, mandating masks, and centrally quarantining anybody found to be positive. Ideally, this would lead to an outcome that dominates a mask mandate alone across all worldviews.

We might also consider whether or not a "very light lockdown" might be better. If we could identify the "low-hanging fruit" so to speak, that would have very little impact on the economy or liberty but might help with mitigating the virus. Part of the success of the mask mandate strategy was that it had an impact on the spread of the virus with little associated cost. If other countermeasures with a similar impact-to-cost ratio could be identified, they should be incorporated. Or perhaps neither of those ideas will perform as expected, and that information can be used to generate further new scenarios.

Model uncertainty is an important factor in decision-making under deep uncertainty. No single model should be used as the sole basis for a decision. Several different models should be used, with different plausible structures and assumptions. Only a perfect model can perfectly capture all of the uncertainties, and no model is perfect. A model that's a little bit wrong, or missing only one piece, can create a large deviance in the output. Thompson and Smith (2019) call this the "Hawkmoth Effect" (as a foil to the more popular "Butterfly Effect"). Ideally, this decision process would be iterated through multiple times using different models.

An important limitation of this research is that many of the figures provided, e.g., for the value of life, are based on data from the United States. While the overall structure of the RDM model will remain the same, the specific parameters will vary with the decision frame in terms of economy and culture, as well as the biological properties of the pandemic.

Lastly, this model aims to inform high-level policy decision-making. It may aid in political message framing to help build consensus by highlighting potential benefits that are recognized across worldviews. Further analysis might characterize constraints such as political capital and logistical feasibility.

2.8 Conclusion

We have both theoretical and practical contributions to the literature on robust modeling and the Covid-19 pandemic. The robust approach incorporates an SEIR epidemiological model containing variables for policy levers of interest; random simulation is used to generate a range of policy results, and these are evaluated through a linear multi-attribute utility function structured in terms that reflect the discourse about pandemic policy. Simulation model input values are varied to reflect uncertainty, while utility function parameter values are varied to reflect different worldviews. This approach provides a framework to incorporate robustness against worldview differences into quantitative modeling. Rather than relying on the personal worldview of the modeler or the decision-maker, this framework allows the decision-maker to see how robust the results are in the face of differing worldviews. This has applications outside of pandemic modeling. For example, in climate modeling (e.g., Anthoff & Tol 2014), the value of life and the value of a square kilometer of wetlands are used in the analysis, and these values may differ from person to person. This "worldview robustness" could be an interesting extension to a lot of existing research.

Furthermore, our particular formulation of this utility function, incorporating liberty into the life-economy tradeoff, could be useful in other research. Any policy problem which includes a value of life calculation, and a possible impingement of liberty could use this utility function to aid in decision-making.

On the practical side, we define several pandemic management strategies in terms of the degree of masking, lockdown, and quarantine. We evaluate the range of impacts arising from each strategy using each worldview, and then compare the strategies in terms of utility and regret in order not only the practical but also the political implications of different plans.

This can provide some qualitative insight into the opinion dynamics of epidemic responses. For example, we found that a mask mandate was robust against worldview differences, even for those who want to maximize liberty. This is counterintuitive because one would expect people who want to maximize liberty to not want to be forced to wear a mask. However, they may prefer to wear a mask if they were aware of the potential downsides of doing nothing, especially in the early days of the pandemic when the disease characteristics were unknown. Furthermore, as the pandemic evolves, variants of the model here may address different policy questions that arise such as those involving vaccines, as well as adding more subtle attributes of utility that are emerging in public dialogue as, for example, duration of impacts becomes salient. Thus, not only can modeling for robustness against futures and worldviews aid in decision-making but it can also aid in political communication and consensus-building. The findings here provide a template for analyzing future situations fraught with deep uncertainty and conflicting societal objectives.

2.9 Appendix – Tableau dashboard

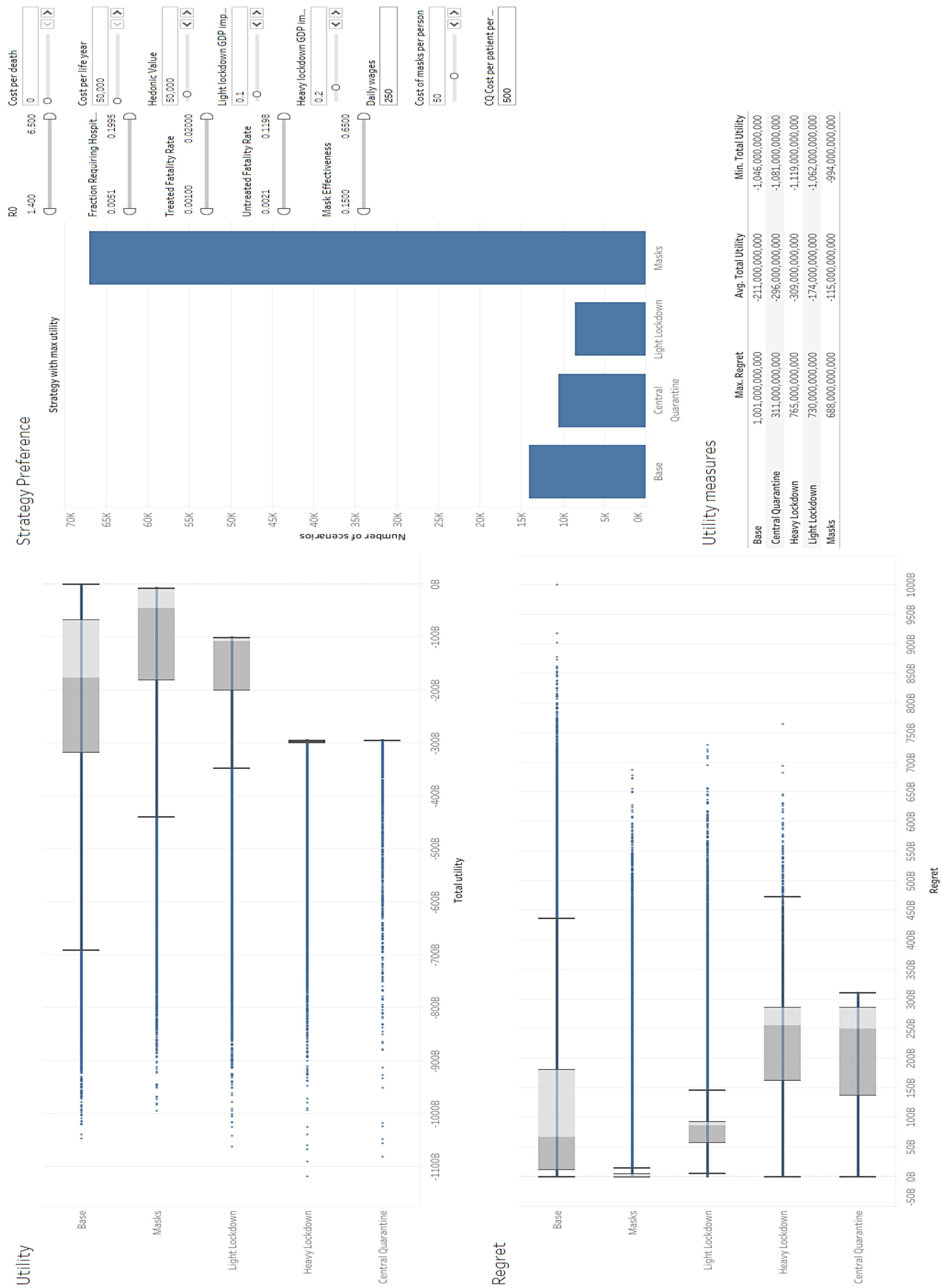


Fig. 2.13 *Screenshot of the decision support dashboard built in Tableau*

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CHAPTER 3

AGENT-BASED SIMULATION OF POLICE FUNDING TRADEOFFS THROUGH THE LENS OF LEGITIMACY AND HARDSHIP

3.1 Introduction

Police funding has become a prominent issue since the summer of 2020 in the wake of the Black Lives Matter protests. Calls to “defund the police” were a hot-button social issue in the 2020 elections in the US (Eaglin 2020). The specific messaging of “defund the police” has fallen out of favor (Otterbein 2021), so we avoid using the term in this paper. Here, we will be examining the tradeoff between police funding and social funding.

Several cities have begun to experiment with reducing police funding in response to the aforementioned protests (McEvoy 2020), but those experiments are too recent to have generated any empirical data. So, for a baseline, we will start with the argument from both sides as well as data from previous research.

Proponents of reducing police spending argue that shifting funding to social programs will not only help people on its own but will also lead to a decrease in crime (e.g. American Civil Liberties Union 2020). There are some empirical studies to support the idea that increasing social welfare spending (for example, cash payments to the poor and preschool subsidies) leads to a decrease in crime (e.g. Savage et al. 2008; Donohue III & Siegelman

1998). Opponents of reducing police spending argue that a reduction in police spending will lead to an increase in crime, and even if social programs decrease crime, it will be more than offset by the increase caused by the reduction in police.

Overall, the literature on the impact of police spending and social spending on crime is mixed. When evaluating the impact of police spending on crime, endogeneity is a problem when using regression-based methods. In particular, there is a simultaneity bias in which changes to police and social funding cause changes in crime, and changes in crime cause changes in police and social funding. To untangle these effects, we use a bottom-up, agent-based modeling approach to investigate the impact of shifting funding between police and social programs.

Lastly, the question of police legitimacy is impacted by police spending and plays a role in crime rates. If police lack legitimacy, they may not get cooperation from the public in investigating crimes (Tyler & Fagan 2008), and members of the community may be more willing to engage in criminal activity themselves (Kane 2005).

In this paper, we want to answer the following:

1) What is the effect on crime when funding is shifted between social programs and police?
2) What is the impact of individual hardship on the optimal allocation of funds been police and social spending?
3) What is the impact of the public’s view of police legitimacy on the optimal allocation of funds between police and social spending?

3.2 Literature Review

The impact of social funding and police funding on crime, as well as the tradeoff between the two, is a tricky question to answer because there are many complex interactions involved and those interactions are different from jurisdiction to jurisdiction.

To help address this, there are three threads of research that we weave together here. The first involves public funding decisions and crime, especially social welfare spending and police spending. Increasing social spending may reduce social causes of crime, while increasing police funding may reduce crime through deterrence and arresting criminals. However, there are costs and tradeoffs involved with both. One such tradeoff is the idea of "police legitimacy" which refers to the public's perception of police and the impacts that perception has on policing, and is the second line of research we follow. The third line of research is agent-based modeling (ABM) in general, and in particular applications of ABM which involve criminology and civil violence. This allows us to bring together the previous two lines of research in a controlled manner.

3.2.1 Public Spending and Crime

There is a connection between social and economic hardship and crime rates. Factors such as unemployment, poverty, and income inequality have a positive relationship with crime rates. (DeFronzo 1983, 1996; Burek 2005). Therefore, it stands to reason that social welfare spending to reduce those hardships should lower crime. However, empirical data is mixed.

DeFronzo (1983) found that public assistance to poor families decreased homicides, rape, and burglary, but not auto thefts or robbery. Savage et al. (2008) looked at social spending and crime across multiple countries and found that there is a small, but nonzero, reduction in crime following an increase in social spending. On the other hand, Burek (2005) found no relationship between the Aid to Families with Dependent Children program and property crime rates between 1980 and 1990. Akpom & Doss (2018) also found there was no correlation between welfare spending and crime.

What we can surmise from the literature is that social spending may reduce crime, but any particular program is not guaranteed to do so. Exactly which social programs reduce which crimes under what conditions is still an open question in criminology literature.

On the other hand, one logical way to reduce crime is to increase police spending. However, empirical studies on this are mixed as well. Akpom & Doss (2018) found that there was a positive relationship between police spending and crime, which the authors say was "not expected." This might be due to the simultaneity issue discussed earlier (i.e. higher crime causing more police funding). Kollias, Mylonidis, & Paleologou (2013) found the same result in Greece, even after controlling for many sources of endogeneity. Di Tella & Schargrodsky (2004) found that when police in Buenos Aires were deployed to a location after a terrorist attack, car thefts on that specific block decreased, but there was no impact on car thefts even one block away.

Conversely, some studies found that an increase in police spending does lead to a small decrease in crime (Kovandzic & Sloan 2002; Atems 2020).

So, it seems that neither police spending nor welfare spending has a clear impact on crime rates. It seems highly dependent on the exact policy and jurisdiction under consideration. We explore this phenomenon further in section 3.3.

3.2.2 Police Legitimacy

The concept of police legitimacy is an important topic in criminological research. Government legitimacy is the public's perception that the government's actions are justified and appropriate (Dahl 2020). A lack of government legitimacy can damage the long-term effectiveness of government policies (Wallner 2008) and is driven by distributional justice and procedural justice (Mazepus & Leeuwen 2020), where distributional justice is related to the fairness of outcomes and procedural justice is related to the fairness of procedures.

Narrowing the issue from government legitimacy in general to police legitimacy in particular, Tyler & Fagan (2008) note that people are more likely to cooperate with police if they have a high view of their legitimacy. Rosenbaum (2006) and Rinehart Kochel (2011) point out that so-called "hot spot" policing, in which police heavily focus their attention on high-crime areas, can negatively impact police legitimacy among disadvantaged populations. Such populations often have a lower view of police legitimacy to begin with, and hot spot policing can reduce that legitimacy even further among some members of those populations. Kane (2005) shows that a reduced view of legitimacy is a predictor of violent crime in disadvantaged communities.

In a review article, Weisburd & Telep (2014) indicate that a lot is still unknown about the relationship between hot spot policing and legitimacy. There are several studies mentioned in that summary article that show that sometimes hot spot policing doesn't lead to a decrease in police legitimacy, or in some cases can even increase it in some communities. A common thread seems to be that people with a high view of police legitimacy are likely to keep that high view of legitimacy even when police are more active in their neighborhood, while people with a low view of police legitimacy may see a further deterioration in police legitimacy when many police are active and don't engage in tactics explicitly designed to increase legitimacy.

Other things can impact police legitimacy. Community policing tactics, in which the police form cooperative relationships with the community members, can increase legitimacy (Hawdon 2003; Peyton 2019). This may be due to an increase in procedural justice, in which the community feels included in policing. On the other hand, increased police militarization can lead to the perception that police are more likely to violate civil rights (Moule Jr. et al 2019) which may reduce legitimacy.

3.2.3 Agent-Based Modeling and Crime

An agent-based model is a type of simulation model that builds a system "from the ground up," modeling the behaviors of individual agents and their interactions with other agents and the environment (Macal & North 2005). From those interactions, we can capture the large-scale behavior of the system.

ABMs have been used in criminological research since the mid-2000s, and are useful when data to test a criminology theory are unavailable or when policymakers need a fast answer (Groff, Johnson, and Thornton 2019). In this case, it's not that the data is unavailable, but rather that the data is inconclusive and contradictory.

Groff et al. (2019) find many challenges to using ABMs in criminology research. Namely, existing models are often not described in enough detail to be reproducible, and the parameters are not calibrated based on real-world data. In section 3.4, we will try to address both of these concerns.

An ABM will also allow us to handle some of the endogeneity issues mentioned earlier. Even though ceteris paribus is a tricky concept in public policy modeling since “everything is moving” (Estrada 2011), an ABM will allow us to isolate one effect at a time since the experiment is entirely under our control, unlike empirical research.

Our model will build upon two existing models: Epstein’s (2002) model of civil violence and an extension of that model by Fonoberova et al. (2012). In the Epstein (2002) model, there are police agents and citizen agents. The agents occupy a grid with one agent per cell. Citizens have a level of “grievance” (G), which represents their propensity to engage in civil violence. Grievance is broken down into two components, “hardship” (H) and “legitimacy” (L) parameters. Hardship represents economic or physical deprivations and is heterogeneous across the agents. Legitimacy refers to how legitimate the citizens perceive the government to be, and is homogeneous across the population. These two parameters are highly idealized and not really measurable in the real world. Both values in the model are normalized to a range between 0 and 1, and $G = H(1-L)$.

As citizen agents experience increased hardship, they are more likely to engage in civil violence. As citizen agents view the government as having less legitimacy, they are also more likely to engage in civil violence. Police agents then go around the grid and arrest any “active” civilians, meaning those engaging in civil violence.

This model is highly idealized and isn’t validated by any empirical data. The main contribution was to show that there can be a cyclical component to civil violence, where violence can occasionally “flare up” across the grid followed by long periods with low violence in between flare-ups.

Fonoberova et al. (2012) took the Epstein model and expanded it slightly to incorporate real-world data. Citizen agents use a “risk function” in both this and the Epstein model to determine whether they will become “active” when police are nearby. In

Fonoberova et al. (2012) the authors test several functional forms of this risk function and compare it to real-world crime data. They also test the relationship between crime, the number of police per 1,000 citizens, and the size of the city using empirical data.

This calibration with real-life data is both a useful refinement of the model and a proof-of-concept for further refinements.

3.3 Theory Development

Epstein's (2002) and Fonoberova et al.'s (2012) models have a major issue if we want to use them to test the idea of reallocating money between police and social programs. Namely, both models are structured such that adding more police will decrease crime. There is no mechanism in either model by which an increase in police can lead to an increase in crime. However, as we've seen in section 3.2, empirical data is mixed on the impact of police spending and social welfare spending on crime rates.

One possible explanation for these mixed results is the opportunity cost of funding. The two previous models vary the number of police ceteris paribus. In the real world, money that goes to policing is not money that goes to social welfare and vice versa. Thus, spending more money on police may either create, exacerbate, or fail to relieve hardship on people who may be more inclined to commit crime as a result. Shifting funding in the other direction, away from police and towards social programs, may mean it's harder to catch criminals, but fewer people may become criminals to begin with due to increased social welfare funding.

Another possible explanation revolves around the concept of legitimacy. Adding more police, especially concentrated in a crime "hot spot", could potentially the people's view of the police's legitimacy, especially if it is seen as unjustly targeting a disadvantaged population. This decrease in legitimacy may reduce cooperation from the public, potentially leading to more crime. This would limit the effectiveness of just flooding an area with police. In both Epstein's and Fonoberova et al.'s models, legitimacy is both homogeneous and constant. This has been studied and neither is the case (Rosenbaum 2006, Tyler & Fagan 2008, Rinehart Kochel 2011). Legitimacy varies from person to person and is dynamic. Capturing this feature makes the model more realistic. Putting the above together, we arrive at the conceptual model in figure 3.1.

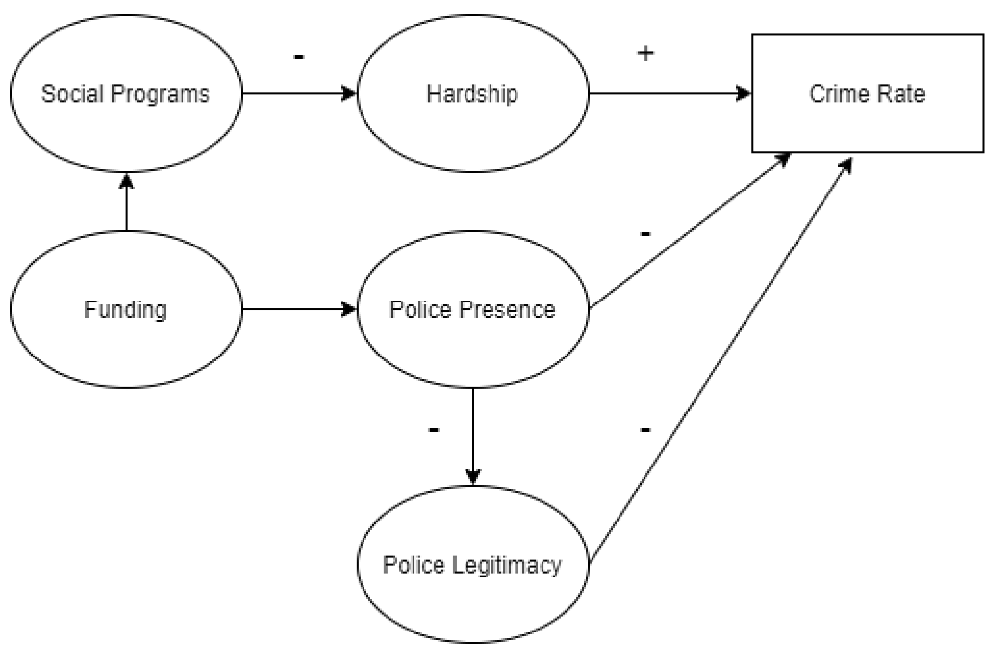

Fig. 3.1: *Conceptual model of the system. Funding can go either to social programs or the police. Increasing police presence can decrease the crime rate, but also decrease police legitimacy, which would lead to a higher crime rate. Meanwhile, social program funding can reduce crime by reducing hardship*

In our conceptual model, we use a term called "hardship," which is also used by Epstein (2002) and Fonoberova et al. (2012) Hardship is not well-defined in either those models or in our model, and it is not calibrated on empirical data. In the real world, hardship will correspond to a nonlinear combination of education, income, mental and physical health, and a host of other terms, including interactions between each of them. In our model, it's just a parameter assigned to the agents, and specifically, it's the proportion of those factors that lead to an increase in crime.

This conceptual model will be operationalized via an ABM similar to Epstein and Fonoberova et al., but in which both hardship and legitimacy are individual parameters rather than global parameters. Sensitivity analysis will provide insights into specific public policies which might be beneficial.

The purpose of this model is not to be prescriptive to any particular jurisdiction or decision-maker; it is far too simple for that. Rather, it is an exploratory model to evaluate the potential impacts on crime of shifting funding between police and social welfare policies as seen through the lens of police legitimacy and the people's hardship. This exploration can help inform public policy discussion at a higher level and more detailed decision models can be built from there to capture the specifics of a jurisdiction.

3.4 System Model

The layout of this section largely follows the ODD protocol (Overview, Design, Details) for describing Agent-Based Models (Grimm 2020). The goal is to aid in reproducibility to address one of the concerns of Groff et al. (2019).

3.4.1 Model Overview

In the model, there are two types of agents placed on a grid: citizens and police. Citizen agents have a "criminal" flag, such that if their "grievance" is above some threshold, the flag is set to "active". Police move around the grid, and if a police agent sees a criminally-active citizen, the police agent “arrests” the citizen, removing it from the model for a random period of time up to the maximum jail term.

Funding will be shifted between police spending and social spending. Shifting funds to the police and away from social spending increases a “hardship” parameter, which is a factor in determining grievance, but also increases the number of police agents in the grid. Shifting funds in the other direction has the opposite effect.

The model will be run many times with different settings for the funding slider, and the average number of active citizens per day for that run will be recorded (this is a metric used in Fonoberova et al. 2012).

The model parameters are calibrated on real-world data to address one of the concerns about agent-based models raised by Groff et al. (2019). The full model is available on COMSeS Net and can be downloaded at https://www.comses.net/codebases/60a21669-865b-4ab6-a59d-93f980f89901/releases/1.0.0/

3.4.2 Model Design and Parameters

The citizen agents’ grievance is taken exactly as in Epstein’s (2002) model, that is:

G = H(1-L), where,

G = Grievance

H = Hardship

L = Legitimacy

Hardship and Legitimacy are each set between 0 and 1 in the baseline model for each agent. Hardship represents the portion of Grievance from derived social welfare spending or lack thereof, while Legitimacy is the portion of Grievance affected by police activity.

Citizen agents are also averse to the risk of being arrested. Each citizen agent has a base risk aversion parameter (K) drawn from a uniform distribution between 0 and 1. A value of 1 indicates that the agent is very risk-averse while a value of 0 indicates that the agent has zero risk aversion. Perceived arrest risk is also impacted by the number of criminals and the number of police in the agent's vision radius (distance in the number of cells on the grid the agent can use in calculations). Seeing more criminals means a lower arrest risk while seeing more police means a higher arrest risk.

The perceived risk function, as seen in both Epstein (2002) and Fonoberova et al. (2012) is given by:

$P = 1\text{-}\exp(-kC/A)$ where:

$k = -9$ (empirically-tuned parameter from Fonoberova et al. rounded to one digit.)

C = Police agents in a citizen's vision radius

A = Criminally active citizens in a citizen's vision radius

The net risk parameter (N) is a combination of the risk aversion constant and the above risk function, such that:

$N = KP$

A citizen becomes criminally active when $G - N > T$, where T is a criminality threshold, drawn for each agent between 0 and 1. T represents an individual's willingness to resort to crime. Someone with a T of 0 will turn to crime as soon as they have any grievance whatsoever if they don't think they'll get caught. Conversely, someone with $T = 1$ will not turn to crime even with maximum hardship and minimum legitimacy. An active citizen ceases to be active when $G - N < T$.

So far, all of these parameters have followed Fonoberova et al. (2012) and Epstein (2002). The main difference is that L is a global parameter in those models and a dynamic individual one here. We introduce a few additional parameters. The full list is shown in table 3.1.

Table 3.1: List of parameters used in the agent-based crime model

Parameter	**Description**	**Value/Range**	**Source**
Hardship (H’)	Baseline hardship. Contributing factor to criminality, affected by social spending	0 to 1	Epstein (2002)
Legitimacy (L’)	Initial legitimacy. Contributing factor to criminality, affected by police presence	0 to 1	Epstein (2002)
Risk aversion (K)	Willingness to become an active criminal when chance of arrest is high	0 to 1	Fonoberova et al. (2012)
Criminality threshold (T)	Threshold to determine when a citizen becomes an “active” criminal	0 to 1	Epstein (2002)
Initial social budget	Initial social budget	$2250 per citizen	Urban Institute (2020), Tax Policy Center (2021)

Fraction citizens	What fraction of the grid is populated by citizen agents	70%	Initial condition similar to Epstein (2002) and Fonoberova et al. (2012)
Fraction police	What fraction of the grid is populated by police officers	Determined by police budget, baseline value is 0.36%	Federal Bureau of Investigation (2019) Full-time law enforcement employees
Legitimacy impact multiplier (X)	Percentage that legitimacy is decreased when police are active in an area	0-20%	Sensitivity analysis test parameter
Hardship multiplier (M)	Percent reduction in Hardship as a function of Social spending	0-100%	Sensitivity analysis test parameter
Cost per officer	Annual cost of a police officer	$150000	See discussion
Police vision	Radius of cells that police agents can see	16	Initial condition

Citizen vision	Radius of cells that citizen agents can see	14, 16, 18	Lower, same, and higher than police vision as in Fonoberova et al. (2012)
Police	Multiplies the initial police budget	0-3	Main test parameter
Maximum Jail Term	Maximum jail term for arrested citizens	30	Epstein (2002)

The initial social budget is set at $2250 per citizen agent. This approximates the value we see in the real world, which is roughly $2264 spent per citizen on average on public welfare expenditures (Urban Institute 2020; Tax Policy Center 2021). In principle, we could also have included education and health expenses in this number, since the social budget is what determines "hardship" in our model, and health and education can impact hardship. However, not every dollar spent on public welfare goes to reducing hardship, nor does every dollar spent on education. We assume these effects roughly cancel out and perform sensitivity analysis on this parameter to see how much of an impact this decision has.

The other budgetary parameter we use is the cost per police officer. This also varies by location, but several sources point to a similar range of values. Chicago's ward 43 alderman put out a detailed breakdown of the annual cost of a police officer (Chicago ward 43, 2015), including equipment and supervision, and came up with a value of $149,362. The Boston Police Department has an annual budget of roughly $400 million (City of Boston

2021) and has roughly 2139 uniformed officers (Federal Bureau of Investigation 2019), leading to an annual cost per officer of around $187,000. Some of these costs will be fixed and some are unrelated to actual policing, so it makes sense that the number is a bit high. Our estimate of $150,000 per officer is in line with what we'd expect in an urban police department. Small deviations from this number didn't substantially change the behavior of the model.

The spending per officer and per citizen need to be multiplied by the number of officers and the number of citizens respectively. We use a grid size of 100 x 100 for 10,000 total cells. 70% are occupied by citizens, for 7000 total. The initial number of police agents is 25, which is 0.36% of the citizen agents. That number lines up closely with the number of police officers per capita in the FBI's Uniform Crime Reporting data (2019). This leads to a baseline budget of $19,500,000, where $15,750,000 is for social welfare and $3,750,000 is for police. The ratio between the two, 4.2, lines up well with real-world data, as seen in Figure 3.2.

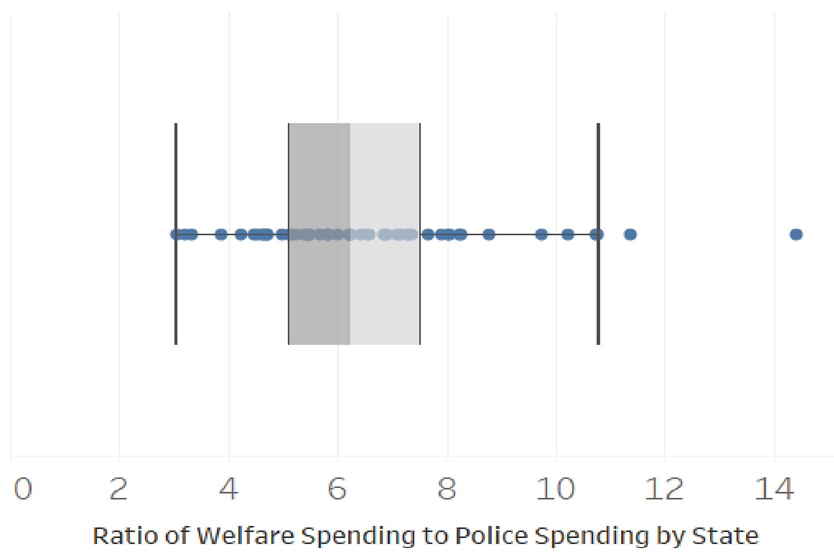

Fig. 3.2: *Ratio of public welfare spending to police spending by US state. Spending data is from Tax Policy Center (2021). The baseline spending ratio in our model is 4.2*

A key part of the model is dynamic legitimacy. When police make an arrest, citizens nearby (determined by their vision) will have their view of legitimacy reduced by the legitimacy impact multiplier. In other words, $L = L' * (1-X)$.

This isn't necessarily realistic. Weisburd & Telep (2014) show in their summary article that in some cases police activity increases the view of police legitimacy of the citizens, especially among those with a high view of legitimacy to begin with and among affluent citizens (low hardship). In our model, those with a high view of legitimacy and low hardship are unlikely to become active even if L decreases by a small percentage. Thus, it doesn't matter whether L increases or decreases for them if they don't become criminally active either way. However, those with a high H, low L, or both (as is often the case in disadvantaged communities), are more likely to become an active criminal when L is lowered further, and this lines up well with previous research (e.g. Kane 2005). We perform sensitivity analysis on X, not only to test the robustness of the model but also as a policy lever. As noted earlier, different police tactics can affect the view of police legitimacy, and this parameter gives us a way to model that.

At the end of each tick of the model, half of the missing legitimacy is recovered, such that:

$L = L + (L'-L)/2$

This means that occasional encounters with police won't have a lasting impact, but repeated interactions (as in hot spot policing) will add up over time.

Police vision is set to 16, which means at each step they look in a 16-cell radius to see whether there are any active criminals to arrest. Citizen vision determines net perceived risk and the legitimacy impact of seeing police arrests. Citizen vision was tested at a little lower than, the same as, and a little higher than police vision. This was previously tested by Fonoberova et al. (2012) and found to be significant with regard to the level of crime. With the addition of dynamic legitimacy tied to citizen vision, we expect this to be an important parameter.

The main funding lever is the police budget multiplier. The police budget is determined by the initial police budget ($3,750,000) multiplied by the police budget multiplier. The number of police agents on the grid is equal to the total police budget divided by the cost per officer, rounded down. Increasing the police budget decreases social funding. As social funding changes, so does hardship. Each agent is assigned a baseline hardship value from 0 to 1, which is then modified by the level of social funding, such that:

$H = H' * \exp(M * (1-(SB/2250)^2))$,

where SB is the social budget per citizen. This is calculated by taking the initial budget of $19,500,000, subtracting the total police budget, and dividing it by 7,000 (the number of citizens). M, the hardship multiplier, is used to test the sensitivity of our model to the assumption that hardship actually changes as the budget changes.

This functional form was chosen so that hardship was bounded as the social budget went to 0. The functional form of $H = H' * (2250/SB)$ was also tested, but that leads to infinite hardship as SB goes to zero.

3.4.3 Model Implementation and Experimental Design

The model was built in NetLogo version 6.2 (Wilensky 1999). We perform global sensitivity analysis (Wagner 1995) using the BehaviorSpace tool within NetLogo. This tool allows us to vary multiple parameters simultaneously. We collect the average number of criminally-active citizens, the average number of jailed citizens, the average hardship, and the average legitimacy of the citizens for each run. A screenshot of the model is shown in figure 3.9 (in the appendix.)

Each run of the model ran for 100 ticks, which is long enough for the averages to come to an equilibrium. The pseudocode is as follows:

- Set police funding and other parameters (e.g. social funding)
- Generate agents on the grid (police and citizen)
- Loop 100 times:
    - For each citizen, If citizen Grievance – Net Perceived Risk > Criminality Threshold, become "active", otherwise inactive
    - For each police agent:
        - Loop 20 times:
            - If an active citizen is within police vision radius, "arrest" the closest active citizen (set jail term to [0, Max Jail Term])
                - Reduce the legitimacy of citizens within citizen vision radius by the legitimacy multiplier
            - Else move randomly within police vision radius
    - For each citizen, recover half of missing legitimacy
    - Recalculate Grievance
    - Increment loop counter

Table 3.2 shows the parameters which were varied for each run. There were 2,196 combinations of parameters tested.

Table 3.2: Parameters varied during global sensitivity analysis in BehaviorSpace

Parameter	**Range**
Police funding multiplier	0-3 in increments of 0.05
Legitimacy Impact multiplier	0, 0.5, 0.1, 0.2
Citizen Vision	14, 16, 18
Hardship Multiplier	0, 0.5, 1

We tested the maximum jail term during early runs of the model and found that it had no impact anywhere from 10 to 50, so we kept it at 30 during the main data collection runs. We also tested whether allowing the citizens to move had an impact and found none.

3.5 Results

The primary output variable we're concerned with is the average number of criminally-active citizens per tick, which is a proxy for the crime rate. This was the method used by Fonoberova et al. (2012) to calibrate their model output with FBI crime data. We also consider the average number of citizens in jail per day as a secondary measure. This is a little trickier to tie to a specific real-world value (like the percent of the population that is incarcerated) because our model does not attempt to accurately depict jail terms. However, it does provide insight into how many different citizens commit crimes. For example, in a scenario in which there is a robust social welfare system but a smaller police force, very few people may want to resort to crime, but the ones that do might be harder to catch. On the other hand, in an authoritarian police state with no social welfare system, many people may resort to crime out of desperation but are caught quickly. These situations may end up giving a similar crime rate (or in the model, active citizens per tick), but the reality would be very different, which is why the secondary measure of “average jailed citizens” is used. Figure 3.3 shows our main results.

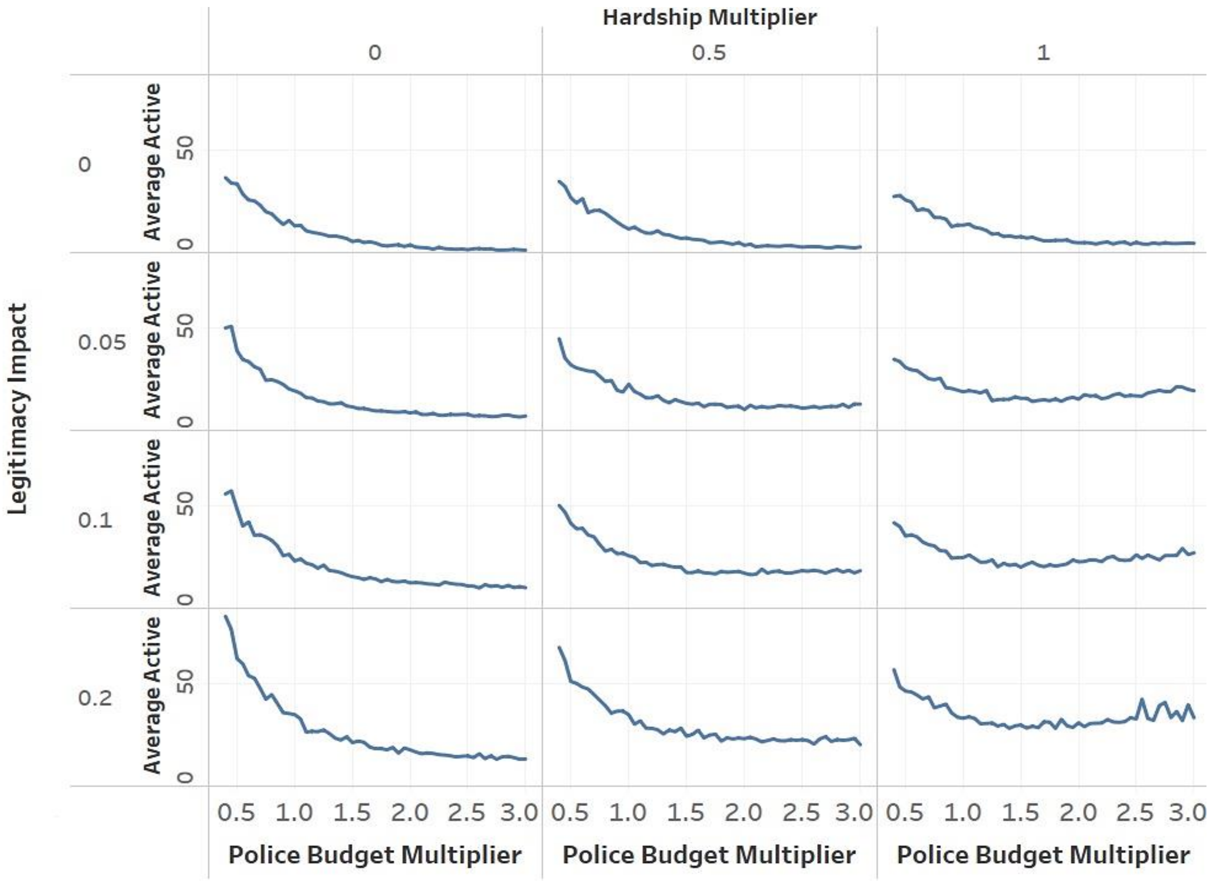

Fig. 3.3: *Average number of criminally-active citizens per run for each combination of hardship multiplier, legitimacy impact multiplier, and police budget multiplier. Citizen vision is set to 16 and the police budget multiplier ranges from 0.4 to 3.0. Values below 0.4 lead to large increases in crime which makes the rest of the results difficult to see.*

There are two ways to interpret this data. The first way, which is most useful for policy-making, is to consider an increase or decrease in funding in one jurisdiction. The second way is to consider differences in funding decisions between jurisdictions. This model was designed with the first interpretation in mind. One benefit of using an ABM is being able to change a policy lever like police funding and keep everything else constant. When comparing different jurisdictions, virtually everything is at least a little different.

We are mainly concerned with the overall shape of the “Average active” curve. Comparing raw numbers across different parameter values isn’t as useful. For example, when the legitimacy impact is 0.2, there is simply more crime across all runs compared to when it is 0. However, the crime reduction when going from a budget multiplier of 0.4 to a multiplier of 3 is larger when the legitimacy impact is higher. The shape of the curves changes dramatically as we move from the upper-left corner of figure 3.3 to the lower right. When either hardship or legitimacy (or both) is 0, the curves closely fit a power-law relationship. However, when both factors are taken into consideration, a power-law relationship is a very poor match. The best power-law fit generates a 0.984 R^2 value for the upper-left graph and only a 0.035 R^2 for the bottom-right graph.

Previous research, such as Fonoberova et al. (2012), had output that looked similar to the upper-left chart of Figure 3.3. As more police were added to the model, crime decreased precipitously. If there were in fact a power-law relationship between police spending and crime, the relation between the two would be much easier to see in empirical studies.

When hardship and legitimacy are taken into account, the curves are much flatter, and therefore the relationship between crime and police spending is much subtler. This flattening mainly occurs when the police budget multiplier is 1.5 or above, which would be a large increase in police funding for a particular jurisdiction. When considering a small change in police funding, say between a 10% decrease and a 10% increase, crime only increases or decreases (respectively) by roughly 3% in the bottom-right graph of figure 3.3.

We used a citizen vision value of 16 for the results in figure 3.3, meaning both citizen agents can "see" 16 cells away in any direction, but all three values tested were almost identical with one exception. While Fonoberova et al. (2012) found that vision played an important role, the effect was much smaller here. In fact, for the vast majority of runs, citizen vision has no impact. This changed when the police budget multiplier was very high, hardship multiplier was set to 1, and the legitimacy impact was set to 0.2. When a citizen's vision is greater than the police's vision where the number of police was very high, crime rates rose. (Fig. 3.4)

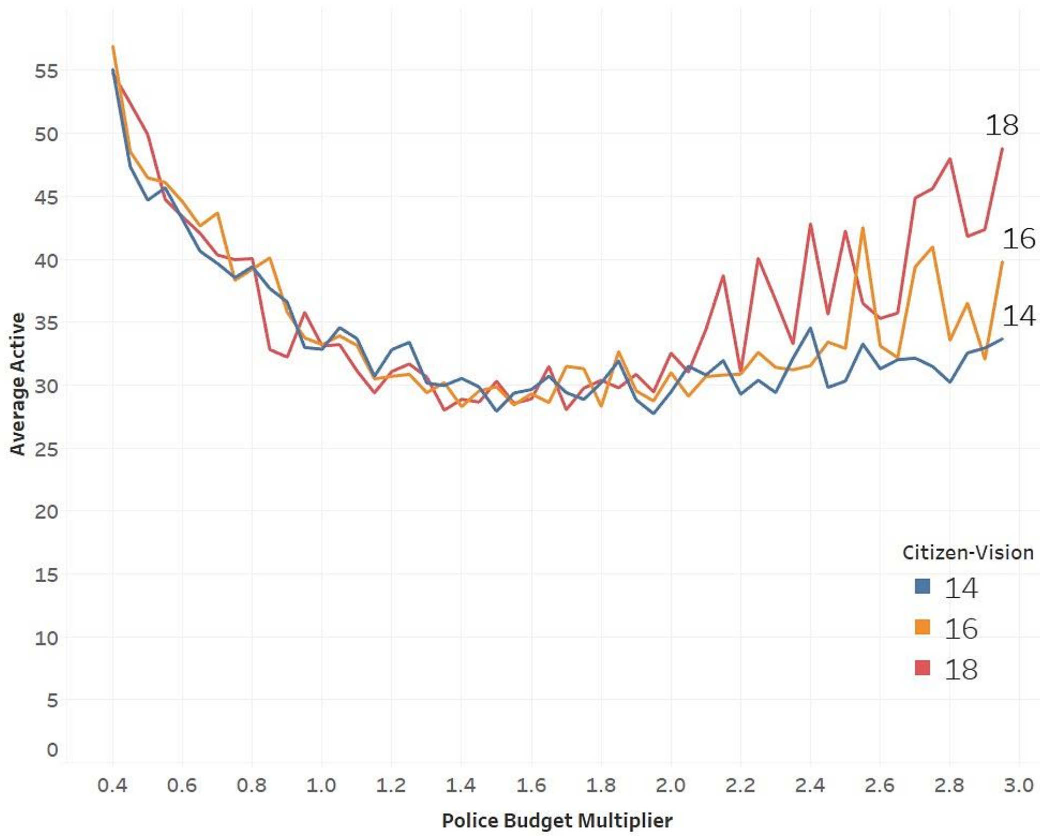

Fig. 3.4: *Police budget multiplier vs average number of active criminals for each of the 3 values of citizen vision. Hardship multiplier is set at 1 and legitimacy impact at 0.2. Police vision was fixed at 16. At very high police budget multipliers, citizen vision becomes important.*

Instead of just looking at the number of criminally-active citizens, we can also consider the number of people in jail as a metric to determine the effectiveness of budget decisions. Figure 3.5 shows the same runs as figure 3.3, but with the average number of jailed citizens during the run as the dependent variable.

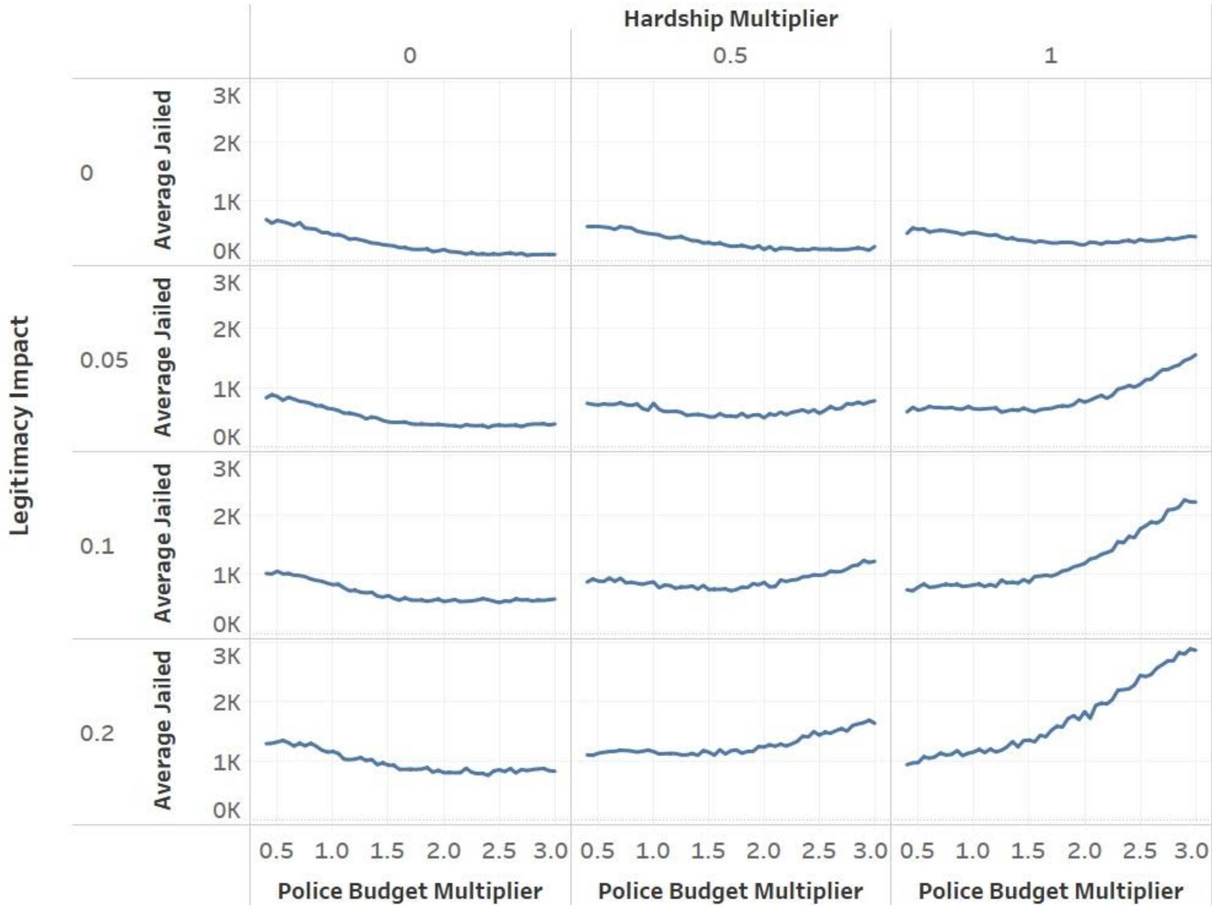

Fig. 3.5: *Average number of jailed citizens per run for each combination of hardship multiplier, legitimacy impact multiplier, and police budget multiplier. Citizen vision set to 16. Police budget multiplier ranges from 0.4 to 3.0 to match the results in figure 3.3.*

The intuition behind the results in figure 3.5 is that the more citizens with a grievance above their criminality threshold, the more people commit crimes. More police officers mean that those active criminals get jailed quickly, and therefore are not active for long, but there are simply a higher number of criminals. When the hardship multiplier and legitimacy impact are 0, there is no increase in grievance, and therefore no increase in criminals as the number of police increases. In fact, the police presence increases the risk of getting arrested, and thus prevents citizens with a high grievance from becoming active in the first place. This does not hold when hardship and legitimacy are taken into account. The suppressive effect of having more police cannot keep up with the increase in grievance. Cutting social programs to add more police is counterproductive by this metric under those circumstances.

3.5.1 Post-hoc Analysis

One interesting check of the reasonableness of our model is to compare it to empirical data. The difficulty with this, however, is that our model was designed to be different realizations of a single hypothetical jurisdiction, keeping everything else constant. There are too many variables, many interacting in nonlinear ways, to easily compare the impact on crime of funding decisions of different jurisdictions.

That said, a difference between our model and empirical data led to questioning one of the assumptions of the model; that the number of police and the impact on legitimacy per interaction with the police were independent.

Figure 3.6 shows our results framed in terms of the ratio between social spending and police spending. Figure 3.7 shows the same ratio for each US state plotted against the violent crime rate in those states.

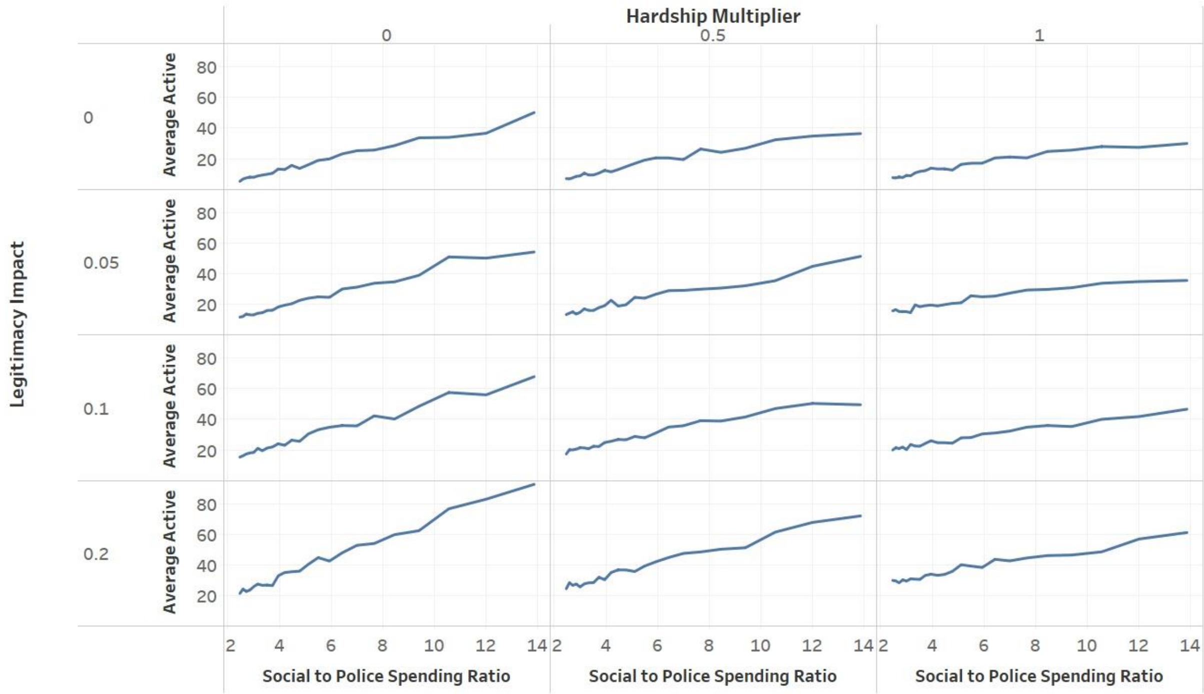

Fig. 3.6: *Average number of criminally-active citizens per run for each combination of hardship multiplier, legitimacy impact multiplier, and police budget multiplier framed as a ratio of social to police spending. Citizen vision set to 16. Police budget multiplier ranges from 0.35 to 1.5 which generates a social-to-police spending ratio ranging from 2.47 to 13.86*

The relationship is nearly linear, so to get a clearer picture of the above results, we performed a linear regression in Tableau, and the results are seen in table 3.3. There is more crime overall when the legitimacy impact is higher, but within each subset of runs in which the legitimacy impact is held constant, a higher hardship multiplier leads to a flatter relationship between the spending ratio and crime.

This does not match empirical results when comparing the same spending ratio to violent crime rates for each US state in 2019, as seen in Figure 3.7. There is simply no relationship between the two without controlling for anything else. This is in line with what Akpom & Doss (2018) found.

Table 3.3: Linear regression results from figure 3.6

Legitimacy Impact	Hardship Multiplier	Linear coefficient	Standard Error	t-value	p-value
0	0	3.61513	0.103748	34.8453	< 0.0001
0	0.5	2.81563	0.11136	25.2841	< 0.0001
0	1	2.17449	0.118099	18.4124	< 0.0001
0.05	0	4.0493	0.120682	33.5535	< 0.0001
0.05	0.5	3.09936	0.120625	25.6942	< 0.0001
0.05	1	2.0549	0.113984	18.028	< 0.0001
0.1	0	4.51401	0.127265	35.4695	< 0.0001
0.1	0.5	3.09998	0.121379	25.5397	< 0.0001
0.1	1	2.30464	0.075429	30.554	< 0.0001
0.2	0	6.34285	0.125712	50.4556	< 0.0001
0.2	0.5	4.23944	0.121164	34.9893	< 0.0001
0.2	1	2.79876	0.103947	26.9249	< 0.0001

As mentioned above, we don't expect our model to closely match empirical data at this level of analysis, since each jurisdiction is a unique complex system, and we were only considering a change in one system with everything else being held constant. When comparing US states, nothing is being held constant. However, this result naturally leads to the question "What would our model need to look like to match the empirical data?"

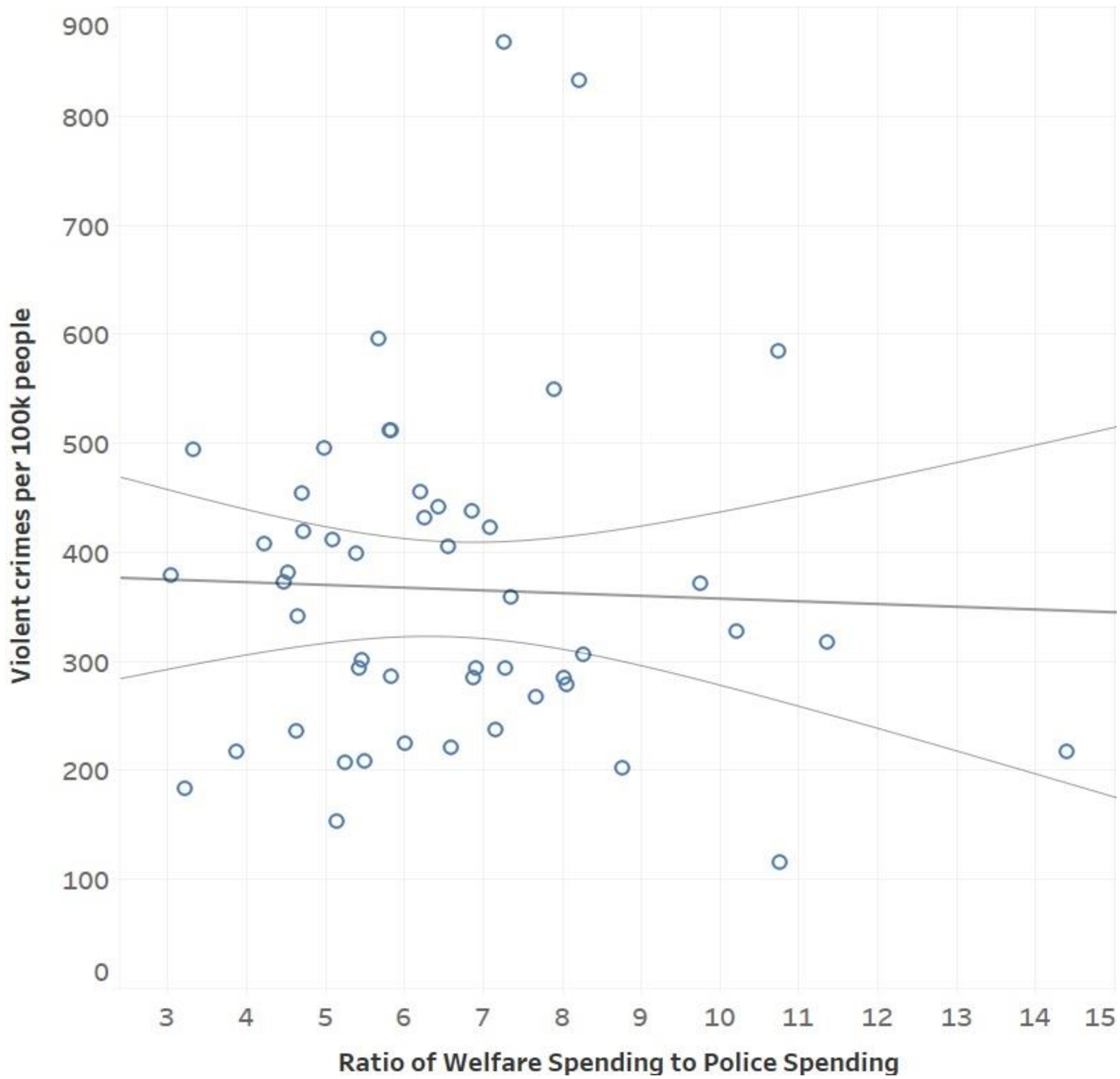

Fig. 3.7: *Violent crimes per 100k people vs ratio of social welfare spending to police spending by US state in 2019. Spending data is from the Tax Policy Center (2021) and crime data is from the FBI's Uniform Crime Report (2019). There isn't any apparent relationship between the spending ratio and violent crime, as shown by the trend line with confidence intervals.*

In our model, we assume that the legitimacy impact of being near a police officer is independent of the number of officers. With many officers, the cumulative impact of interacting with officers leads to a lower legitimacy, but each interaction had the same effect. The intuition behind this assumption is that if more officers are chasing the same or a diminishing number of criminals, the officers may need to bother innocent citizens more often, leading to a larger reduction of legitimacy per interaction. Conversely, if there are few police officers, the interactions they have may be more likely to be seen as legitimate.

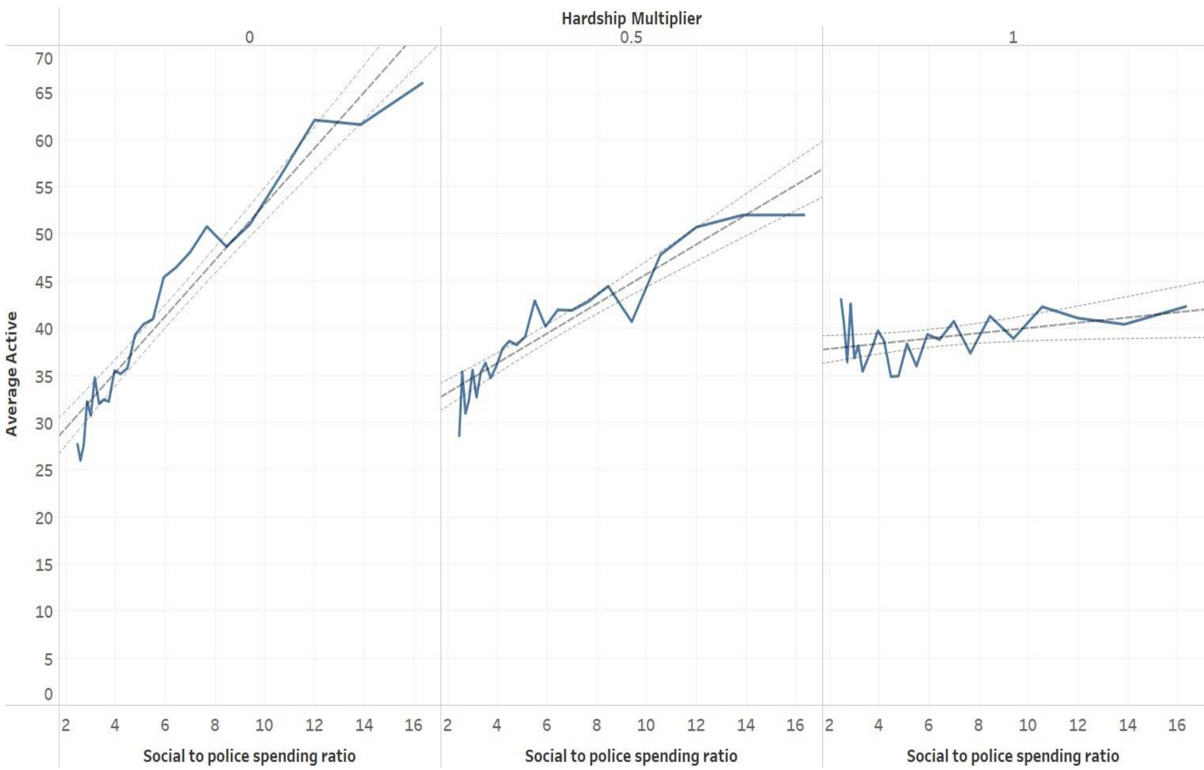

Fig. 3.8: *Social spending to police spending ratio vs criminally-active agents in a model with dynamic legitimacy impact. With a hardship multiplier of 1, there is no relationship between spending decisions and crime rate within the social-to-police spending ratio range of 2.47 to 13.86.*

To model this, we performed another set of 183 runs in which the legitimacy impact was set to the initial police density (which was the number of police divided by the number of squares in the grid expressed as a percentage), citizen vision was kept at 16, and the rest of the parameters were the same. Thus, if 0.16% of the grid were police officers, the legitimacy impact would be 0.16. This leads to the result seen in Figure 3.8. In the case where the hardship multiplier is 1, there is no relationship between the spending ratio and crime in the dynamic legitimacy version of the model.

The decision to reduce police funding to increase social spending is clearer if the jurisdiction in question is better described by this version of the model. This may be the case if there are specific activities by the police that impact legitimacy more than others. Shifting funding from those high legitimacy impact activities to social welfare may be justified.

3.6 Discussion

Our results may provide one reason why different funding decisions don't seem to have a clear impact on crime in the literature. In our model, the crime rate is somewhat insensitive to a large range of funding allocations between police and social spending when hardship and legitimacy are taken into account. Under certain conditions, a dollar spent on either the police or social welfare can reduce crime by roughly the same amount. This was an interesting result. We might expect crime to be high when there are no police or there is almost no social funding, so there should be at least one minimum point between the two extremes. The broad, flat area of funding insensitivity was somewhat unexpected.

In our model, this funding insensitivity is particularly prominent when the hardship and legitimacy multipliers are high, or when the legitimacy multiplier is a dynamic value based on police funding as in the post-hoc model. When only hardship or legitimacy is considered separately, this insensitivity is not present. There is a clear decline in crime when police funding is added when considering only hardship or legitimacy; the interaction between the two seems important. This lines up well with Kane (2005) who noted that legitimacy was a predictor of violent crime among disadvantaged populations. If being disadvantaged is interpreted as a hardship in our model, this is the same interaction between hardship and legitimacy our model demonstrates. This could have implications for real-world policy levers.

The hardship multiplier is related to the efficiency of welfare spending on reducing crime. If real-world social spending is well-targeted to reduce the types of hardship that lead to crime then it correlates to a high hardship multiplier in the model. The legitimacy multiplier is related to public opinion of the police and the willingness of the public to help the police do their jobs. Different police policies and actions may have differing impacts on police legitimacy. In fact, one could imagine a world in which the legitimacy multiplier is negative, meaning interactions with police increase police legitimacy, regardless of starting hardship or legitimacy values.

Combining the above, we conclude that shifting funding away from police activities that have the biggest negative impacts on legitimacy into social funding which has the biggest deterrent on crime could mean either no change in the crime rate or even feasibly a decrease in crime. As each jurisdiction is a unique complex system, as previously described, what might work in one jurisdiction might not work in another.

This naturally leads to the question: “If there is no impact on crime rates, why change funding at all?” The simple answer is that there are more objectives to optimize for in society than the crime rate. Reducing the hardship of its citizens is a reasonable goal for any government. In fact, one interesting question not explored here is to what extent people would actually tolerate an *increase* in crime in exchange for better social programs.

3.7 Conclusion

Revisiting the research questions in the introduction, we find that in our model, what happens to the crime rate when funding is shifted between police and social programs depends on the interaction between legitimacy and hardship. When there is no legitimacy impact of police spending or no hardship impact of social spending, adding more police monotonically reduces crime. However, when both legitimacy and hardship are taken into account, especially when the hardship multiplier is high (meaning the social programs are particularly effective), shifting money away from police to social programs doesn't have much of an impact on crime rates.

This research has important theoretical and practical implications. Theoretically, this research is a further refinement of Epstein's (2002) model of civil violence and extends Fonoberova et al.'s (2012) application of agent-based modeling to criminology. Where Epstein's model had hardship and legitimacy as nebulous concepts, we have grounded the two terms in existing criminology research. Notably, we allowed police legitimacy to be heterogeneous and dynamic, which is more realistic and can be an anchor point for future research.

Additionally, our model can help explain mixed results in empirical criminology research, where neither police spending nor social spending seems to have a clear impact on crime rates. The tradeoff between police and social spending, mediated by the concepts of hardship and legitimacy, can lead to the observed mixed results.

Practically, politicians and administrators can use the insights here as a lens to view their own specific jurisdiction when making budgeting decisions. As they're deciding what to cut and what to expand, the impact on legitimacy and hardship can help guide their process.

For example, if they come across a program or policy that has a large negative impact on police legitimacy, scrutiny may be warranted. This also demonstrates that there may exist a scenario in which increasing the police budget beyond a certain point can actually increase crime, which is a counterintuitive result. And even if it doesn't reach that level, there appear to be diminishing returns to simply adding more police. This exploratory model should not be interpreted as prescriptive advice for any particular public policy; rather it shows a plausible interaction between hardship and police legitimacy. A public policy decision-maker may want to consider these impacts when voting on or implementing new policies or budgets.

3.7.1 Limitations and Future Research

Our model has some limitations, any of which can lead to opportunities for future research. In general, this is a very high-level model that cannot provide specific policy recommendations for any specific jurisdiction. A system would need to be modeled in much more detail to be prescriptive. For example, each interaction with police and each crime is considered the same in our model. Different crimes may be impacted by hardship and legitimacy differently, and police interactions may have a heterogeneous impact on legitimacy. There is also a time delay on many interventions. Improving child care or reducing environmental lead may reduce crimes, but it may involve a large lag between when the expenditure is made and when the results are seen.

Another shortcoming is that no attempt was made to model jail terms in any realistic way. This model could in theory be used to examine the effectiveness of different incarceration policies. When a citizen in our model is released from prison, they're released with the same legitimacy, hardship, risk aversion, and criminality threshold parameters as they went in. In real life, prison might change a person, for good or for ill. This model could be adapted to explore the impacts of prison reform on crime.

One other possibility, as mentioned in section 3.6, is to consider the tradeoff between the objectives of reducing crime and providing for the general welfare of the population. People may have differing political opinions and worldviews about what amount of financial hardship is equivalent to the hardship of being the victim of a crime. For example, is it worse to have $100 stolen from you, or to lose $100 in benefits? A version of this model could be used to explore that tradeoff.

3.8 Appendix: Screenshot of NetLogo setup

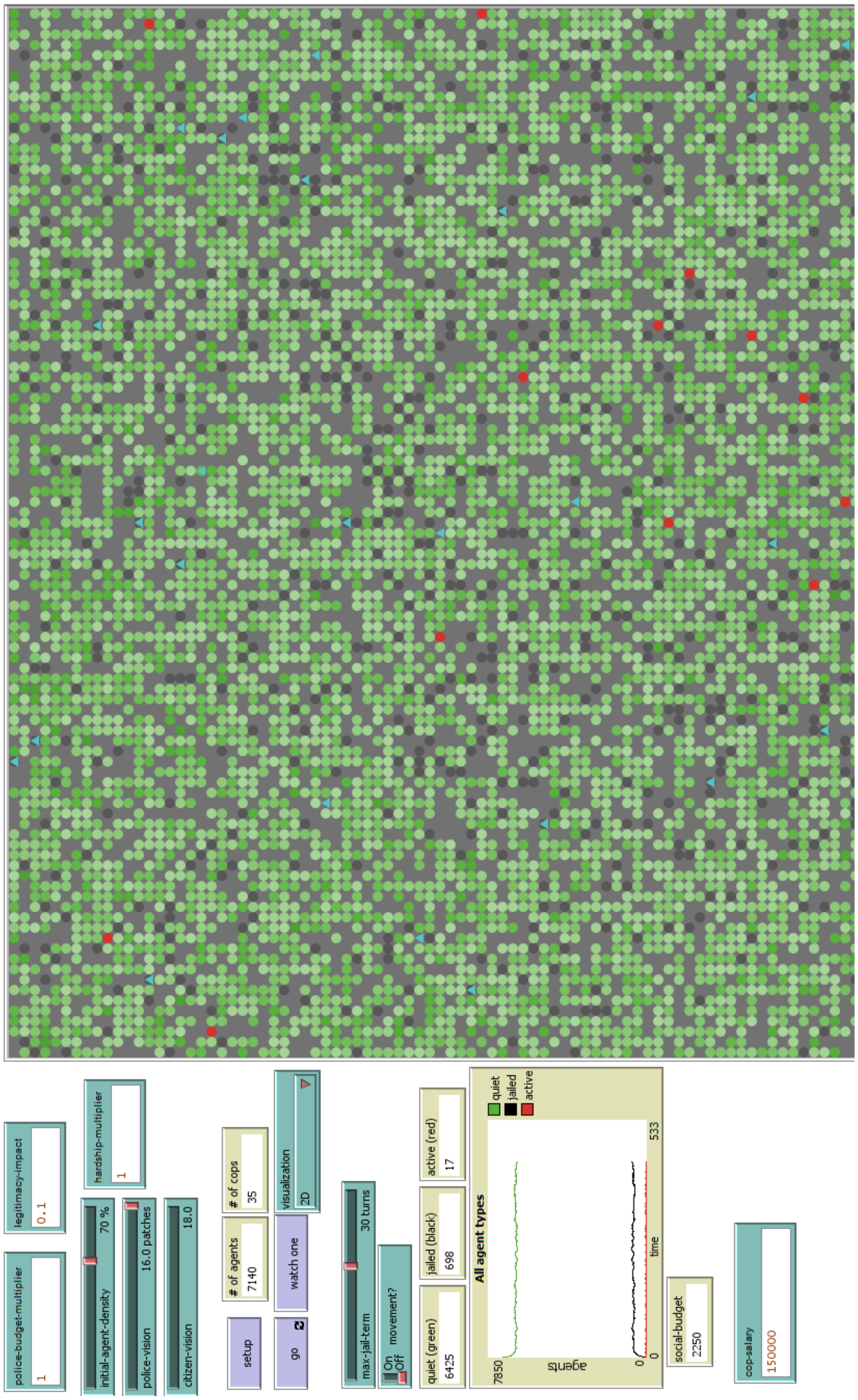

Fig. 3.9: *Screenshot of NetLogo setup after a run. The red dots on the grid are active criminal agents, the green dots are "quiet" citizens, the teal triangles are police agents, and the dark grey dots are jailed citizens.*

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CHAPTER 4

JUST AND ROBUST MULTIPLE CRITERIA DECISION-MAKING IN A PUBLIC POLICY CONTEXT

4.1 Introduction

Decisions involving multiple stakeholders are a challenge for decision-makers (DMs) because of the conflicting needs, desires, and beliefs of the stakeholders. This is particularly true in public policy problems due to the large number of disparate stakeholders involved and the multiple criteria they evaluate outcomes on. This issue is not limited to the public policy sphere, but some of the most salient issues in the world today run into this problem.

In this paper, I encapsulate the above as differences in “worldview,” in which worldview is defined as the set of needs, desires, and beliefs held by an individual or a group of individuals that generates a set of weights on a preference function. It may be as simple as valuing a “success” as a 1 and a “failure” as a 0. Or it may be as complicated as a large multi-attribute utility function. Different worldviews lead to different interpretations of outcomes. Making a decision that satisfies as many different relevant worldviews as equitably as possible is a matter of justice, which I describe in more detail in section 4.2.

Another problem with many public policy issues is that there are large uncertainties in the outcomes of any particular policy. Society is a complex system, and it’s not always clear what the results of pulling a policy lever will be. Just trying to maximize the “expected value” of the outcome is not generally sufficient because in many cases it is difficult or impossible to come up with the probabilities of any given scenario playing out, and any probabilities generated by a model might not be accurate.

Simultaneously dealing with both of those issues is what makes public policy interesting and challenging. In practice, public policy problems are often handled through a process of “mudding through” in which only small, incremental changes to the status quo are considered (Lindblom 1959, 1979). Lindblom argues (ibid.) that the “rationalist-comprehensive” (i.e. traditional multiple criteria decision analysis) view of decision-making is unrealistic in part due to the challenges described above, which is why only those small, incremental changes get considered.

Artificially limiting the decision space to small, incremental changes can lead to missing out on better decision alternatives, making society as a whole worse off. However, a big change brings the risk of a big failure. Not only can the policy fail on quantitative measures, but it can also fail politically.

In this paper, I build a Multiple Criteria Decision Analysis (MCDA) framework, herein called the “Robust and Just Decision Framework” (or RJDF), to simultaneously address issues of justice and equity between stakeholders and of deeply uncertain outcomes. The goal is to provide a method for decision analysts to identify decision alternatives in a public policy context that limits the downside risk of both bad outcomes and bad public sentiment. A robust alternative handles the former, and a just alternative handles the latter.

4.2 Literature Review

To tackle the complex problem of incorporating both justice and robustness in a single decision model, I take an interdisciplinary approach. Here, I consider lines of research in which issues of justice and robustness are considered separately, show connections between the two concepts, and explore existing attempts to handle both.

4.2.1 Multi-attribute preference modeling

A common approach to handling multiple criteria in a decision problem is to combine the preferences along with the strength of preferences in a single function that outputs a cardinal number. In Multi-Attribute Value Theory (MAVT) (Dyer & Sarin 1979) this is called a value function, in Multi-Attribute Utility Theory (MAUT) (Keeney & Raiffa 1976), and in Social Choice Theory this is a cardinal social welfare function, or sometimes a Bergson–Samuelson social welfare function (Bergson 1938, Samuelson 1947).

For the sake of brevity, I will use the term "utility function" to refer to any cardinal multi-attribute preference function and "utility" to refer to the output of the function. There are subtle differences between the different types of such functions, and the reader is referred to Greco, Ehrgott, and Figueira (2016) for an in-depth survey of the various methods leading to the different ways to measure preferences. I choose the term utility function because it may be more recognizable to those outside of the field of decision analysis (for example, anybody who has taken a microeconomics course).

In all of the cases, the utility function is comprised of a set of numerical criteria, each with a "weight" related to the strength of the preference of that criterion or the tradeoffs between the criteria.

The framework developed in section 4.3 is not sensitive to the particular style of utility function used, even if it's a mono-attribute function.

4.2.2 Justice

One challenge in analyzing a decision with more than one stakeholder (especially those with different worldviews) is the issue of justice. Justice has several dimensions. Here, I follow Williams et al. (2022) in focusing on three such dimensions of justice: distributional, recognitional, and procedural. In that paper, the authors developed a framework for agent-based modeling which incorporated those three dimensions of justice, but many of their arguments in favor of incorporating justice hold for any type of model, including decision models.

Distributional justice is what many may think of when they hear "equity" and it involves the equal allocation of resources or equal avoidance of hardship. Rawls sought to achieve this by measuring outcomes on how the worst-off in society are treated (Rawls 1971, 2001), though there are many other measures of equity and normative theories on what constitutes fairness.

Recognitional justice is about recognizing the differences and unique circumstances of a group (Fraser 1995). In theory, wealth in society could be divided evenly, but one in-group could still be seen as superior to some out-group. Recognitional justice is a sort of spiritual equality in which concepts like dignity and respect are considered. In the context of decision modeling, this means incorporating a group's worldview into the model, and not just their material gains.

Procedural justice refers to the ability of different groups to participate in the decision-making process and influence outcomes (Tyler 2000). This reflects the ability of a group to control its own destiny and is one reason democracy is valued.

Justice is particularly important in public policy issues since all three facets of justice have been shown to impact government legitimacy (Bottoms & Tankebe 2012). In turn, it has been shown that government legitimacy impacts policy effectiveness (Wallner 2008). Thus, a more just policy should be a more effective policy, all else being equal. A good decision framework will take into account all three dimensions of justice.

4.2.3 Robustness

Another concern facing DMs is that of robustness, which refers to the ability of a decision to perform reasonably well against many different outcomes. In the same way that a just decision reduces variability between how different groups are treated, a robust decision reduces variability between the uncertain outcomes. In some ways, justice can be interpreted as robustness against differences in how groups are treated.

In a decision-making process, once potential outcomes have been evaluated, there are many decision rules to decide between them. For example, the maximax rule picks the alternative with the highest potential gain, even if it isn't likely. Conversely, the maximin rule selects the alternative with the best worst-case scenario. McPhail et al. (2018) have a list of such decision rules in order of robustness.

Whereas the uncertainty in the outcomes can be considered an "external uncertainty", the robustness of a chosen decision alternative consideration with regard to the "internal uncertainty" of a model (Stewart & Durbach 2016) is also important. Stewart & Durbach (ibid.) go on to say "Less easily resolvable problems may arise when different stakeholders generate different sets of criteria which are not easily reconciled." The authors recommend appropriate sensitivity and robustness analysis in cases where internal uncertainty is not easily resolvable.

4.2.4 Simultaneous handling of uncertainty and justice

The unifying principle between robustness and justice is minimizing variability. A just outcome will minimize variability in how different people and groups are treated (whether it be in the outcomes or the decision process), while a robust outcome minimizes variability between the possible outcomes.

There have been some attempts to handle uncertainty in outcomes and irreconcilable worldviews simultaneously, but each has drawbacks.

When dealing with a group decision where members of the group have different worldviews, one common method is to aggregate the worldviews into some singular group utility function. This can be achieved in many ways, including but not limited to voting, averaging individual utility functions, or just picking one that seems representative. The main drawback here is that it doesn't necessarily take into consideration equity between the worldviews. It may lead to a "tyranny of the majority" in which a majority group dominates a minority group.

Other possible approaches include fuzzy set theory (Zadeh 1973), rough set theory (Pawlak 1985), and grey systems theory (Julong 1989). Detailed descriptions of these three approaches to preference modeling are mathematically complicated and describing them is beyond the scope of this paper, but all three aim to incorporate the uncertainty or incompleteness of preference information provided by stakeholders. The main drawback is that they are so mathematically complicated that it can be difficult for a DM to understand.

According to Belton & Stewart (2002), “the most useful approaches [to MCDA] are conceptually simple and transparent.”

Bose, Davey, and Olson (1997) note that some group decisions are made without aggregating a group preference. In these cases, the preferences of the stakeholders were listed out and used as a discussion tool among the participants in the decision-making process. The model developed in section 4.3 does not aggregate a group preference, but it is not as ad hoc as the cases that Bose et al. describe.

4.3 Theory Development

A successful decision framework will need to simultaneously address the complexity of handling the “internal uncertainty” of differing worldviews and the “external uncertainty” of outcomes while still being comprehensible to the DM. It should also be a repeatable process, rather than ad hoc.

Here, I propose a practical framework to address those issues. The key point is *to evaluate each outcome by the least-happy worldview*. This is conceptually simple and transparent (as recommended by Belton & Stewart [2002] for an approach to be useful), however, it requires some justification. There are two ways to interpret this approach:

Interpersonal utility comparison: The most natural interpretation, that the worldviews represent different stakeholders, requires being able to compare interpersonal utilities, which is a controversial topic (Harsanyi 1990). I argue that interpersonal utility comparisons are justified in some circumstances. In a case with only two stakeholders, one may have stronger feelings about a decision either way than the other. On a scale from 0 to 1, one stakeholder’s “1” may be bigger than the other’s. However, when dealing with large groups, who roughly share a worldview, these effects should cancel out presuming each side has a similar distribution of people who care strongly about the issue. If the situation is such that one group doesn't have strong feelings about a topic either way, this should be taken into consideration when developing the utility functions. Appropriate framing of the decision and elicitation of values helps to validate this interpretation.

Sensitivity analysis: Considered another way, however, this method is a form of sensitivity analysis integrated directly into the model. Belton & Stewart (2002) note that sensitivity analysis on the weights of a utility function is a way to get a "group perspective" on a problem. Generally, when sensitivity analysis on a decision problem is performed, it's done *ex ante*, that is, at the beginning of the decision problem before the uncertainty has been resolved. This is important for maximizing the expected value of the results. Sometimes, a "good decision" (i.e. one that maximizes expected utility) will lead to bad results due to luck. However, those affected do not experience those unrealized positive potential futures; they only experience the one outcome that occurred, and that's how the decision will be judged.

By applying sensitivity analysis on the DM's utility function to the state of the world *ex post*, that is to say, after uncertainty has been resolved, the DM can use the model to minimize bad outcomes rather than trying to maximize the expected value of outcomes. Focusing on sensitivity analysis of the DM's assumptions also somewhat sidesteps the controversial issue of interpersonal comparison of utilities since the DM could have used any of the weights on the utility functions. That those weights roughly correspond to the weights different DMs from different stakeholder groups would have used is somewhat beside the point.

In the case in which there is no uncertainty in the outcome, this approach reduces to Rawls' maximin principle (Rawls 1971, 1974). One simply evaluates the only outcome by the worst-off stakeholder. In the case in which there are no worldview differences, this framework reduces to a standard MCDA under uncertainty problem, in which any decision rule can be used, including the maximin decision rule. This ties together the Rawlsian and MCDA maximin principles in the same framework. The seven steps to the RJDF are shown in figure 4.1 and are as follows:

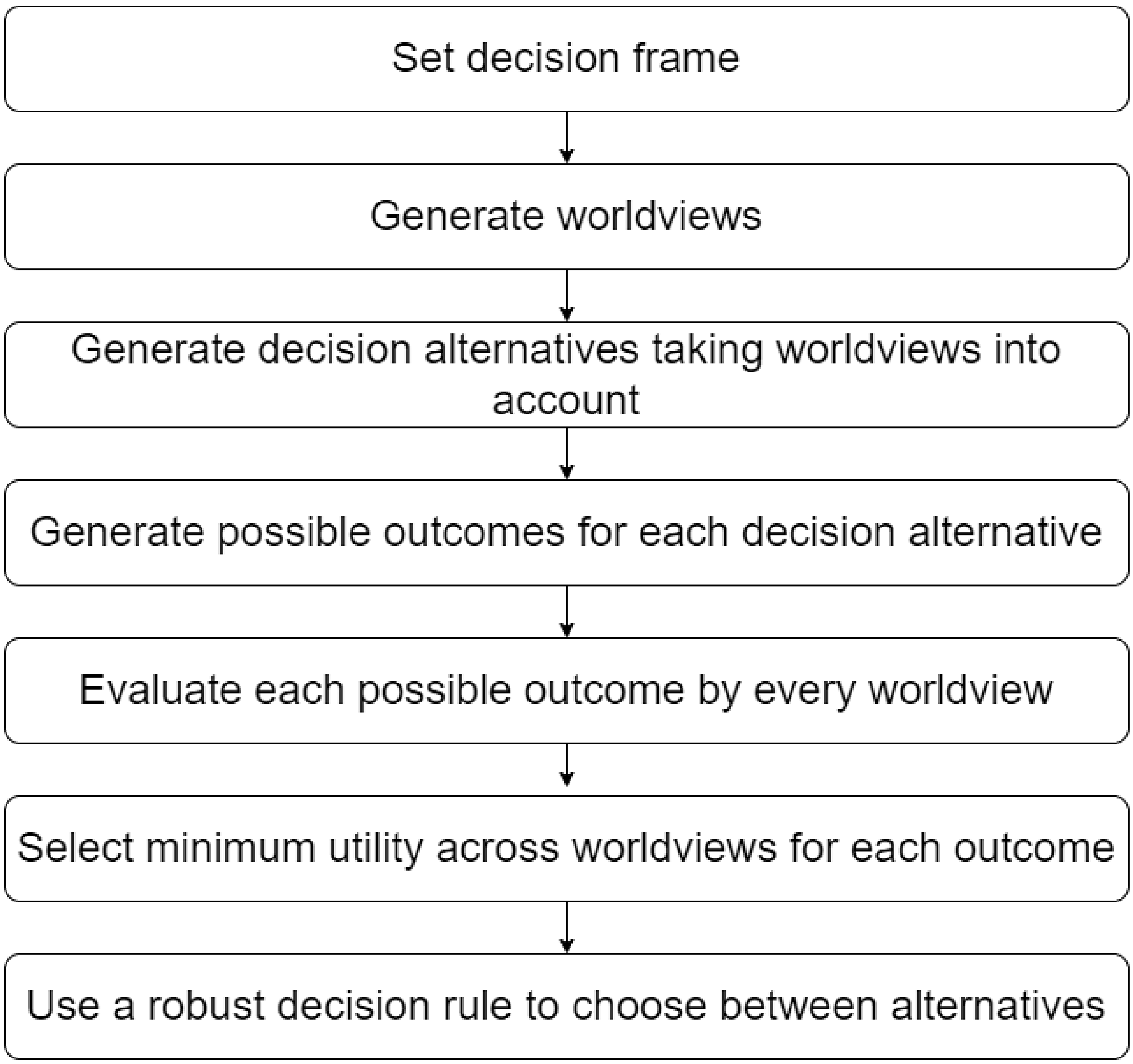

Fig. 4.1: *Steps of the RJDF, outlining the decision process when worldviews are uncertain or highly contested and outcomes are uncertain*

Step 1: Set decision frame: This is the first step in any decision problem. It is important to determine exactly what problem is being solved and what problem is not being solved and whether or not this is a one-off decision or a recurring one. This step also helps determine the relevant stakeholders in conjunction with step 2.

Step 2: Generate worldviews: Elicit utility functions from all relevant stakeholders. It may not be practical to get a separate utility function for each stakeholder, but one can at least capture broad archetypes of utility functions representing various groups. This is a way to incorporate procedural and recognitional justice into the decision model.

The decision analyst needs to use some discretion when generating worldviews; not every worldview needs to be recognized. For example, a sadist might place a positive value on the suffering of others. The analyst should not feel compelled to include such worldviews in the analysis. Similarly, a worldview that isn't materially impacted by a decision need not be included. On the other hand, the analyst should take care to include all relevant worldviews, especially from traditionally marginalized groups whose values might otherwise be missed.

Step 3: Generate decision alternatives taking worldviews into account: This step recommends a value-focused thinking approach (Keeney 1996) in which underlying values (determined during worldview development) can help generate decision alternatives that maximize those underlying values. It is useful to engage the stakeholders directly to help generate these decision alternatives. This is a central focus of community-based operations research (Johnson & Simolwitz 2007), and it can lead to decision alternatives that would otherwise have been missed. Taking this approach is a form of procedural justice.

Step 4: Generate possible outcomes for each decision alternative: This is a common step in decision analysis. There are many methods to generate possible outcomes, including expert elicitation, simulation modeling, and using empirical data. To make the model more robust against unexpected outcomes, the analyst should try to identify a comprehensive set of plausible outcomes rather than just the most likely ones.

Step 5: Evaluate each outcome by every worldview: This step, as well as the next one, is a departure from traditional decision analysis. Rather than picking a utility function to evaluate the outcomes (which can be difficult and controversial), the analyst can use all of the utility functions identified in step 1 and evaluate each outcome by each utility function.

Step 6: Select minimum utility across all worldviews for each outcome: The previous step makes the decision problem more complicated than a standard MCDA problem. To make the problem more tractable, the utility function providing the lowest utility for each outcome is used. Each outcome may use a different utility function.

Step 7: Use a robust decision rule to choose between alternatives: The specifics of this final step depend on the details of the problem being solved and the risk aversion of the DMs. There are myriad decision rules at varying levels of robustness (McPhail et al. 2018). If regret is to be used as a decision rule, then regret should be calculated in place of utility in the previous step. These last two steps enhance the distributional justice of the decision model by avoiding very unjust decisions. Any outcome in which the average group is very happy but one group is very unhappy will show up in the analysis as having a very poor outcome.

Following the RJDF leads to a situation in which no matter the outcome, the DM took the views of those impacted most by the decision into account. It may lead to situations in which nobody is particularly happy with an outcome, as long as no one is extremely unhappy with it. However, for situations in which justice is a concern, or perhaps if political unrest is a possibility, the values of the least-happy group may be the most important.

4.4 Application

To demonstrate the effects of applying the minimum utility across all worldviews on a decision problem under uncertainty, I will provide two examples. The first is a very simple example taken from Ben-Porath, Gilboa, & Schmiedler (1997). The second is from Mitcham & Keisler (2022) which explored the complexities of decision-making during the early stages of the COVID-19 pandemic when uncertainties were extremely high and there were multiple conflicting views about how to value lives, liberty, and the economy.

4.4.1 Simple example

To begin, consider the following simple example outlined by Ben-Porath, Gilboa, and Schmeidler (1997) in which there are two stakeholders and three decision alternatives, each with two possible outcomes with an equal chance to occur. The stakeholders each have a utility function such that an outcome that favors them is valued at a 1 and one that doesn't is a 0. This is depicted in table 4.1.

Table 4.1: Sample decision with 3 alternatives, 2 stakeholders, and 2 outcomes per decision alternative

Alternative 1		**Stakeholder A**	**Stakeholder B**
	Outcome x	1	0
	Outcome y	1	0
Alternative 2		**Stakeholder A**	**Stakeholder B**
	Outcome x	0	1
	Outcome y	1	0
Alternative 3		**Stakeholder A**	**Stakeholder B**
	Outcome x	0	0
	Outcome y	1	1

From an expected utility standpoint, the three alternatives are equivalent. However, the outcomes are inequitable in the first two alternatives. Ben-Porath et al. (ibid.) note that alternative 1 demonstrates inequality in both ex-ante inequality and ex-post inequality since both the expected values and actual outcomes favor stakeholder A. Alternative 2 exhibits ex-post inequality, even though ex-ante both stakeholders have the same expected value. Alternative 3 exhibits no inequality. Applying steps 4-6 to this scenario leads to the results shown in table 4.2.

Table 4.2: The decision depicted in Table 4.1 after applying the RJDF by valuing each outcome by the minimum utility across all stakeholders

		Stakeholder A	Stakeholder B	Minimum Utility
Alternative 1	Outcome x	1	0	0
	Outcome y	1	0	0
		Stakeholder A	**Stakeholder B**	**Minimum Utility**
Alternative 2	Outcome x	0	1	0
	Outcome y	1	0	0
		Stakeholder A	**Stakeholder B**	**Minimum Utility**
Alternative 3	Outcome x	0	0	0
	Outcome y	1	1	1

The RJDF does not differentiate between alternatives 1 and 2. Applying a strict maximin decision rule wouldn't differentiate alternative 3 either, but since it is the only one with a chance to have a nonzero utility, it is clearly favored over the other two.

The situation gets a little more complicated if the outcomes of alternative 3 are less than 1. If one interprets the utilities as dollars won in a game and keeps the amounts small such that the utility is roughly linear, this framework still prefers alternative 3 for any value greater than 0. This is one reason this framework is better suited to problems in which the stakes are high. If a utility of 0 means you don't win a dollar in a coin flip, there's a very different situation than if a utility of 0 means your city sinks under the ocean due to global warming.

4.4.2 Revisiting Mitcham & Keisler (2022)

Here, I will revisit the results from Chapter 2 of this manuscript (which is Mitcham & Keisler 2022) in which multiple worldviews were used to evaluate the output of an epidemiological-economic simulation model to gauge the potential effectiveness of non-pharmaceutical interventions early in the COVID-19 pandemic when uncertainty was very high. The model was run 500,000 times, comprised of an outer loop of 100,000 sets of disease and community characteristics and an inner loop in which 5 interventions were tested for each set.

That paper did not follow the early steps of the RJDF in that stakeholders weren't engaged to generate worldviews or decision alternatives. The general views were salient topics of discussion in the news and the specific utility functions were generated as natural extremes of those positions. The decision alternatives were the ones being debated by various government agencies at the time.

Instead of eliciting utility functions from stakeholders, the authors defined 5 worldviews (maximum life, maximum life-years, maximum economy, maximum liberty, and minimum economy) and applied each of them to the 500,000 scenarios generated by the model. Comparing and contrasting the differences in the worldview results was done on an ad hoc basis across multiple visualizations, one worldview at a time. This can be tedious and confusing for DMs.

By applying the RJDF, those multiple visualizations were collapsed into a single visualization. Rather than visualizing every worldview on a separate graph, each run of the model is measured only by the worldview that ranks the outcome the lowest. Figures 4.2 and 4.3 show the output after the RJDF was applied.

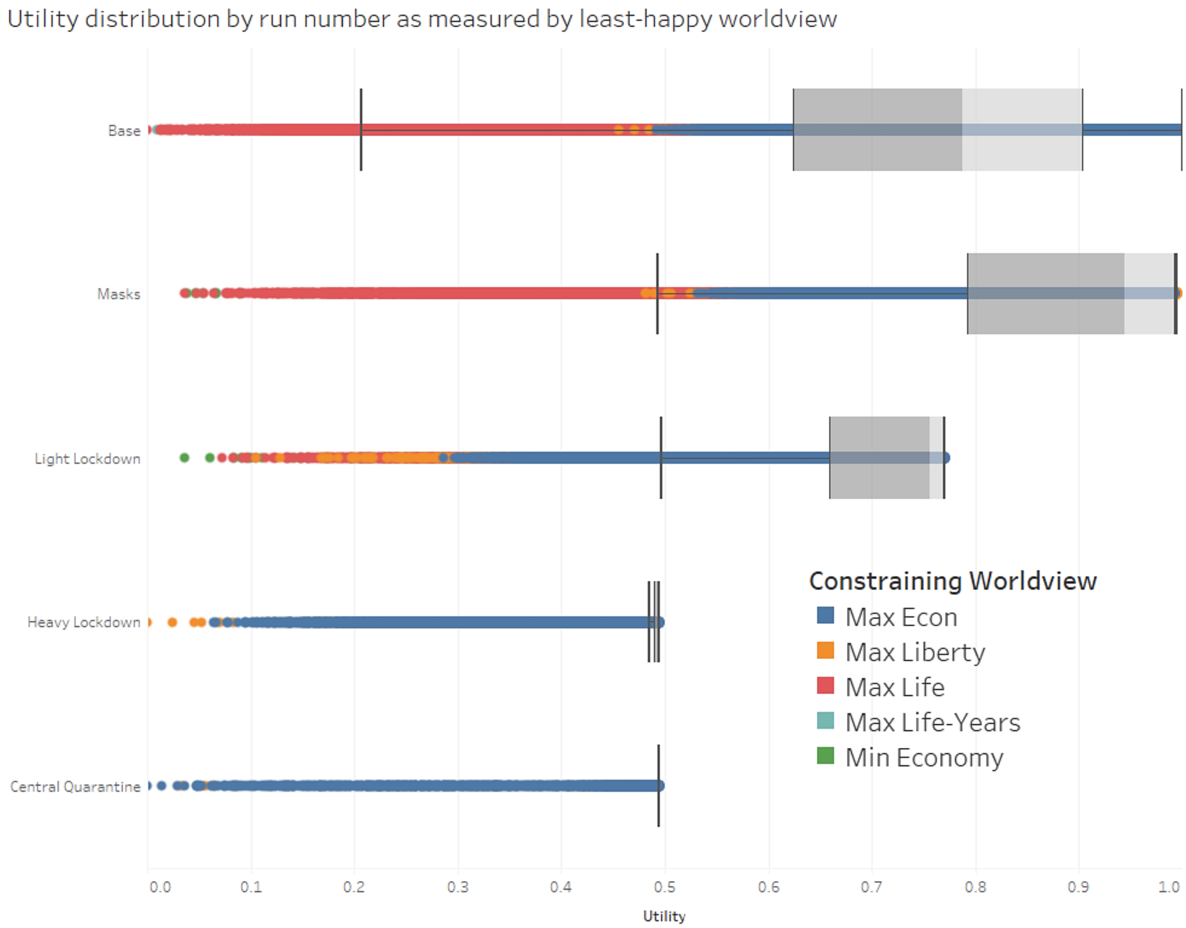

Fig. 4.2: *The main results from Mitcham & Keisler (2022) condensed into one graph. Each dot represents a scenario as measured by the utility function with the lowest output for that scenario. Which worldview generated that utility function is represented by the color of the dot.*

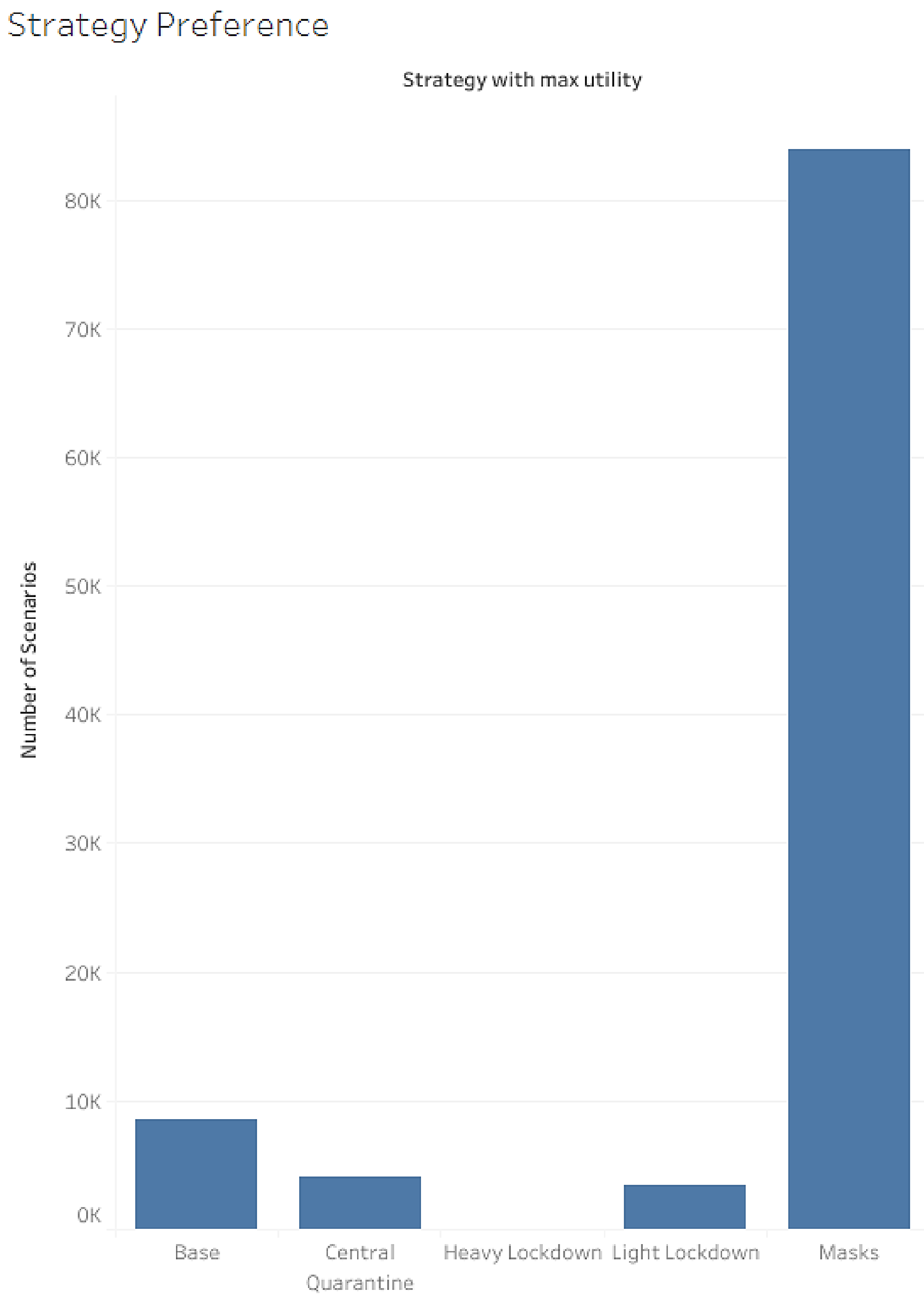

Fig. 4.3: *The same data as in Fig. 4.2 as examined at the level of the "outer loop" of 100,000 sets of disease and community characteristics.*

In the original paper, the authors used a value function to weigh tradeoffs between life, liberty, and the economy. Life and liberty were measured in terms of the economy; the output of the value function could be interpreted as US Dollars, but these values couldn't be compared across worldviews. Functionally, each worldview had a different weight on the economy in terms of the other criteria. The tradeoffs were in relative terms, not absolute terms.

To enable interpersonal utility comparisons, each value was scaled from 0 to 1, such that:

$U_{ni} = 1 - V_{ni}/Min(V_i)$

Where:

n is the output from a given run of the model

i is the set of worldviews

V is the value given by a combination of model output and worldview

U is the utility derived from the scaled value.

In other words, the utility is equal to 1 minus the original value given to a run by a worldview divided by the worst-case scenario as viewed by that worldview. The worst-case scenario will give a utility of 0, and the best-case scenario will approach 1. In this case, a utility of 1 would mean no deaths, no impact on the economy, and no liberty restrictions, which didn't occur in any of the scenarios generated.

To interpret figure 4.2, a DM could use any decision rule. A strict maximin approach would recommend a light lockdown at the outbreak of the pandemic, though, in most scenarios, it will cause a lot of unhappiness, especially among those who want to maximize liberty. Requiring masks, on the other hand, seems to have better favorability across a larger range of outcomes, which is made clear in figure 4.3. When using each run of the "outer loop" as the unit of analysis and comparing how each strategy fared, a mask mandate was preferred to the other options in over 80% of the cases. However, sometimes the life-maximizers were unhappy when the mask mandate alone wasn't enough to save lives.

4.5 Discussion

Problems in which there are concerns about deeply uncertain outcomes, equity, and differing worldviews (common to public policy problems) can be very complex. It can be difficult for DMs to keep track of all of those components of the problem at once. The RJDF provides one path forward to eliminate some of the dimensionality of the problem, as seen in the example in section 4.4.2. Those results aligned closely with what was found in Mitcham & Keisler (2022), but the insights were much easier to see at a glance. While the original model allowed the DM to explore the assumptions that go into the tradeoff through the use of an interactive dashboard, it could be confusing and didn't give a clear recommendation. In the original paper, the results were summarized over the course of fourteen graphs whereas the results of this framework were presented in two. If a DM just wants a recommendation that wants to minimize the maximum unhappiness, this method might be more useful.

Furthermore, this method provides a repeatable framework for a decision analyst to use when aiding with a complex decision problem involving worldview differences and uncertainty. Rather than performing sensitivity analysis on worldview assumptions on an ad hoc basis after the main part of the analysis is complete, sensitivity analysis on worldview is integrated directly with the model such that justice is taken into account.

When applying this method, some information is lost in the process. In particular, the DM is abandoning the idea of maximizing expected utility as the possible states of the world are only viewed through the lens of the worst-off stakeholders. An outcome in which everybody is slightly unhappy is valued the same as an alternative in which one group is slightly unhappy but everybody else is extremely happy.

It is important to recognize that the RJDF is not appropriate in all situations. When the stakes are low, the maximum unhappiness in absolute terms (rather than just relative terms, which the RJDF is concerned with) may be inconsequential. Additionally, there may be situations in which diametrically opposed groups have an equal chance of a bad outcome, and the RJDF cannot distinguish between the decision alternatives.

The RJDF can be used in conjunction with another decision model to help mitigate some of the downsides. There may be a situation in which a few unjust alternatives can be eliminated by applying this method, but there may remain a jumble of alternatives with similar outcomes. Just as in some decision contexts a DM may choose an alternative with the second-highest expected value if it is more robust against other assumptions, a DM here could choose the second-most-just alternative if it leads to larger gains in other ways.

4.6 Conclusion

The framework developed in this paper allows decision analysts and DMs to identify decision alternatives that are simultaneously robust to uncertain outcomes and differences in worldview. This is accomplished by evaluating each possible outcome on an *ex post* basis such that the utility function giving the lowest utility is used for that outcome. Combining this with a decision rule that is robust against uncertain outcomes leads to a decision alternative that is more robust and just than determining a single utility function to use and trying to maximize the expected utility.

Additionally, this method is conceptually simple and can be understood by non-technical DMs. It can simplify decision problems in which all worldviews need to be taken into account and sidesteps the potentially problematic decision of choosing a single utility function to evaluate outcomes on.

This method comes at the expense of rejecting alternatives with large, inequitable gains that otherwise might be desirable. An alternative in which nobody gets anything is valued the same as an alternative in which one person gains and nobody loses. For that reason, this framework is best employed in situations in which equity and justice are particularly large concerns.

There are several avenues for future research along these lines. First, case studies could be performed using this technique from beginning to end. The example in section 4.4.2 was taken from existing research. Second, I developed the RJDF as a more practical guide to decision-making. A more mathematical, axiomatic approach could be developed to explore the ramifications of this framework. I conjecture that the RJDF reduces the variability of outcomes simultaneously between potential futures and between worldviews within a realized future, but this could be proven (or disproven) mathematically.

Lastly, while the RJDF was developed with public policy issues in mind, it could in theory be applied to other decision contexts. Future research may uncover such uses.

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CHAPTER 5

CONCLUSION

Across the previous three chapters, I explored the concepts of robustness, justice, and the connections between the two in a public policy decision-making context. The approaches taken in this manuscript could in theory be applied to decision contexts outside of public policy, though I feel that the public policy domain provides the best illustration of the benefits of these approaches.

Chapter 2 focused on robustness, and while that chapter didn't explicitly use the term "justice," the sensitivity analysis around worldviews was a similar concept. A robust decision limits the variability of outcomes based on sensitivity analysis of the assumptions in the decision model. Justice involves limiting variability in how different groups are treated. Therefore, performing sensitivity analysis on worldviews is a form of justice, even though it isn't often conceptualized that way.

Chapter 3 involved the concept of government legitimacy, and government legitimacy is derived in large part from justice. The more just a government's actions are, the more legitimate they are seen to be, which has direct impacts on the efficacy of government functions such as policing.

Chapter 4 ties those two chapters together in a single framework. It uses the example in Chapter 2 with some justifications laid out in Chapter 3. A just decision should be seen as more legitimate by the people and therefore should lead to a more effective policy with better outcomes. The framework laid out in Chapter 4 should lead to more just decisions in certain situations.

Throughout this manuscript, I used simulation modeling extensively as a methodology. One key technique to handle both robustness and justice is sensitivity analysis, and simulation modeling is a useful tool to perform sensitivity analysis in a complex system.

I used both agent-based modeling and systems dynamics modeling techniques and in both cases, I was able to test assumptions on underlying factors. In Chapter 2, a systems dynamics model was appropriate because there are many feedback loops in play. I was able to perform sensitivity analysis on granular aspects of the disease, such as incubation time, which would have been harder to accomplish in a regression model due to the nonlinearities in play. In Chapter 3, I opted for an agent-based model due to the spatial effects and the importance of heterogeneity, and in that model, I performed sensitivity analysis on assumptions such as the impact of legitimacy, the vision of the agents in the model, and more.

In both cases, simulation modeling allowed me a programmatic way to test assumptions, iterating through thousands (or in the case of Chapter 2, hundreds of thousands) of model runs. In Chapter 2, sensitivity analysis on worldviews was performed on an ad hoc basis and didn't provide a clear recommendation, which could be daunting for a decision-maker. That is where having a framework to simultaneously handle sensitivity analysis on outcomes and worldviews is useful. Chapter 4 introduced such a framework. When faced with a small handful of potential outcomes, ad hoc sensitivity analysis on worldview is not nearly as daunting as trying to evaluate 500,000 possible outcomes by 5 variations of worldviews as was generated by the simulation modeling in Chapter 2.

Taken as a whole, this manuscript outlines an approach to difficult public policy decisions that embraces complexity without sacrificing equity and justice concerns. Additionally, it is done in a way that allows for practical decision-making.

Public sector decision-makers can be afraid to make big changes not only because of the risk of the decision leading to a bad outcome but also how some parts of the public might react even if it leads to what the decision-maker would consider a *good* outcome. The "robust and just" simulation modeling approach I took throughout this manuscript addresses both of these concerns and could lead to better public-sector decision-making and more effective governance.

BIOGRAPHICAL SKETCH OF THE AUTHOR

Before joining the Information Systems for Data Science and Management Ph.D. program at UMass Boston's College of Management, Jack Mitcham received an M.S. in Finance from UMass Boston and a B.S. in Physics from Towson University. He also served as the Director of Business Intelligence for a small startup and founded the mattress review site Mattress Nerd. Jack's research interests involve using modeling and decision analysis techniques to tackle complex real-world issues.