A MODEL OF GIVING

The purpose of this research is to explore, build upon, and test hypotheses surrounding the notion that philanthropy and charity as development assistance have very different impacts on the recipient society. Development and development assistance are so complex, even if there were more robust data than what was presented in the case study, little can be said with much confidence about the actual process and isolated effect. The main contribution of this research is to take a first step in addressing this gap.

Specifically, this research hypothesizes that charity hampers the development process and can have destabilizing effects for a society. The reasoning behind this is straightforward. When there is an influx of resources in a society without the society doing anything to generate this wealth, it interferes with and possibly destroys the underlying mechanisms for individuals to solve their own problems (Root, 2008). In addition to this, the funding mechanisms behind charity are not stable but are subject to unpredictable donor priorities. Therefore, charity-based development assistance brings resources into a society that may or may not have anything to do with the underlying social structure and/or priorities. The recipient society may or may not be able to predict the flow of resources and plan accordingly.

In contrast to charity, the other half of the story has discussed what has been successful in enabling development to emerge and sustain itself. Productive entrepreneurship is argued to be a necessary requirement for development to initially emerge. Philanthropy, combined with productive entrepreneurship, is hypothesized to promote self-sustaining entrepreneurship and development over time.

However, philanthropy was created in a developed world context with existing productive entrepreneurship and the institutions that support it (Acs 2013, Appleby 2010, Zunz 2012). Without productive entrepreneurship, philanthropy still may provide some benefit. Specifically this research hypothesizes that philanthropy does not harm the recipient society, even if it alone is not enough for development to emerge. The reason for this is that unlike charity, philanthropy works to help people become better problem solvers. This problem solving is within the existing context and is much less disruptive to underlying structures than charity. Without productive entrepreneurship, philanthropy is likely to help the recipients become more efficient at acquiring the resources that are available over time.

Methodology

While case studies can help to illuminate the breakdown of development assistance, they can only do so much to test these hypotheses in a rigorous and generalizable manner. Computational, agent-based modeling (ABM) provides a way to address this limitation. ABM simulates complex systems, such as societies, and can test alternative competing hypotheses. It also provides a bridge between qualitative research that has a narrow but deep focus, and quantitative research that is broad but relatively shallow and not process-oriented.

Agent-based modeling (ABM) is a methodology that attempts to recreate complex and emergent phenomena, such as development, using computer simulations. It is a bottom-up approach focusing on individual agents, their interactions, environment, and the resulting emergent phenomena. A computer can pursue the logic of scenarios many orders of magnitude further than a human brain can. Therefore, it is a good way to study complex adaptive systems, including societies (Cioffi-Revilla & Rouleau 2010).

A model is a representation at some level of abstraction, and a simulation as an operation of the model over time. It is up to the modeler to determine which level of abstraction is appropriate. In ABM, modelers start with defining agent behavior through a simple set of rules that reflect agent goals. Initially the model is very basic, but complexities can be added in future iterations. As agents interact and have experiences, certain individual attributes change (Banks & Sokolowski 2010). However, explanatory power decreases as interactions and environments increase in complexity (Camerer 2003). It is also impossible to completely remove all arbitrariness from the modeling.

What is most compelling about using ABM to test these hypotheses is the opportunity to understand processes, dynamics, and emergent phenomena (Cioffi-Revilla & Rouleau 2010). Development is both a process and an emergent phenomenon. Case studies, statistics, theoretical research, and experiments each can provide a piece of the puzzle but do not illuminate the entire picture in a rigorous and intuitive manner. An agent-based model, on the other hand, can explore the implications of a researcher's hypotheses and assumptions by taking them to their logical conclusions. Using such a model, researchers can actually visualize these interactions, processes, and emergent phenomena and/or patterns.

Specifically, researchers can have a hypothesis (or set of hypotheses) about a phenomenon. From there, they can program this into a model to test these hypotheses. Many alternative competing hypotheses can be tested, giving the researchers a range of likely phenomena if the model presents findings. If it does not present findings, the researchers can then use that feedback to modify their theory and assumptions, continuing with the research.

Agent-based models compel researchers to define and describe their theory in an extremely rigorous and precise manner. In fact, this description has to be so precise that it can be written into code for a computer program. This program not only has to function, but resemble the underlying theory. The process of transforming theory into a computational model helps to tighten theoretical work and sort through any logical inconsistencies or other issues that may exist. Computational models (in this case ABM) can take testable hypotheses within a theoretical framework a step further and explore what the implications might be.

The hypotheses that charity and philanthropy are fundamentally different, and that these differences affect social systems (including development) are fairly intuitive. Testing these hypotheses using an agent-based model is the best first step in moving forward theoretically. Output generated from simulation runs cannot take the place of real-world data, but it provides a low-cost, ethical way to test hypotheses without having to experiment with different policies (and hence people's lives). It can also refine theory and provide guidance for data collection and therefore make the best use of scarce resources. Knowing what questions to ask is a very important first step, and agent-based models can help refine and guide this process.

This research seeks to make a contribution to development theory and to the literature covering agent-based insurgency models such as described in the literature review. To construct these models, agents are programmed with various aspects and interact with their environment and other agents according to rules. Over time (or a set of "ticks" or rounds within a simulation) phenomena and patterns may or may not emerge.

A good model will help to tease out what is most relevant and what is noise or less relevant. To model well, it is best to start at the simplest possible set of agents and rules, then increase levels of complexity from there. The strength of an agent-based (or any model) comes from providing a powerful explanation from as simple of a model as possible.

The entrepreneurship literature is rich with descriptions and explanations of entrepreneurship. This includes the entrepreneurial function, entrepreneurial personality traits, types of entrepreneurship, history, etc. In addition to this, the development literature provides very rich explanations as to what is necessary for development, how it emerges, how policy can influence this, and many other factors. However, these pieces do not present a holistic, coherent picture for what matters most for the development process. This chapter contributes by filling in a part of this gap.

The counterinsurgency (COIN) literature can also benefit from testing these hypotheses. As relevant as charity and philanthropy are to development assistance, this assistance is central to the "build" component of the clear-hold-build COIN strategy. Specifically, the US government (and her allies) assumes that once the counterinsurgents are in control of an area, they can, through assistance, "build" the area under control. There is an inherent assumption in this strategy that development assistance in these controlled and relatively stable areas leads to development or at least stability. It also assumes that this development (or stability) benefits foreign counterinsurgents, in this case the US. Testing these hypotheses will shed light into how realistic these goals truly are and provide insight into how and why neither development nor stability emerges.

There is no empirical evidence to justify the assumptions underlying this "building" in COIN for a very simple reason: no foreign counterinsurgent force has conducted COIN operations that have led to development. Beyond this, even if development had occurred, there are no success stories to justify or refute this assumption. This model is a first step towards testing these underlying assumptions, along with starting to unpack the implications of the prevalence of charity and philanthropy in the development assistance package.

Model Description

This chapter presents a basic development assistance model, specifically showing the impacts of development assistance on a simulated society. It is designed to explore various charity/philanthropy combinations, preferences, and overall prevalence in the society.

Entrepreneurship is a main element that is left out at this stage. While it is through entrepreneurship that wealth is created, the focus of this research is to understand the development assistance effects, if any. Adding entrepreneurship at this point would have required major assumptions and/or data to make it accurate and applicable to the recipient country. Societies that receive development assistance have varying levels of productive entrepreneurship, and it is important to focus on one type of phenomena that is generalizable to all before adding more complexity to the model.

This model is a variation of Sugarscape, an agent-based model created by Epstein and Axtell (1996).[1] The reason why this model was chosen to modify for this dissertation is because it is the simplest model that simulates population dynamics and resources. In Sugarscape, agents move, use resources (sugar in this case), are born, die, and can even accumulate wealth. Sugarscape does not include wealth creation, or entrepreneurship, but simply population dynamics given a resource distribution within an environment.

Also, Sugarscape is currently in NetLogo, and this model builds upon it using the same platform. This provides continuity, along with the fact that NetLogo is a platform powerful enough for the model in this chapter, yet is intuitive, accessible and relatively easy to learn. It is a main goal of this chapter to present a model that is easily understandable, reproducible, and can be a platform upon which additional research can build. Using NetLogo (as opposed to Java) has made the model more feasible to construct, and will hopefully make this more accessible to a wider range of researchers.

The purpose of this model is to assess and understand on very simple terms, the impacts of development assistance, the charity/philanthropy breakdown, and preferences on a recipient

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[1] The specific variation modified in this model is Sugarscape 3: Wealth Distribution (Li and Wilensky 2009, Wilensky 1999, Epstein and Axtell 1996). Sugarscape 3 has only one resource (sugar) and no trade. The wealth distribution that emerged in the original version of this model resembled what is observed using actual data.

country. As in society, charity is an influx of resources to a certain population with immediate payoffs. Philanthropy, also an influx of resources, has long term payoffs that result in an increased productive capacity for those who participate in programs to benefit. These resources are not necessarily stable—they do not grow back endogenously and donors are not always predictable. Also, charity does not necessarily correlate to the previously existing resources or to the productive capacity of a society.

Sugarscape Description

Sugarscape is currently in NetLogo, an agent-based modeling platform well suited for constructing simple models. For every round, or "tick", each agent looks around, and travels to the open spot it sees with the most sugar and consumes it. It acquires the sugar on the spot and metabolizes sugar as well. If the agent has less sugar than is required, it dies, and if it has more than its metabolism requires, it saves the sugar for future rounds.

In Sugarscape, the agents have two attributes: metabolism and vision. Metabolism determines how much sugar is consumed per round, and vision determines how far the agents can see (between 1 and 4 spaces). Agents consume sugar, which is set on the model landscape as two hills. This sugar grows during each tick.

Each simulation starts with the agents randomly distributed throughout the model landscape. After a while, most agents accumulate around where most of the sugar is, and this becomes relatively stable. Also, certain real-world phenomena are reproduced, such as income inequality, as measured by the GINI index, which also appear relatively stable over time. The agents with greater vision and slower metabolisms accumulate wealth, which in this model is unused sugar.

Modifications to Sugarscape

Charity is a redistribution of resources, whether endogenously or from external sources. Endogenous charity is seen locally, while charity from external sources is seen in phenomena such as development assistance. In addition, philanthropy is often endogenous. However, since the model for this dissertation involves development assistance, both charity and philanthropy are treated as exogenous.

It is acknowledged that in reality charity and philanthropy are not necessarily random. However, this model assumes that predicting development assistance on any given patch is difficult if not impossible. The USAID data supports this assumption in that the programs and program types tend to vary greatly from year to year. Shifting donor country priorities tend to be the main driver, making the level and type of assistance fairly unpredictable for a given "patch" in a recipient country. Therefore, random assistance allocation throughout the simulated landscape is the best way to simply model this phenomenon.

Specifically, charity and philanthropy are added to the landscape at random locations. The resource landscape from the original Sugarscape model is still initially in place, but the allocation of charity and/or philanthropy are unrelated to this landscape. For any given patch, the probability of there being charity and/or philanthropy are represented by sliders and varied throughout the simulations. In ABM, sliders are ways in which a researcher can easily alter the parameters of a model within a given range. For example, the probability of there being charity (or philanthropy) on any given patch can vary from 0 to 100%. The slider is a type of button that allows the researcher to literally slide across to set the value (i.e. 65%). Sliders such as these make it easy to alter the parameters of the model for various simulation runs.

Also, the ability to delay gratification was added to the model so that agents could prioritize between looking for and using charity versus philanthropy. For this, agents are assigned a random number from 1-100, to act as a proxy for the ability to delay gratification. During each tick, an agent can either move to an empty space with sugar and immediately eat, or move to a space with "vision" increases, which will increase their vision over time.

Another difference involves agent reproduction. Just as in the original model, they can run out of sugar or die of old age. However, instead of an agent reappearing automatically in the model when another dies, agents reproduce in this model when their wealth accumulates above a certain threshold (in this case, 2000 but the slider allows for a larger range).[2] When an agent reproduces, they metabolize the same amount of sugar otherwise used in a move. The reason for this is that population stability is not something that should be assumed, and this provides a way for a lack of stability if appropriate. It also simulates more realistically how humans require a certain degree of health and/or resources to reproduce, and they reproduce at some cost.

Agents metabolize sugar whether or not they move, unlike the original Sugarscape where they only metabolize sugar when they move. This serves two purposes. First, without this and the sugar consumed upon reproduction, agents quickly overpopulate within the first few ticks, shutting down the model and consuming all of the sugar. Not only does the simulation not run, but also it is unrealistic to have an area full of agents with nothing left to consume. Secondly, it is more realistic for agents to consume sugar when they move, reproduce, gain productive capacity, and with the passage of time.

A final major change to Sugarscape was visual. Since each patch could hold more sugar than the original model, the range of color was increased to reflect this. Other rules in this model

[2] As the birth and death rules are an artifact of the model, the numbers selected for the simulations allowed for enough stability in the model to form conclusions in a relatively short time frame. If agents live longer and/or reproduce with less sugar, overpopulation can result more quickly. The opposite is true for agents having a lower max-age and/or needing more sugar to reproduce—it takes longer for the model to show stability or instability. The parameters selected allowed for either all agents dying or the model stopping due to overpopulation within 200-300 ticks. By 400-500 ticks, if the model run was to be stable, it had reached stability by this point. Altering these parameters should not influence the simulation in any substantive way, only how quickly the model reaches stability or ends on its own.

have stayed the same as the original Sugarscape. These include agent vision, metabolism upon movement, the rules governing agent movement, and the ability for them to accumulate wealth. Also, while additional sugar was added to the model, the original distribution was kept intact. Finally, the actual landscape (other than the additional sugar) is identical to the original model.

Model Description

Agents in this model have the following characteristics: sugar, metabolism, vision, ability to delay gratification, age, and the maximum age an agent can attain. Sugar represents the level of wealth an agent has at any given point, and metabolism represents how much is used up during a tick, or round of the simulation. Vision represents how far an agent can see, and is a proxy for the productive capacity of an agent. This representation is appropriate since greater vision translates directly to a greater ability to acquire the most sugar in any given round. Over time, this is expected to lead to greater wealth accumulation.

As described earlier, agents have variables that approximate the ability to delay gratification called "discount" and "discount-cutoff". Discount-cutoff is represented as a slider in the model. If discount (determined randomly) is higher than discount-cutoff, agents look for vision first, and then look for sugar if no vision squares are available. At the same time, if discount is lower than discount-cutoff, the reverse is true. Agents do not distinguish between sugar grown back naturally and sugar placed in the simulation from charity. To measure a proxy for average productive capacity, a monitor for average vision was added to the model.

Squares, or patches, on a grid represent the environment. Patches have attributes, and in this model, these are the resources. There is sugar that grows naturally, or psugar, and sugar that is added externally and at random.[3] This is charity in the model. Specifically, the variable charity

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[3] Max-psugar is the maximum amount of sugar that can be on the patch and is set to a very high number so as not to place artificial limits.

represents the probability of a given patch having natural growback rules (1 unit of sugar per tick) or charity. If a patch receives charity, then it is assigned a sugar value randomly between 0 and 4.

This charity rule is especially important when modeling development assistance. In the real world, development assistance projects are difficult to predict. Sometimes, an area or program can receive a lot of resources, but other times they can receive nothing. Most of project resource allocation is external to the recipient environment. This can include agency rules and/or priorities, political dynamics, or many other factors that overall make resource allocation extremely difficult to predict, especially for the local recipients. Random allocation between 0 and 4 was the most appropriate way to simply model a very unpredictable dynamic.

Patches also have philanthropy, which are vision points that agents can consume and accumulate. For this model, one unit of vision is added at a time. The rule is based on the assumption that unlike sugar (resources), there are limits to which a single agent (person) can benefit from philanthropy at any given time. This assumption is justified in that philanthropy takes time and effort to truly reap the benefits and is not a short-run solution. For example, if a person is benefitting from a university scholarship, there are limits to how fast he/she can earn the degree. Benefitting from philanthropy is often a gradual, long-term process and it was important to reflect this in the model.

Model Steps

Each simulation begins with an empty grid. It then creates and distributes the initial agent population and the resources onto the grid. Agents are assigned random locations and attributes such as metabolism, vision, and initial sugar. Metabolism is set randomly between 1 and 4. In other words, agents consume between 1 and 4 units of sugar each tick. Sugar is initially set randomly between the minimum and maximum sugar variables (represented as sliders). Vision is initially set randomly between 1 and 6. All of these numbers are integers.

They are also assigned preferences, or a "discount" variable as a random number between 1 and 100. That number will dictate if the agent will look for vision or sugar first. Specifically, if the discount number is greater than the discount-cutoff (represented by a slider that can have values between 0 and 100), the agent will look for vision first. If the discount number is less than the discount-cutoff, the agent will look for sugar first. The discount-cutoff number is the probability of an agent preferring charity to philanthropy.

During a tick, each agent first looks around. It can look horizontally and vertically but not diagonally for resources and can see as far as its vision points allow. If it has vision points of 4, for example, it can see a distance of 4 squares in each direction. Then, if it prefers vision, it looks around for unoccupied patches with vision. If there are any available, it moves to the closest patch with the highest amount of vision. It then consumes the vision and any sugar that may also be on that patch.[4] Then, it metabolizes sugar according to its metabolic rate (so a metabolism of 2 means that the agent consumes 2 units of sugar for each tick). Finally, it updates its parameters by adding 1 to age, updating sugar and vision values, and reproducing or dying if applicable. The patch on which the agent consumed resources sets all resources to 0.

If an agent prefers vision but does not find any unoccupied patches with vision, it then looks for sugar. If there are any unoccupied patches with sugar, it goes to the closest patch with the most sugar, consumes the sugar, and updates its parameters according to the same rules. The same rules apply if an agent prefers sugar, only it looks for sugar first, then vision.

[4] Patches with vision may also have sugar on them. The reason for this is that people who benefit from philanthropy do not necessarily stop consuming, but in this model they are not necessarily active rent-seekers. An example of this is a college student who still eats, pays rent, etc. It would have been more unrealistic to have vision and consumption be mutually exclusive and would have been likely to affect the simulation outcomes in a substantive way.

Regardless of preference, if an agent finds neither vision nor sugar, it consumes an amount of sugar equal to its metabolism and updates accordingly. When all patches have agents on them (as with the case of simulated overpopulation), then there are too many agents consuming to move and seek resources. The simulation ends at that point. At the same time, if all agents die, the simulation ends as well.

After each tick, the environment updates. Patches grow back according to a variety of rules and recolor themselves accordingly. The philanthropy variable is a slider that dictates the probability of a patch having vision. If a patch has vision, it will increase its vision by 1. The charity variable is similar to the philanthropy variable in that it is a slider dictating the probability of a patch being subject to charity growback rules. If the patch is subject to charity, then the sugar is set to a random number between 0 and 4, for reasons explained earlier. If it is not subject to charity, then sugar is increased by 1. It is entirely possible that a patch can have both charity and philanthropy on the same patch. However, this is not likely to be problematic since it is the preference of the agent that dictates which type of resource it looks for first and is indifferent to how the resource grew.

Finally, the global variables are updated after each tick. Global variables include the GINI index and Lorenz curve, along with keeping track of average wealth and average vision. The Lorenz Curve, GINI Index, and average vision all have their own methods, or actions that update these global variables. Average wealth (measured by average sugar) is calculated as a part of updating Lorenz and GINI. A simple way to track these over time in any given simulation is through the reporters that continuously update graphs.

Assumptions

Most people respond to incentives that are perceptible. Therefore, agents in this model respond to incentives present and apparent to them. This model assumes that the incentive structures present and visible encompass enough of the incentive structures in real life for this model to be informative and useful.

Another assumption is that people within an insurgency may plan for the future enough to prioritize gaining from philanthropy over charity. The simulation runs cover every possible combination, but this assumption may be incorrect and in reality the recipient population may not value philanthropy. This assumption is especially critical when testing the hypotheses relevant to COIN.

Model Setup

Parameters

This model contains a set of parameters displayed below in Table 13. It includes the parameter name, definition, base case, and range. In this case, for the parameters that did not vary in the simulation runs (Max_Age and Reproduction), the base case was the parameter value used. For Philanthropy and Charity, the base case was that of no development assistance (or zero), as null hypotheses. While the USAID data may have been used, subsidies and consulting (not in this model) were far too prevalent for this to be a meaningful base case. Also, since the focus of this dissertation is on countries that are experiencing violence and instability, time preferences can be assumed to be very short-run focused as a base case. Therefore, the base case for charity preferences was set to 100, meaning that an agent had 100% probability of preferring Charity to Philanthropy. As described in the Parameter Sweep section, most of the parameters were varied across a given range when performing the simulation runs. When the range for a parameter is wider than that used in the simulations for this chapter, it is indicated by a footnote.

Table 13 Model Parameters

Parameter	Definition	Base Case	Range
Max_Age	The maximum age (or number of steps) an agent can survive in a simulation	100 steps	50-150 steps[5]
Reproduction	The amount of sugar (resources) needed for reproduction	2000 units of sugar	1000-2500 units of sugar[6]
Philanthropy	The probability of any given patch in a simulation of having vision in a particular step	0%	0-100%
Charity	The probability of any given patch in a simulation of having charity growback rules in a particular step	0%	0-100%
Preferences[7]	The probability of any given agent in a simulation preferring charity to philanthropy.	100%	0-100%

Variables

Final_Pop: This is the population level of a particular simulation run at the final step or tick. The final step could be at 500, or it could be whenever the simulation ends on its own in less than 500 steps.

Final_Gini: This is the Gini coefficient of a particular simulation run at the final step or tick. The final step could be 500, or it could be whenever the simulation ends on its own in less than 500 steps.

Final_Avg_Wealth: This is the average wealth in a particular simulation run at the final step or tick. The final step could be 500, or it could be whenever the simulation ends on its own in less than 500 steps.

Final_Avg_Vision: This is the average vision, or distance agents can see in a particular simulation run at the final step or tick. The final step could be 500, or it could be whenever the simulation ends on its own in less than 500 steps.

Min_Pop: This is the minimum population level in a given simulation run. If all agents die, then this value will be zero.

Min_Gini: This is the minimum Gini coefficient in a given simulation run.

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[5] This parameter was set to 100 steps for all simulation runs for this chapter.

[6] This parameter was set to 2000 units of sugar for all simulation runs for this chapter.

[7] To make the statistical analysis more descriptive, this parameter name was changed from Discount_Cutoff to Preferences.

Min_Avg_Wealth: This is the minimum average wealth in a given simulation run. If all agents die, then this value will be zero.

Min_Avg_Vision: This is the minimum average vision, or distance agents can see in a given simulation run. If all agents die, then this value will be zero.

Max_Pop: This is the maximum population level in a given simulation run. If there is simulated overpopulation, in the case of there being an agent on every patch, then this number will be equal to the number of patches.

Max_Gini: This is the maximum Gini coefficient in a given simulation run.

Max_Avg_Wealth: This is the maximum average wealth in a given simulation run. There are no limits to how high this value can be.

Max_Avg_Vision: This is the maximum average vision in a given simulation run. There are no limits to how high this value can be.

Mean_Pop: This is the mean population level in a given simulation run.

Mean_Gini: This is the mean Gini coefficient in a given simulation run.

Mean_Avg_Wealth: This is the mean average wealth in a given simulation run. There are no limits to how high this value can be.

Mean_Avg_Vision: This is the mean average vision in a given simulation run. There are no limits to how high this value can be.

Final_Steps: This is the number of steps, or ticks, representing the duration of the simulation run.

Parameter Sweep

NetLogo has a useful tool called BehaviorSpace. What this does is perform a parameter sweep for any parameters/variables of interest. In this case, max-age and reproduction were fixed (100 steps and 2000 units of sugar), while charity, philanthropy, and discount-cutoff (preferences) were varied. All three variables have a range from 0-100. The parameter sweep was performed using every combination of values for these variables at 5-point intervals. This resulted in a total of 9,888 simulation runs. During the parameter sweep, the following output was generated:

Population: This was measured at each step, along with minimum, maximum, mean, and final agent population.

Gini: This was measured at each step, along with minimum, maximum, mean, and final Gini coefficient. In this way, income inequality can be examined.

Average Wealth: This was measured at each step, along with minimum, maximum, mean, and final average wealth measured in units of sugar.

Average Vision: This was measured at each step, along with minimum, maximum, mean, and final average vision measured in vision points.

Final Steps: This is an integer variable measuring the number of steps the simulation went through before either ending itself or ending at 500 steps. It tells the researcher if the simulation run achieved stability.

Part of performing simulation runs involves knowing when to stop. Sometimes the simulation stops itself, such as when the population goes to zero (simulating famine) or when the environment is completely full (simulating overpopulation). However, when a simulation run is stable, it can go on indefinitely without telling the researcher much more from letting it go on. With these parameters, if a simulation run was going to be stable, it generally made it past 300-400 steps. The output from the simulation runs supported this, as few simulations had their final number of steps be between 300 and 400 steps.

Figure 1 shows this using a histogram of the Final_Steps variable. This histogram shows the density of the various Final_Steps values across all simulation runs and parameters. The purpose of this figure is to provide a visualization of simulation stability or lack thereof.

Specifically, if a simulation run reaches 300 steps without ending on its own, it almost always makes it to 500 steps. Therefore, automatically ending a simulation run at 500 steps, assuming it would go on indefinitely, is justified.

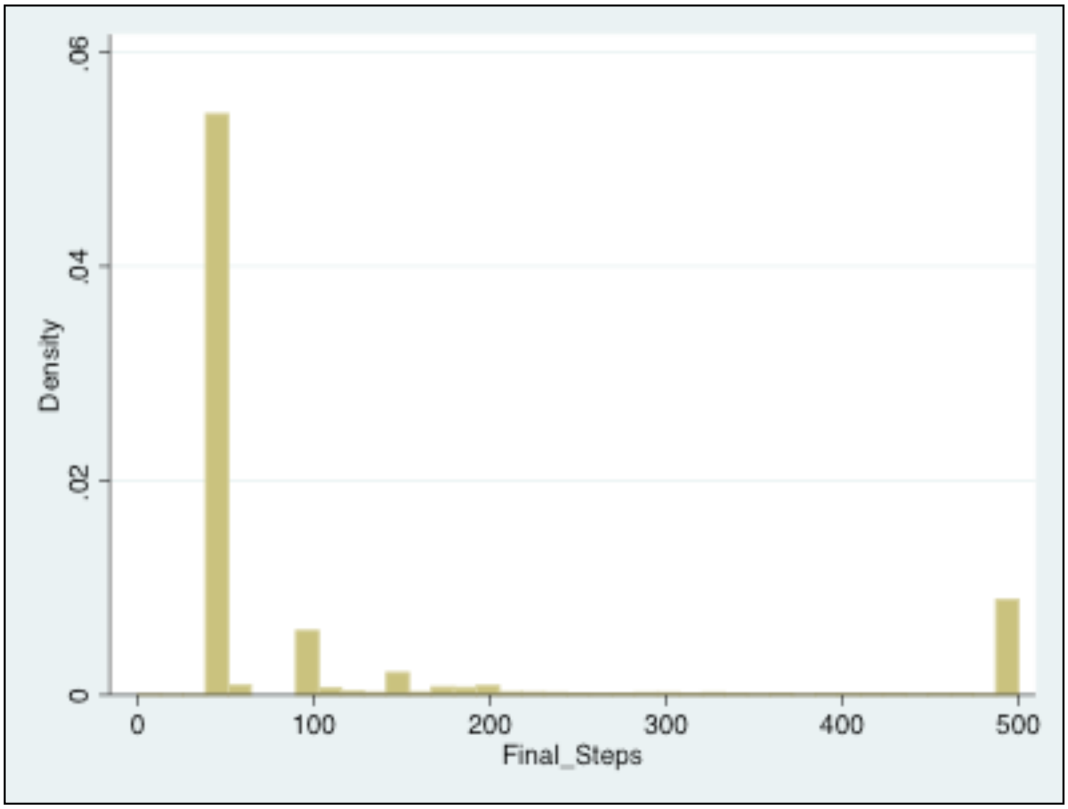


Figure 1 Histogram—Final Steps

Model Output Analysis

The model output analysis in this chapter is divided into four sections. First, typical simulation runs are presented. Second, the relationships between philanthropy, Charity, and preferences for Charity and population stability are explored. Then, hypothesis testing is conducted to test whether the effects of philanthropy and Charity are statistically significantly different from each other. Finally, regression analysis is performed to explore the relationships between philanthropy, Charity, and preferences for Charity and the following dependent variables: population, Gini coefficient, average wealth, and average vision.

Typical Simulation Runs

Understanding the aspects of a typical simulation run can provide meaningful insight into a computational model. Often, there is an empirical and/or theoretical foundation on which to base the parameters of the typical simulation run. The original intent in this dissertation was to use the data from Chapter 4 as an empirical foundation for this. However, as discussed in Chapter 4, the USAID programs in Afghanistan (both in number of programs and funding) consisted of subsidies and consulting more than Charity and/or Philanthropy. As subsidies and consulting are not included in the model at this stage, a typical run using parameters set from the USAID program data available would not be very useful or meaningful.

Instead, this section describes a set of several typical runs with various sets of parameters. This model is constructed in such a way that provides the potential for literally thousands of typical runs, depending on the combination of parameters set for the run or set of runs. Four of these are presented in this section. As this model is theoretical, it made sense to first cover the theoretical base cases of zero Charity or Philanthropy (no development assistance), all Charity with no Philanthropy, and all Philanthropy with no Charity. The three cases explore what a typical model run would look like, given these theoretical extremes.

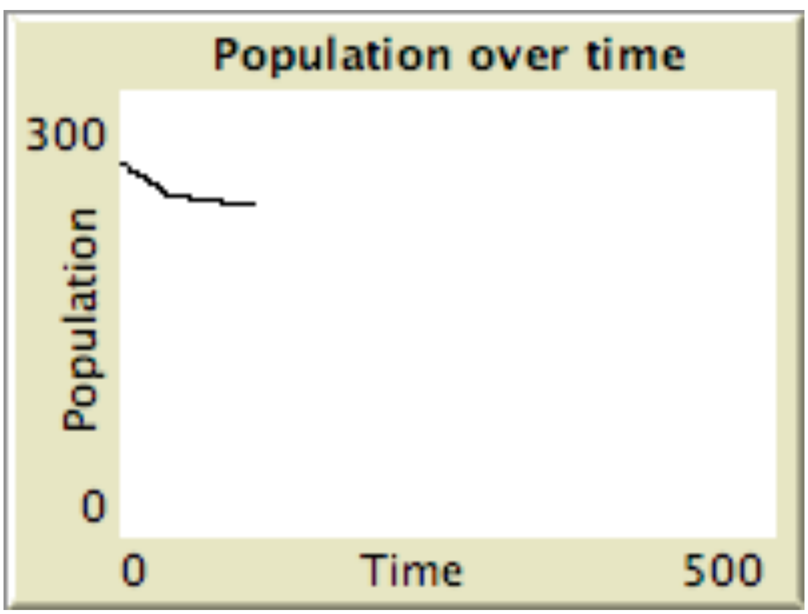
A fourth theoretical base case is presented with 75% Charity and 25% Philanthropy, to describe what a charity-heavy assistance package could look like. This is the parameter set that most closely resembles the USAID program data. While effectively lumping subsidies with charity, the focus is more on short-run versus long-run payoffs. With that, in all base cases, typical runs are presented with the parameter of Charity Preferences for any given agent set to 75%. This captures the hypothesis that in a conflict-laden, uncertain environment such as

Afghanistan, people are more likely to seek out short-term gains than they are to make long-term investments. Finally, to understand a typical run given a set of parameters, 500 simulation runs were conducted for each of these four cases.

No Development Assistance

Out of 500 runs with this set of parameters, the final steps (model stability) ranged from 49 to 134 ticks, indicating a lack of stability before intervention[8]. The average number of final steps was only 54, with a standard deviation of roughly 13. On average, the final population was only 6 agents, and with a standard deviation of around 50. However, the range was between 0 and 435 agents, which is rather large. In most, but not all cases, the agents run out of sugar and die off. This paints a picture that with no development assistance intervention and a high Preference for Charity, the majority of the simulation runs do not become stable.

For the simulation run presented below, agents simply ran out of resources, but did exhibit increasing wealth per agent over time.



[8] While the original Sugarscape is stable, the modifications made to this model (such as reproduction rules and maximum age) are a contributing factor. The parameters and reproduction rules chosen for this model (and these simulation runs) outline where stability can be found across a wide range of parameters. Since this model is theoretical at this point, and since a lack of stability is in line with an insurgency situation, this is not problematic.

Figure 2 No Development Assistance—Population Over Time

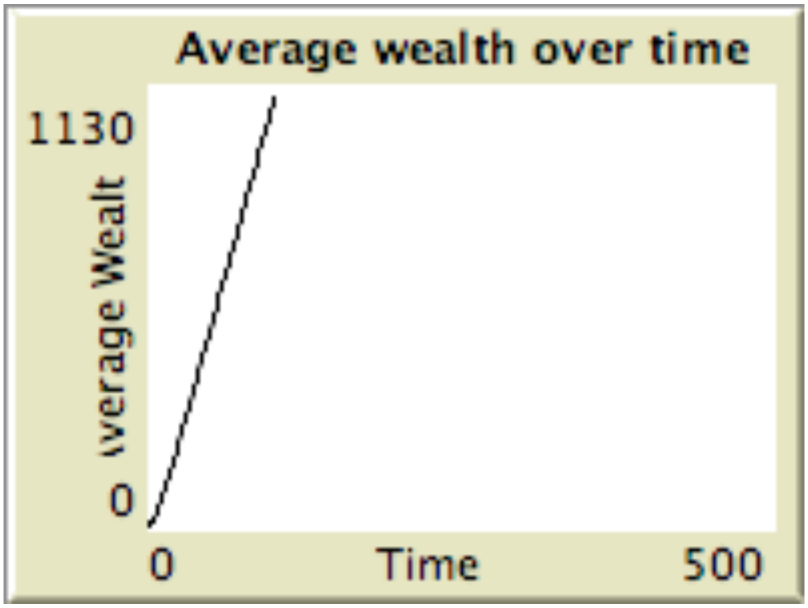


Figure 3 No Development Assistance—Average Wealth Over Time

<u>Charity Only</u>

Out of 500 runs with this set of parameters, the final steps (model stability) ranged from 49 to 500 ticks (or model stability). The average number of final steps was only 139, with a standard deviation of roughly 171. On average, the final population was 440 agents, and with a very large standard deviation of around 1032. The range was between 0 and 3312 agents (or likely overpopulation), which is also rather large. Overall this would indicate that Charity alone adds instability to the model in most (but not all) cases.

Below are graphical representations of a typical all-Charity simulation run. Regarding the population over time, it appears to spike and then crash. In addition to this, even for the simulation's short duration, average wealth also appears to spike and then crash over time. This indicates a lack of predictability in the model when only Charity is introduced. As the rest of this section demonstrates, Charity is also strongly associated with a lack of model stability, which would be consistent with what is shown here. The notion that Charity alone has unpredictable and potentially destabilizing consequences supports the hypothesis presented in this dissertation.

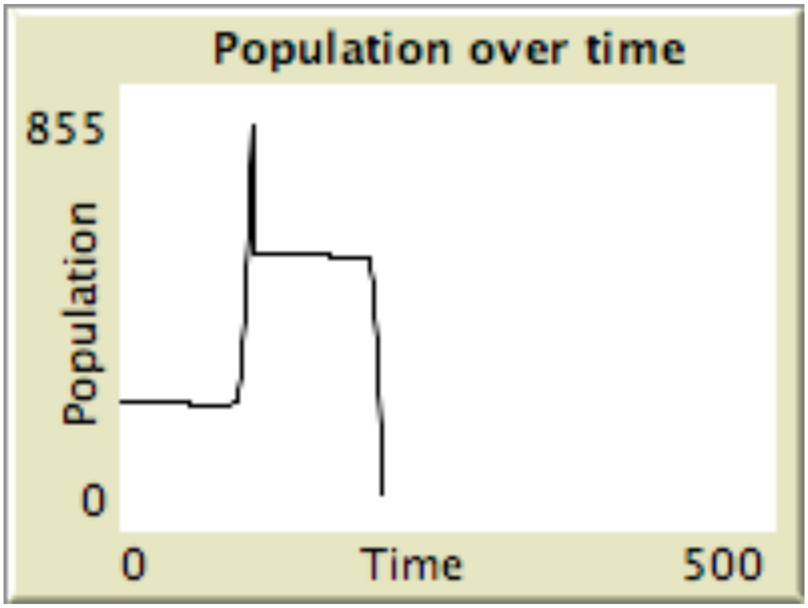


Figure 4 Charity Only—Population Over Time

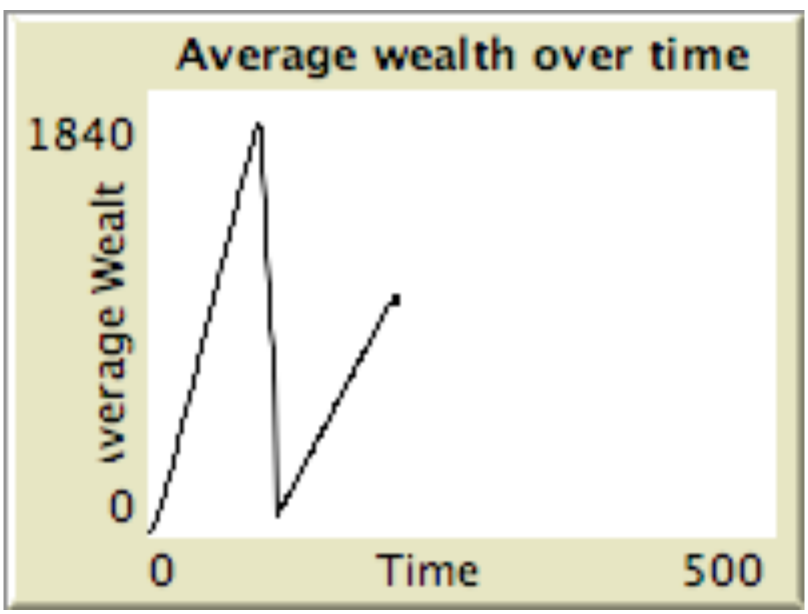


Figure 5 Charity Only—Average Wealth Over Time

<u>Philanthropy Only</u>

Out of 500 runs with this set of parameters, the final steps (model stability) ranged from 49 to 169 ticks. The average number of final steps was only 54, with a standard deviation of roughly 14. On average, the final population was only 4 agents, and with a comparatively large standard deviation of around 44. The range was between 0 and 449 agents, which is also rather large. Overall this would indicate that Philanthropy alone changes the model very little when compared to no intervention at all.

Below are graphical representations of a typical all-Philanthropy simulation run. Regarding both the population over time and wealth over time, this looks very similar to the typical run with no intervention. This indicates that Philanthropy alone neither harms nor helps a system with high Preferences for Charity. The rest of this section supports this claim and suggests overall that while Philanthropy alone is not a magic fix, it is also less likely than Charity alone to add instability to an already unstable situation.

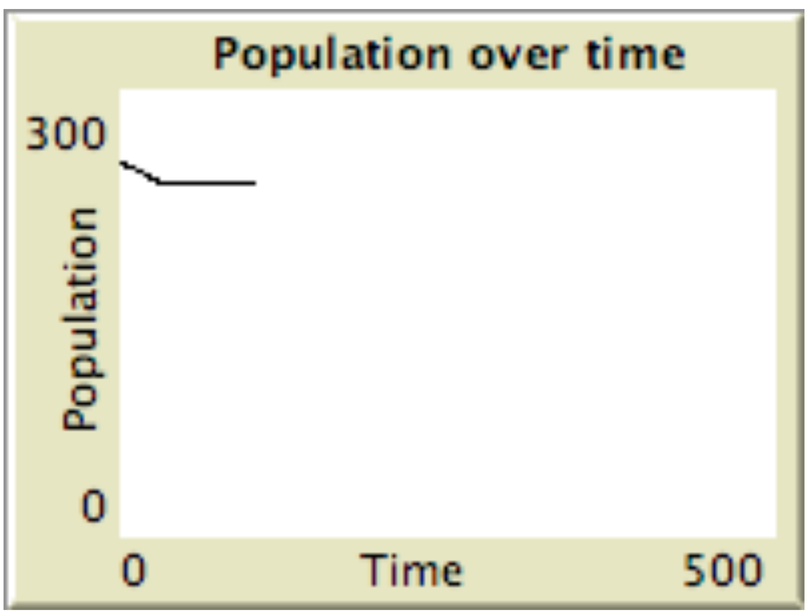


Figure 6 Philanthropy Only—Population Over Time

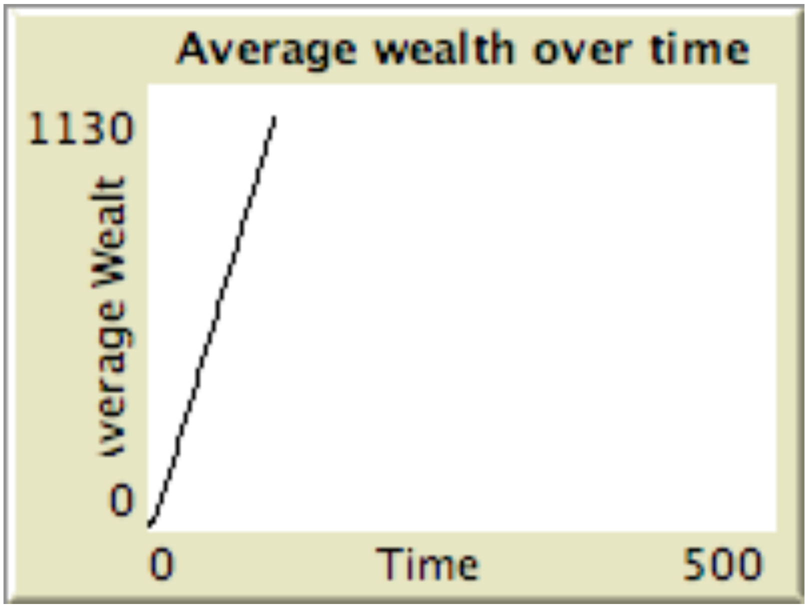


Figure 7 Philanthropy Only—Average Wealth Over Time

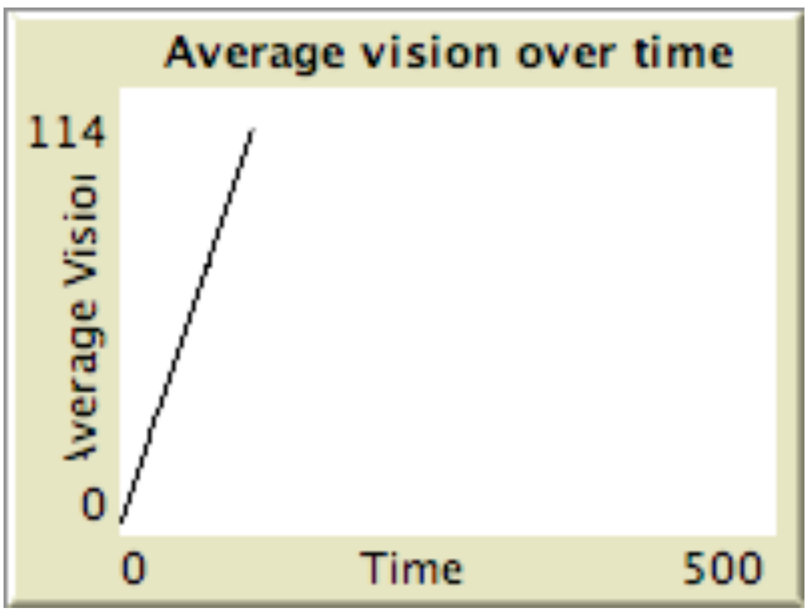


Figure 8 Philanthropy Only—Average Vision Over Time

<u>Charity-Heavy Assistance Package</u>

Out of 500 runs with Charity at 75% and Philanthropy at 25%, the final steps (model stability) ranged from 49 to 289 ticks. The average number of final steps was 63, with a standard deviation of roughly 38. On average, the final population was only 6 agents, and with a comparatively large standard deviation of around 54. The range was between 0 and 500 agents, which is also rather large. Overall this would indicate that a small amount of Philanthropy could mitigate the instability associated with Charity and Charity Preferences. However, it does not seem to be sufficient to have much meaningful improvement over no assistance at all.

Below are graphical representations of a typical Charity-heavy assistance package simulation run. While the averages and standard deviations appear to be more similar to the zero-assistance and Philanthropy only runs, the simulation over time shows similar (but less extreme) instability to the Charity-only simulation run. This indicates that some Philanthropy can mitigate the negative overall effects of the high degree of Charity and Charity Preferences, and is consistent with the rest of this section.

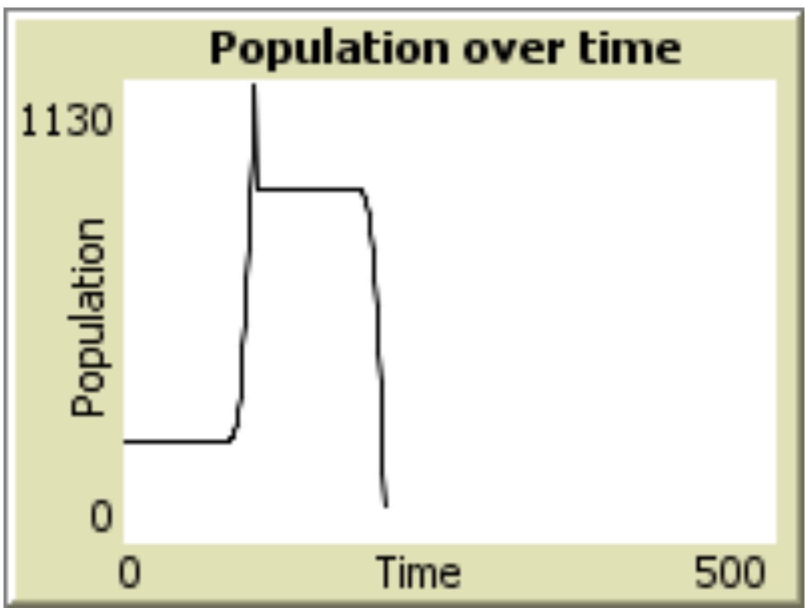


Figure 9 Charity-Heavy Assistance Package—Population Over Time

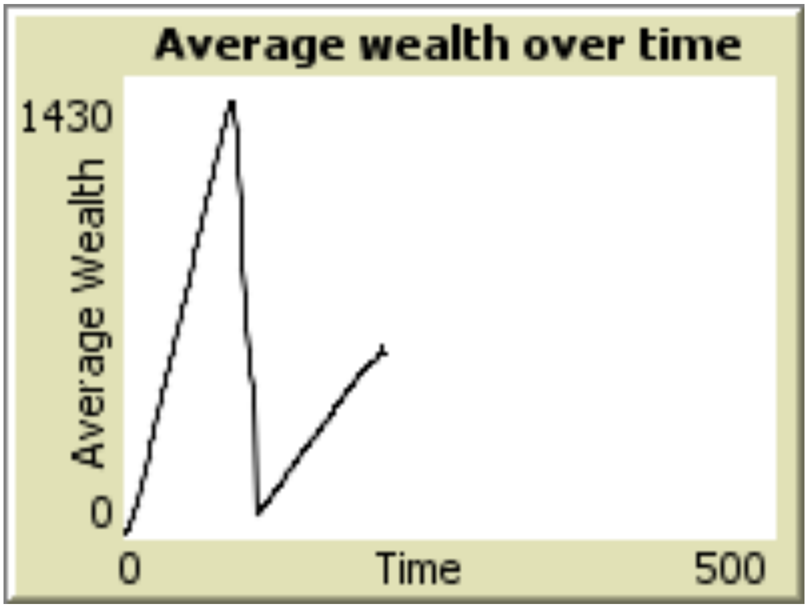


Figure 10 Charity-Heavy Assistance Package—Average Wealth Over Time

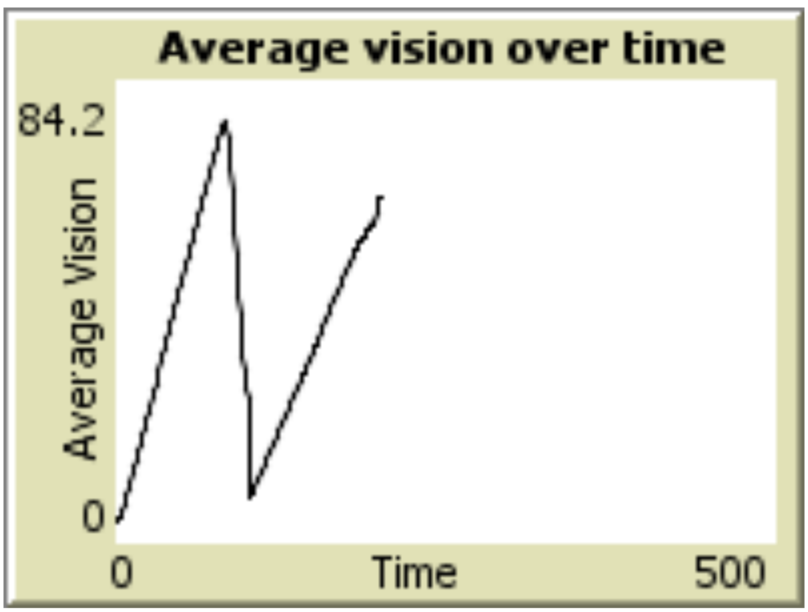


Figure 11 Charity-Heavy Assistance Package—Average Vision Over Time

Population Stability

As described earlier, a simulation run was seen as stable if it made it to 500 steps. This is incredibly theoretically important since Charity is seen as destabilizing for a society and Philanthropy is seen as stabilizing. Histograms were used to visually display the relationships between Philanthropy and stability, Charity and stability, and Preferences for Charity and stability. The computational model produced the following results:

Philanthropy: Figure 2 is a histogram portraying the relationship between Philanthropy and population stability (Final_Steps were set to equal 500). Philanthropy did not have much of an effect on stability, whether stabilizing or destabilizing. Regression results were consistent with this in showing almost no relationship.[9]

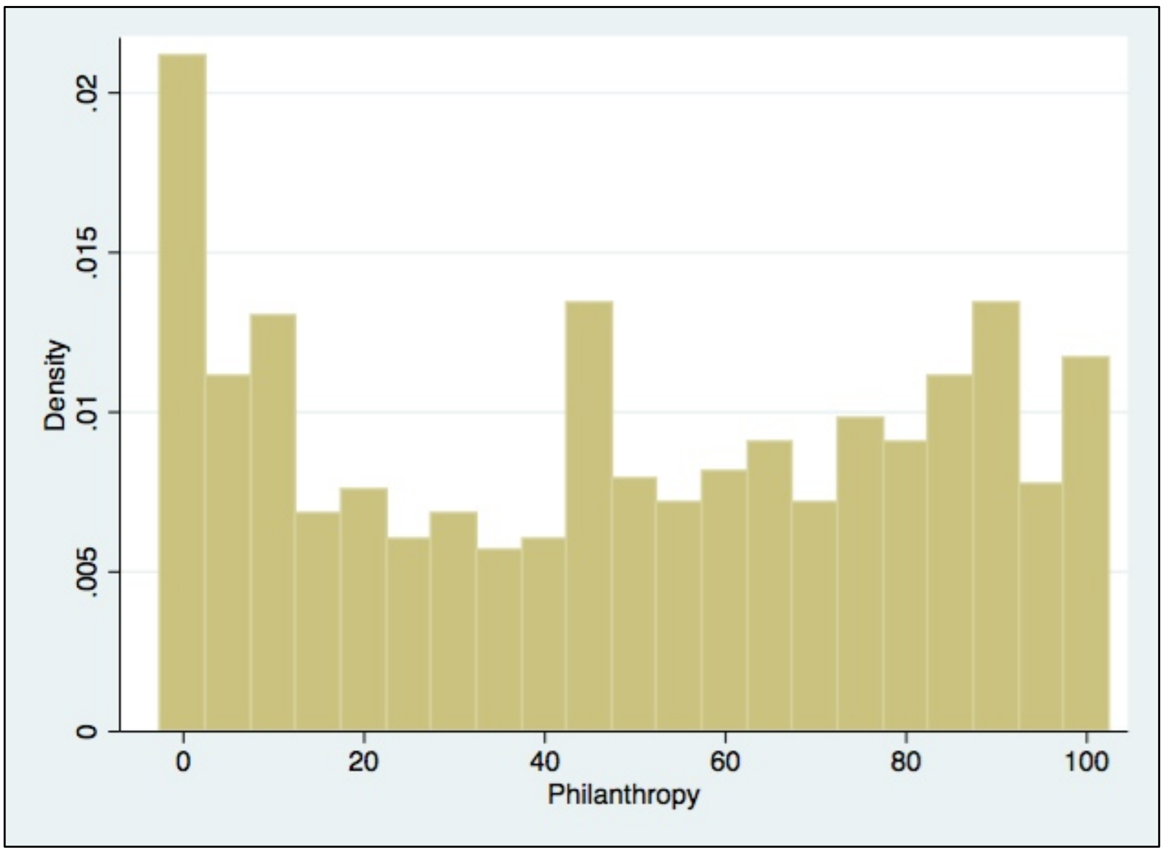


Figure 12 Histogram—Philanthropy and Population Stability

Charity: Figure 3 is a histogram portraying the relationship between Charity and population stability (Final_Steps were set to equal 500). The histogram shows a clear relationship between Charity and population stability, supporting the hypothesis that Charity is destabilizing.

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9 For this regression, the relationship was extremely statistically insignificant, with the relationship being only significant at the $p > .938$ level. The r-squared was zero, and the coefficient was -.0001647, so close to zero.

Regression results were consistent with this in showing a negative relationship between Charity and Final_Steps, significant at the p >.001 level.[10]

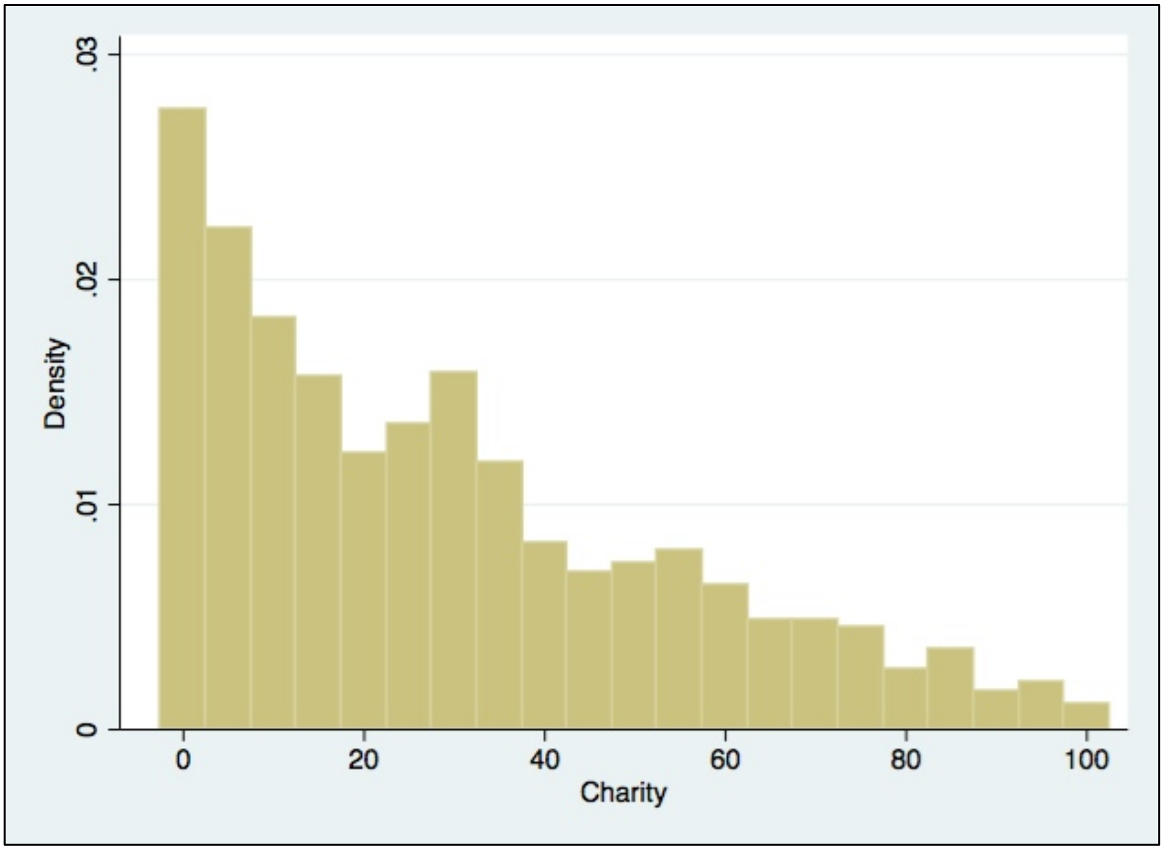

Figure 13 Histogram—Charity and Population Stability

Charity Preferences: Figure 4 is a histogram portraying the relationship between Preferences for Charity and population stability (Final_Steps were set to equal 500). The histogram shows a clear relationship between Preferences for Charity and population stability, supporting the hypothesis that preferring Charity over Philanthropy is destabilizing. Regression results were

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[10] While the relationship is highly statistically significant, the coefficient was only -.0545453, meaning that for every percentage increase in Charity, Final_Steps decreased by approximately 1/20 of a step. In addition, the r-squared was only 0.0684, meaning that the presence of Charity only explained 6.8% of the variation in Final_Steps.

consistent with this in showing a negative relationship between Preferences and Final_Steps, significant at the >.001 level.[11]

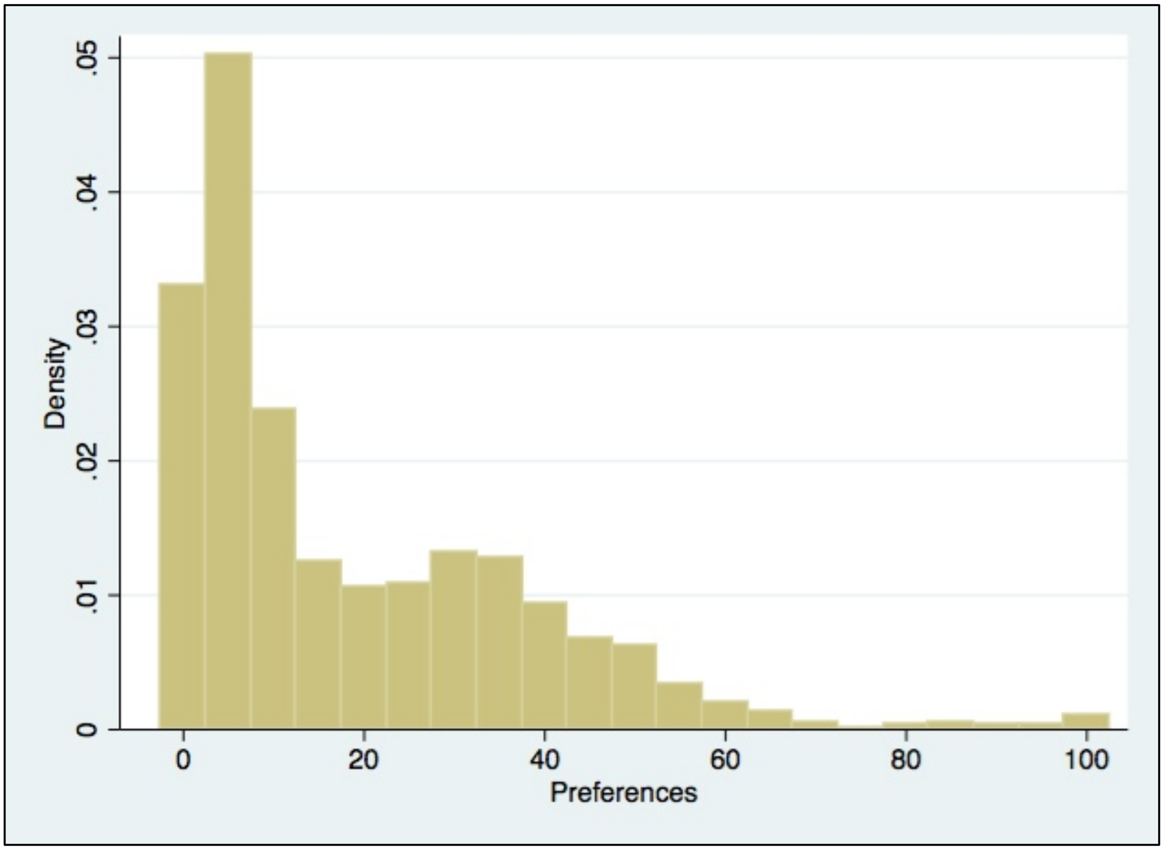

Figure 14 Histogram—Charity Preferences and Population Stability

[11] While the relationship is highly statistically significant, the coefficient was only -.0976262, meaning that for every percentage increase in Preferences, Final_Steps decreased by approximately 1/10 of a step. In addition, the r-squared was only 0.2208, meaning that preferences for charity only explained 22% of the variation in Final_Steps.

T-tests (Mean Comparisons)

As this dissertation has hypothesized that Charity and Philanthropy have different effects in society, it was important to test and see if the output generated from these simulations support this hypothesis. Mean comparison t-tests were used to perform the hypothesis testing in this stage.

When there is population stability (Final_Steps=500), Philanthropy and Charity are statistically significantly different at the >.001 level. Mean Philanthropy is approximately 45.65 and mean Charity is approximately 29.14. The mean Final_Steps if Philanthropy is more prevalent than Charity is approximately 37 steps greater than if Charity is more prevalent than Philanthropy. This difference is statistically significantly different at the >.001 level.

What this means is that, on average, the prevalence of Charity is associated with population instability in the model. This relationship is statistically significant with a meaningful difference between the effects of Charity and Philanthropy on population stability. The conclusion supports the hypotheses that Charity is destabilizing while Philanthropy is either stabilizing or at the very least is minimally destabilizing.

Also, the mean population if Philanthropy is more prevalent than Charity is roughly 160 agents more than if Charity is more prevalent. This difference is statistically significantly different at the >.001 level. Also, the mean Average Wealth if Philanthropy is more prevalent than Charity is nearly 200 units of sugar higher than if Charity is more prevalent. This difference is also statistically significantly different at the >.001 level. The implications of this are that, on average, a greater prevalence of Philanthropy is associated with higher population levels and average wealth.

Finally, if Philanthropy is more prevalent than Charity, agents can see 9 patches farther on average than if Charity is more prevalent. This difference is statistically significantly different at the >.001 level. The mean Gini if Philanthropy is more prevalent than Charity is on average 75 points higher than if Charity is more prevalent. This difference is also statistically significantly different at the >.001 level. This supports the hypothesis that Philanthropy is associated with a higher productive capacity of those who benefit. However, since not all agents (or all people in a society) value this, the average effects on Gini are not surprising.

Regression Results

Finally, regression analysis was performed to explore the relationships, if any, between Philanthropy, Charity, and Preferences for Charity on population, Gini, Average Wealth, and Average Vision. Generally speaking, Philanthropy, Charity, and Preferences for Charity had highly statistically significant relationships with the main dependent variables (Mean_Pop, Mean_Gini, Mean_Avg_Wealth, and Mean_Avg_Vision) but were able to explain very little of the variation. Even though the coefficients were very low, the negative or positive associations were as expected for the most part. Since the parameters for sugar and vision were chosen relatively arbitrarily (4 units of sugar does not directly translate to actual wealth), the low coefficients could be an artifact of the output. Future research with actual data could address this issue, but for purposes of this discussion, the focus is on the significance of the relationships and the negative or positive associations.

<u>Philanthropy</u>: The prevalence of Philanthropy had statistically significant relationships at the >.001 level with Mean_Pop, Mean_Avg_Wealth, and Mean_Avg_Vision, and a statistically significant relationship at the >.05 level with Mean_Gini. The only negative association was with Mean_Avg_Wealth. This is most likely a function of agent priorities being the same throughout the duration of a simulation run. In reality, a person is likely to acquire human capital (i.e. going

to college), and then at some point alter preferences towards accumulating wealth. Future research could make agent preferences more dynamic once vision reaches a certain point.

For Mean_Pop, Mean_Gini, and Mean_Avg_Wealth, the regression explained very little of the variation.[12] However, as seen below, the prevalence of Philanthropy explained approximately 41% of the variation in Mean_Avg_Vision. Also, for each percentage increase of Philanthropy prevalence, vision increases on average by 1.28 vision points, which shows a meaningful relationship between the two variables.

[12] Specifically, the regression model from Philanthropy on Mean_Pop explained less than 1% of variation in Mean_Pop with a coefficient of only .0024588. The regression model from Philanthropy on Mean_Gini explained less than 1% of variation in Mean_Gini with a coefficient of only .00262. The regression model from Philanthropy on Mean_Avg_Wealth explained less than 1% of variation in Mean_Avg_Wealth with a coefficient of -.018359. The full regression output is in Appendix 4.

Table 14 Regression Results for the Effects of Philanthropy Prevalence on Mean_Avg_Vision

```
. reg  Philanthropy Mean_Avg_Vision

      Source |       SS       df       MS              Number of obs =    9388
-------------+------------------------------           F(  1,  9386) = 6623.53
       Model |   3513502.7     1   3513502.7           Prob > F      =  0.0000
    Residual |  4978879.35  9386   530.45806           R-squared     =  0.4137
-------------+------------------------------           Adj R-squared =  0.4137
       Total |  8492382.05  9387  904.696074           Root MSE      =  23.032

------------------------------------------------------------------------------
   Philanthropy |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
Mean_Avg_Vision |   1.283233   .0157674    81.39   0.000     1.252326    1.314141
          _cons |  -3.597725   .6993739    -5.14   0.000     -4.96865   -2.226801
```

Charity: The prevalence of Charity had statistically significant relationships at the >.001 level with Mean_Pop, Mean_Gini, Mean_Avg_Wealth, and Mean_Avg_Vision. Charity was negatively associated with Mean_Pop, Mean_Gini, and Mean_Avg_Wealth as expected.[13] The more surprising finding was that Charity was positively associated with Mean_Avg_Vision. Specifically, for each percentage increase in Charity prevalence, vision increases on average by roughly .28 vision points, which shows a meaningful relationship between the two variables. However, this regression only explains roughly 2% of the variation in Mean_Avg_Vision.

Table 15 Regression Results for the Effects of Charity Prevalence on Mean_Avg_Vision

[13] Specifically, the regression model from Charity on Mean_Pop explained only 13% of variation in Mean_Pop with a coefficient of only -.0243091. The regression model from Charity on Mean_Gini explained only 9% variation in Mean_Gini with a coefficient of only -.0344843. The regression model from Charity on Mean_Avg_Wealth explained only 23% variation in Mean_Avg_Wealth with a coefficient of -.174921. The full regression output is in Appendix 4.

```
. reg  Charity Mean_Avg_Vision

      Source |       SS       df       MS              Number of obs =    9388
-------------+------------------------------           F(  1,  9386) =  182.57
       Model |  165495.332     1  165495.332           Prob > F      =  0.0000
    Residual |  8508131.39  9386  906.470423           R-squared     =  0.0191
-------------+------------------------------           Adj R-squared =  0.0190
       Total |  8673626.72  9387  924.004125           Root MSE      =  30.108

--------------------------------------------------------------------------------
        Charity |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------+---------------------------------------------------------------
Mean_Avg_Vision |    .278502   .0206116    13.51   0.000     .2380988    .3189053
          _cons |   37.87685   .9142411    41.43   0.000     36.08474    39.66896
```

Charity Preferences: The prevalence of Preferences for Charity had statistically significant relationships at the >.001 level with Mean_Pop, Mean_Gini, Mean_Avg_Wealth, and Mean_Avg_Vision. Charity Preferences were negatively associated with Mean_Pop and Mean_Gini as expected. Not surprisingly, Preferences for Charity was positively associated with Mean_Avg_Wealth (consistent with Philanthropy findings) and Mean_Avg_Vision (consistent with Charity findings).[14] Interestingly, Preferences for Charity was able to explain more variation in the dependent variables than Philanthropy or Charity Preference. For example, as seen below, Preferences explain 12% of the variation in Mean_Avg_Wealth. Also, each additional percent of the population preferring Charity is associated with an average additional 1/8 unit of sugar increase in average wealth.

Table 16 Regression Results for the Effects of Preferences for Charity on Mean_Avg_Wealth

[14] Specifically, the regression model from Charity preferences on Mean_Pop explained only 6% variation in Mean_Pop with a coefficient of only -.0168825. The regression model from Charity preferences on Mean_Gini explained only 13% variation in Mean_Gini with a coefficient of only -.0418089. The regression model from Charity preferences on Mean_Avg_Vision explained less than 1% of variation in Mean_Avg_Vision with a coefficient of only .0684722. The full regression output is in Appendix 4.

```
. reg  Preferences Mean_Avg_Wealth

      Source |       SS       df       MS              Number of obs =    9388
-------------+------------------------------           F(  1,  9386) = 1286.68
       Model |  1037677.61     1  1037677.61           Prob > F      =  0.0000
    Residual |  7569572.12  9386  806.474763           R-squared     =  0.1206
-------------+------------------------------           Adj R-squared =  0.1205
       Total |  8607249.73  9387  916.932964           Root MSE      =  28.398

--------------------------------------------------------------------------------
   Preferences |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
Mean_Avg_Wealth |   .1252248    .003491    35.87   0.000     .1183816    .1320679
         _cons |   5.959435   1.262125     4.72   0.000     3.485396    8.433474
```

Robustness

While both the prevalence of Charity and Preferences for Charity are generally associated with instability in the model, it was important to understand the robustness of the model and some boundary conditions. To do this, the model was explored computationally to search for simulation runs in which stability was achieved with high levels of Charity and/or Preferences for Charity. Out of a total of 9,888 simulation runs, 1,059 of these achieved stability, reaching 500 steps. Out of these runs, 82 had Charity prevalence greater than or equal to 75%, and 249 simulation runs had Charity prevalence greater than or equal to 50%. In other words, less than a quarter of the stable simulation runs had Charity prevalence of 50% or greater, and less than a tenth of these had Charity prevalence of 75% or greater.

Regarding Preferences for Charity, out of the 1,059 simulation runs achieving stability, 15 runs had Charity Preference greater than or equal to 75%, and only 87 simulation runs had Charity Preference greater than or equal to 50%. In other words, less than a tenth of the stable simulation runs had a Charity Preference of 50% or greater, and even less had a Charity Preference of 75% or greater.

Of these, there was only one simulation run with both high Charity prevalence (90%) and high Charity Preferences (100%). However, this was also accompanied with 75% Philanthropy prevalence. Out of 12,500 additional simulation runs (for a total of 21,888), 3,262 achieved stability. 380 of these had both high Charity prevalence and Charity Preferences, which is less than 15% of all stable simulation runs. However, most of these were accompanied with a high degree of Philanthropy prevalence (at least 75%) as well.

These results imply that while Philanthropy alone is neither stabilizing nor destabilizing, in a Charity-heavy environment, high Philanthropy prevalence can be the stabilizing element needed. In fact, roughly 2/3 (2181 simulation runs) had at least 50% Philanthropy prevalence. A low Charity Preference rate (same as high Philanthropy Preference rate) tells a similar story with 1960 simulation runs achieving stability.

Conclusions

This output generated from these simulation runs supports the hypothesis that charity has destabilizing effects for a society. However, since entrepreneurship was not included, inferences on the direct effects of charity on entrepreneurship and development cannot be made. That being said, the destabilizing effects of charity are important and make a strong case that charity on such a system-wide level would have a negative effect on development. It would be useful for future versions of this model to include entrepreneurship and test this hypothesis directly.

Also, the output generated from these simulations supported the hypothesis that philanthropy without productive entrepreneurship may provide some benefit even if this alone is not enough to lead to development. Specifically, the increases in average wealth associated with philanthropy, while statistically significant, were minimal. Any increases in average wealth are likely due to a higher population that is more efficient at obtaining resources (higher average sugar). Even though wealth increases are inherently limited due to the lack of entrepreneurship, it can be inferred that philanthropy provided benefit to the extent possible.

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