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EXPLORING ADVANTAGES IN THE WAITING lIST FOR ORGAN DONATIONS

Christine Harvey
James R. Thompson

The MITRE Corporation
7515 Colshire Drive
McLean, VA 22102, USA

ABSTRACT

The waiting list for organ transplants is a complex system that affects the lives of thousands of Americans. The current policies in the United States allow patients to register at multiple Donor Service Areas (DSAs) provided they have physician approval and can cover the costs of any additional testing through insurance or personal means. This practice gives rise to ethical concerns, especially among those who believe it allows the wealthy to take unfair advantage of the system. We develop an agent-based, discrete event model that simulates the practice of multiple listings in transplant waiting list queues to explore the effects on the overall transplant system. Our analysis shows that although there are no major impacts at the national or global level, there are potential consequences at the local DSA level depending on the heterogeneity of the DSAs involved.

1 INTRODUCTION

A portion of patients eligible for an organ transplant receive organs from living donors. The remaining eligible patients must receive an organ from a deceased donor and are subsequently added to the national waiting list. In the United States, there are currently over 120,000 people waiting for a transplant from a deceased donor (Organ Procurement and Transplantation Network 2015). According to the United Network for Organ Sharing (UNOS), someone is added to the national transplant waiting list roughly every ten minutes or 144 per day. UNOS also reported 30,969 organ transplants were performed in 2015 or roughly 85 per day, and an additional 22 people die each day on average waiting for an organ. A rough calculation based on these numbers illustrates the growing shortage of organs in the U.S. and underscores the time-critical nature for those who make it onto the national waiting list.

In practice, the United States is divided into 58 different Donor Service Areas (DSAs) that are managed by the Organ Procurement Organization (OPOs), which manages organ donation and transplantation in the geographic area. There are currently no limitations on registering at multiple transplant centers in various DSAs (The United Network for Organ Sharing 2015). The lack of restrictions in regards to multiple registrations is an allowance that some believe gives an unfair advantage to those with the financial means to travel anywhere in the country to receive medical care.

In this paper we develop an agent-based model of patients in the United States on the waiting list for a kidney transplant. The patients are added to one or more queues representing the regional DSA waiting lists. Some patients have greater advantages than others and are able to register in more than one DSA. We refer to these patient in the model as the Advantaged patients. The model enables us to analyze the effects on the overall transplant system when a portion of the patients have the means to register in multiple DSAs.

The remainder of the paper is laid out as follows. Section 2 describes the background of the transplant problem along with a brief literature review. The model outline and implementation are discussed in Section 3, along with a description of the input data and experimental design. Section 4 presents the subsequent results of our experiments. We close in Section 5 with a brief discussion and avenues for extending this research.

2 BACKGROUND

Various conditions and diseases may cause a person's organs to shut down. Modern medicine allows functioning organs to be transplanted from one person to another. Certain patients can be treated by receiving a new organ, these patients are referred by a physician to be placed on the national transplant waiting list, managed by UNOS (Organ Procurement and Transplantation Network 2015). The UNOS waiting list governs the allocation of heart, lungs, liver, kidney, pancreas, and intestines across the United States.

Patients eligible for a transplant must wait until an appropriate match is found. Many factors are considered in the matching process including blood type, height, weight, the number of HLA antigens in common between the donor and the recipient based on tissue typing, the size of the organ, and geographic location. When an organ becomes available, priority is given to patients based on the quality of the match, the health of the potential recipient, and the amount of time a patient has been waiting. Once the medical attributes are considered the system generally functions as a first-in-first-out queue of matched patients. In most cases — outside of the most severe circumstances — organs are allocated first within the DSA, then throughout the region, and finally across the rest of the country (Friedewald et al. 2013). The waiting list process is shown in Figure 1.

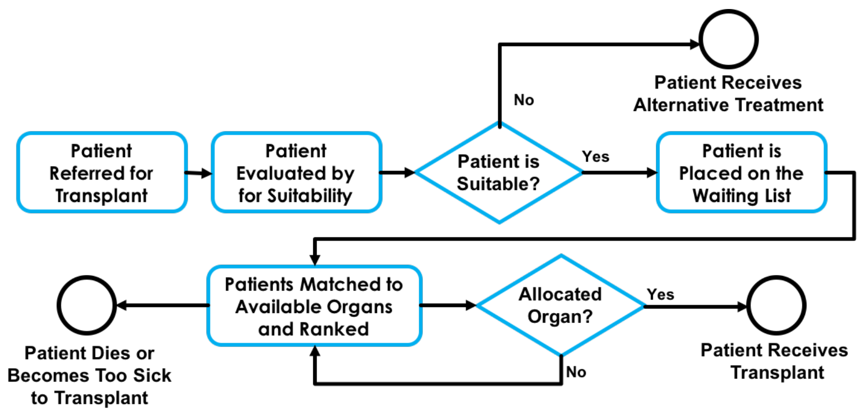


Figure 1: Organ transplant process from the initial referral to receipt of transplant or alternative treatment.

Research has been completed on the organ allocation and transplant system in the United States and various other countries. A 2013 Winter Simulation Conference paper discusses the development of a model of the kidney transplant system, KSIM. This paper described a discrete event simulation at the DSA level to simulate organ allocation policies (Davis and Friedewald 2013). This work did not provide extensive experimentation and focused largely on geographic and demographic information. Additional work in modeling the transplant system has focused on queuing models and waiting time inconsistencies. The focus of this work was the differences in waiting times across different blood types (Stanford, Lee, Chandok, and McAlister 2014). The core research body in this area focuses on allocation policies of organs and not the effects of allowing multiple registrations for candidates (Zenios, Chertow, and Wein 2000, Su and Zenios 2004, Boxma, David, Perry, and Stadje 2011).

There are 58 DSAs and 11 regions in the U.S. As a result of the prioritizing process, registering in a second or even third DSA could prove to be an advantage for a person originally listed in an area with a higher median waiting time (Health Resources & Services Administration 2015). The shortest median waiting time for a kidney transplant across DSAs in 2009 was 6 months compared to the longest median waiting time of 5.22 years (Davis et al. 2014). According to research published in the Journal of Transplantation, the difference in wait times is correlated with heterogeneity in the number of patients suffering from end-stage renal disease, the number of patients listed for transplant, and the organ procurement rates in a given region (Davis et al. 2014).

Due to the wide range in waiting times, patients can choose to register at more than one DSA. However, the lack of restrictions in regards to multiple registrations lead some to believe that an unfair advantage exists for those with the financial means to travel great distances to receive medical care. One of the most well-known examples of multiple registrations is when former Apple CEO, Steve Jobs, received a liver transplant at a hospital in Tennessee despite being a California resident (Cox 2009). This caused public outrage and many considered this a "loophole" existing for the rich to use when faced with the realization that donor organs are in short supply (Cox 2009). More recent studies have shown that patients with the ability to register in multiple DSAs may be more likely to receive a transplant (American Heart Association 2015). In the next section we outline the agent-based model we constructed to investigate the effect that multiple registrations being available to an advantaged few has on the overall transplant waiting list process.

3 THE MODEL

In this section we describe an agent-based model of the organ transplant waiting list with multiple DSAs. The model consists of patients (i.e., agents) that are in need of a kidney transplant and localized waiting lists that represent the DSAs. Our objective is to explore the outcomes when certain patients have advantages in access to healthcare that others do not. Patients with additional resources are able to register in multiple regions beyond their primary region for an organ transplant. Our experimental design investigates the impact that allowing multiple listings has on the transplant system to gain a better understanding of the implications of this practice. The model was programmed in Python version 2.7 using the Mesa package for agent-based modeling (Project Mesa Team 2015) and implemented in Jupyter (Project Jupyter 2015) to enable rapid prototyping, web browser compatibility, and accessible documentation.

3.1 The Patients

The agents in our model are patients who have been deemed eligible for a kidney transplant. Each patient is therefore in one of four conditions; either Waiting, Selected, Transplanted, or Deceased. Waiting patients are on at least one of the regional transplant waiting lists and have not yet been chosen for a transplant. Selected patients were at the front of at least one of the regional waiting lists in the last time step and have just been chosen for a transplant. Transplanted patients have successfully completed the organ transplant process. Deceased patients were in the Waiting state longer than their lifespan and thus died before being Selected and Transplanted.

Upon instantiation, each patient is assigned a primary region and they are added to that region's waiting list. Each patient is also randomly designated as either "Advantaged" or not according to the user-specified distribution of advantaged patients. Patients that are Advantaged are then added to additional waiting lists beyond their primary region. The number of additional waiting lists is selected from a $U(1, \frac{N_{\text{region}}}{2})$ distribution, where N_{region} is the number of DSAs in the model not including the patient's primary region. The uniform distribution is a simplified approach to a complex problem where data on the exact number and frequency of multiple registrations on two or more lists is not known. The upper limit of half the regions as a selection criteria was implemented to show some realistic time constraints on the agents as it is time consuming to travel and apply for multiple waiting lists, although not impossible.

Finally, each patient is assigned a lifespan parameter T_{life} at instantiation. The T_{life} parameter represents the maximum amount of time the patient can be in the Waiting state before moving to the Deceased state. That is, if $T_{\text{wait}} > T_{\text{life}}$ the patient exits the Waiting state and enters the Deceased state. For our base case run of the model, T_{life} of each patient is selected from a $\text{Normal}(98, 5^2)$ distribution, which corresponds to an average lifespan of 98 months. Figure 2 illustrates how this process is implemented in the model.

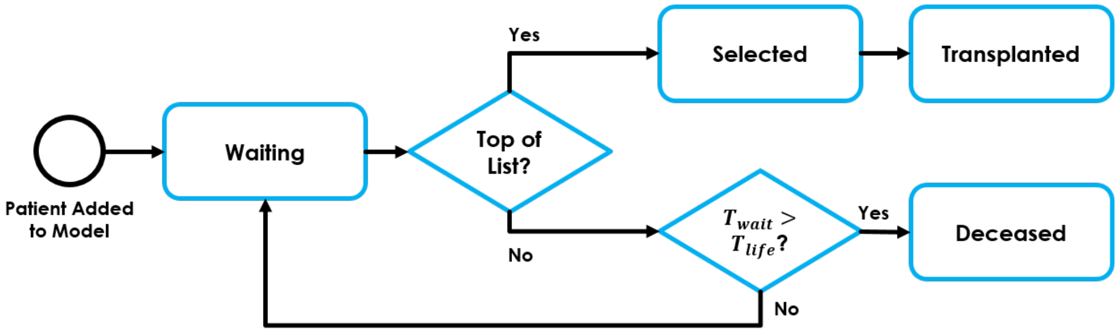


Figure 2: Overview of the states of a patient in the model.

Patients do not inherently have adaptive traits in the model. However, the model does have an option for the Smart Listing. When the model is in Smart Listing mode, the Advantaged patients compute the ratio of transplant arrival rate to queue length, and select the alternate regions with the highest ratio. If the model is not in Smart Listing mode, agents choose their secondary listing randomly from a uniform distribution of the remaining options outside of their primary listing location. In the real world, patients can look up statistical information on transplant rates in different DSAs and choose to register in additional areas with high transplant rates, the Smart Listing mode replicates this knowledge and awareness.

3.2 The Organ Transplant Waiting Lists

Each regional waiting list in our model is implemented as a first-in-first-out queue. However, as mentioned in the previous section, balking exists as patients waiting beyond their lifespan will be removed from the queue before receiving a transplant, and Advantaged patients will be removed from all queues they are in when they receive a transplant from one of their queues.

Upon initialization of the model, each waiting list is populated with a user-specified number of patients already in queue. This population distribution is based on data from the current UNOS waiting list. At each subsequent time step, N_i kidneys become available for transplant in the i^{th} region according to a Poisson process. The first N_i patients on the waiting list are selected to receive a transplant and are thus removed from the i^{th} queue. These patients transition to the Selected state. If the patient selected is Advantaged and listed in other queues, they are removed from those queues before the kidneys in those regions are allocated. The order in which each waiting list is selected is randomized at each time step. Additionally, new patients requiring a transplant arrive at each time step according to another independent Poisson process. The arriving patients are randomly allocated to a primary regional waiting list and Advantaged patients are randomly allocated to more than one list as described previously.

Figures 3a and 3b depict the waiting list structure and the advantage a patient may have by listing in multiple regions. Patient I is an Advantaged patient registered in both Regions 2 and 3. When the first two patients on all three lists receive a transplant, as shown in Figure 3b, Patient I is selected in Region 3 much sooner than if they had only queued in Region 2. However, Patient K missed out on this round of transplants because the Advantaged Patient I was able to list in two regions.

3.3 Model Scheduling and Process Overview

Time is modeled as discrete steps corresponding to approximately one month. Each replication is run for 120 time steps, which equates to roughly 10 years. The sequence of events executed at each time step is as follows. For each regional waiting list i, the number of organs available for transplant N_i is generated from a Poisson process calibrated to the i^{th} region. The order of the waiting list queues is then randomly shuffled to ensure each waiting list is equally likely to be selected first each time. Then, taking each waiting list in turn, the first $N_i$patients are marked as Selected and removed from the queue. If any of those patients

Region 1: [A, B, C, D]
Region 2: [E, F, G, H, I]
Region 3: [J, I, K]

(a)

Region 1: [A, B, C, D]
Region 2: [E, F, G, H, ~~I~~]
Region 3: [J, I, K]

(b)

Figure 3: (a) The status of three regional queues at time $t = 1$ with Patient I listed on both queues. (b) The status of the same queues at time $t = 2$ when the first two patients in each queue have been selected for transplant.

are Advantaged, they are subsequently removed from whatever position they held in the other waiting lists before the organs for that waiting list are allocated.

Once the queues are updated, the patients are updated to reflect the advancement of time. Each of the patients that were not selected increment their waiting time T_{wait} by 1. If the patient is in the Selected stage, the patient transitions to the Transplanted stage. If a patient is still in the Waiting stage and they have been waiting for longer than their predetermined lifespan, the patient will move to the Deceased stage.

Finally, new patients are added to the model according to an independent Poisson process calibrated to each region. A portion of these patients will be Advantaged and therefore listed in multiple regions. The model terminates when there are no longer any patients in the Waiting state or if the number of time steps has exceeded 120. Python's Mesa module provides the *DataCollector* to track patient states in the model over time (Project Mesa Team 2015). Tracking these statistics allows for simple and quick visualizations of the process and model statistics. The user can specify which statistics are managed by the DataCollector at the start of each model run. The model also tracks the number of patients meeting the following criteria:

- Patients transplanted that were a primary listing in the queue
- Patients transplanted that were an alternate listing in the queue
- Patients with a primary listing in the queue that received a transplant elsewhere
- Patients with a primary listing that died before receiving a transplant
- Patients with a primary listing
- Patients listed as alternate

3.4 Calibration and Model Input

Our model follows several basic concepts and theories related to the real-world allocation of organs in the United States. The model directly incorporates different DSAs and allows a patient to join multiple listings in accordance with current policies and practices in the U.S.

The queues are represented at a fairly simple level of complexity, as we do not account for specific rules in the transplant system that give preference to certain individuals such as healthier adults or pediatric patients. The model also does not account for any sort of matching quality. In other words, the patients are homogeneous and all deemed equally matched with the organs that come available. Given the focus of our study was the relative advantage certain patients gain from multiple listings, matching metrics were not crucial to the model design. We do allow for the inherent heterogeneity between regions in the model. For example, each queue has its own arrival rate of organs for transplant and they are calibrated to reflect the arrival rate of new patients to a given regional waiting list. This functionality enables us to explore areas corresponding to specific DSAs.

The model takes in multiple input parameters, most of which are optional. The number of regions, number of initial patients, and number of additional patients to be added each year are the main parameters that need to be defined. The transplant rates for each center can also be customized by the user, as can the arrival rates of new patients to each queue. The Advantage probability specifies the percentage of patients that have an advantage and may be listed at multiple centers. The average lifespan can also be customized before each run, and the user has access to flags that control output and whether the model is run in Smart listing mode. For our experiments, the variables and initial parameters were taken from the OPTN Website (Organ Procurement and Transplantation Network 2015) and are based on aggregate information pertaining to the following DSAs:

- Region 1: CAOP-OP1 OneLegacy
- Region 2: ILIP-OP1 Gift of Hope
- Region 3: INOP-OP1 Indiana Donor Network
- Region 4: MNOP-OP1 LifeSource Upper Midwest OPO

Each of these regions has specific information pulled from the online UNOS database (Organ Procurement and Transplantation Network 2015). The data is representative of kidney transplants in the year 2014.

Table 1: Initial input parameters in the model.

Parameter	Value	Description and Motivation
`regions`	4	The number of separate DSAs
`initial_patients`	16,000	The initial number of patients waiting at time $t = 0$
`additional_patients`	Poisson(230)	Average monthly arrivals of new patients needing transplant
`queue_probabilities`	[0.50, 0.20, 0.10, 0.20]	The portion of new patients allocated to each primary DSA, where each element represents a different region
`transplant_rates`	Poisson([50, 31, 16, 21])	Average monthly transplants N_i in each DSA where i represents the DSA
`advantage_prob`	$\in [0,1]$	Advantaged portion of the population
`output`	True	Write output statistics to a file or not
`average_lifespan`	$\mathrm{Normal}(98, 5^2)$	Corresponds to an average lifespan of just over 8 years
`smart_listing`	True	Determines whether the patient will intelligently determine where to make their alternate listings

General statistics used to compute regional input data are shown in Table 2. The number of arrivals for each region was determined by taking the historical total number of arrivals and subtracting waiting list removals for all reasons besides deceased donor transplantation and death.

Table 2: Annual Donor Service Areas transplant data from the UNOS database 2014.

Region	1	2	3	4
Deceased donor transplant	610	370	188	230
New patient arrivals	2,164	1,354	568	1,057
Transplant-eligible arrivals	1,396	568	273	567
Total patients	7,420	4,427	1,255	2,726
Transplants per patient	0.082	0.084	0.150	0.084

Input data is also used to generate the waiting times for the initial patients on the waiting list. At the start of the model many patients, realistically will have already been waiting for some time. The values displayed in Table 3 show the probabilities that are used to assign waiting times to these initial patients.

Table 3: Number of patients currently on the waiting list by time spent waiting for a transplant.

Months	[0,1)	[1,3)	[3,6)	[6,12)	[12,24)	[24, 36)	[36, 60)	[60, Inf)
Candidates	3,912	7,815	9,897	17,037	27,153	20,471	23,217	18,405
% Candidates	3.1%	6.1%	7.7%	13.3%	21.2%	16.0%	18.2%	14.4%

3.5 Experiment Configuration

We designed our experiment to study the effects on the transplant waiting list system as a whole when a certain portion of the population is Advantaged and thus able to register to be considered in multiple DSAs. All input parameters were held constant at the values shown in Table 1. We employed the batch run feature of Mesa to analyze the effect of different values of the advantage probability parameter on the transplant waiting lists.

Our intention was to explore the impact that Advantaged patients have on the overall transplant system and to analyze whether these patients gain an unfair advantage. The standard queuing measures of waiting times and the number waiting in queue are collected, along with the number of patients transitioning to the Deceased state. To create a fairness metric we collected the percentage of transplants performed on Advantaged patients and compared that to the percentage of the total population represented by Advantaged patients. We also collected the percentage of Deceased Advantaged patients less the percentage of Advantaged patients in the population. If the system is perfectly fair, we expect these differences to be zero. Conversely, if the Advantaged patients receive a disproportionate number of transplants the first metric will be positive. And if the Advantaged patients disproportionately avoid transitioning to the Deceased state, the second difference will be negative.

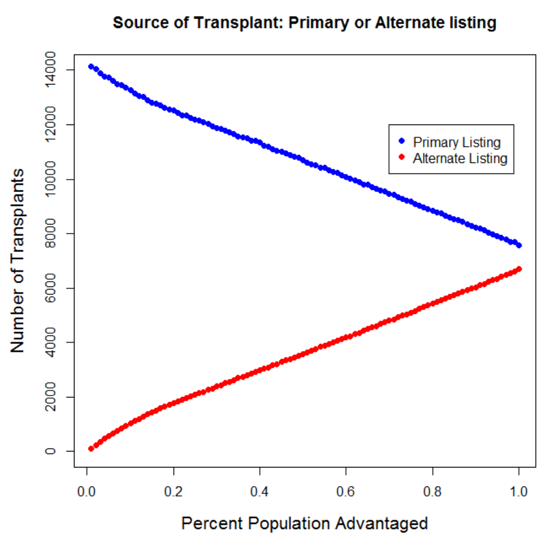
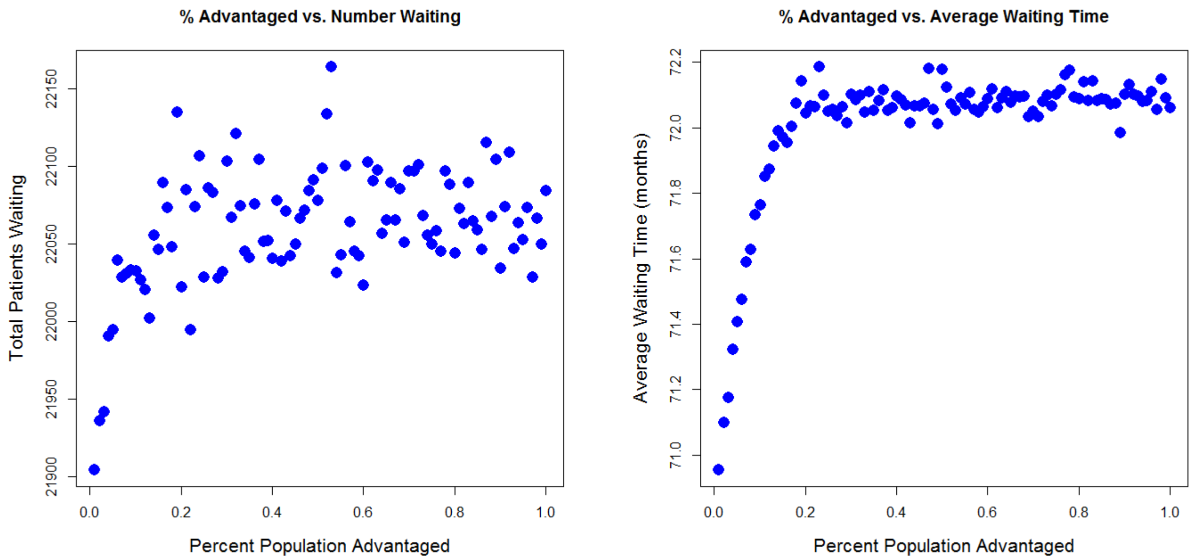


Figure 4: Number of transplants performed at either the primary or alternate listing.



(a) (b)

Figure 5: (a) Total number of patients in the waiting state as the Advantaged percentage increases. (b) The average wait time as the Advantaged percentage increases.

4 RESULTS

As mentioned in the previous section, our objective was to analyze the impact that Advantaged patients have on the overall transplant system. We ran 30 replications of the simulation in Smart listing mode for each of 100 different values of the `advantage_prob` parameter, allowing it to range from 0.1 to 1.0 in increments of 0.01. We then measured the total number of primary transplant listings and alternate transplant listings, which taken together describe the size of the national waiting list. The number of primary listing transplants and the number of alternate listing transplants were also recorded to give the total number of transplants and where they were acquired. We also tracked the number of Advantaged patients receiving a transplant for comparison with the total number of transplants. The average waiting time on the transplant list was recorded for each of the regional waiting lists, along with the number of patients transitioning to the Deceased state in each region.

Figure 4 shows the number of primary and alternate listing transplants performed with the proportion of Advantaged patients ranging from 0.1 to 1.0 in increments of 0.01. The total number of transplants remained consistent across all probabilities of Advantaged patients, averaging 14,278 over 120 months. As expected, the number of transplants being acquired from alternate listings increases as the percentage of the population becomes more and more Advantaged. However, even when the entire population is Advantaged only 47% of transplants are received from an alternate listing.

To analyze the system level impact that Advantaged patients have on the transplant waiting list, we investigated the total number of patients in the Waiting state as the percentage of Advantaged patients increased. Figure 5a shows the average number of patients waiting plotted against the percentage of the population that is Advantaged. Note that as Advantaged patients began to occupy multiple waiting lists simultaneously, the total number of patients waiting increased by roughly 200.

In keeping with a longer queue, the average time spent waiting for an organ also increased as shown in Figure 5b from roughly 71 months to just over 72 months. Note also that this transition to longer wait times and a longer queue happens when only a small percentage of the population is Advantaged. Once

20% or more of the population is Advantaged there is a diminishing impact and the queue length and wait times tend to level off.

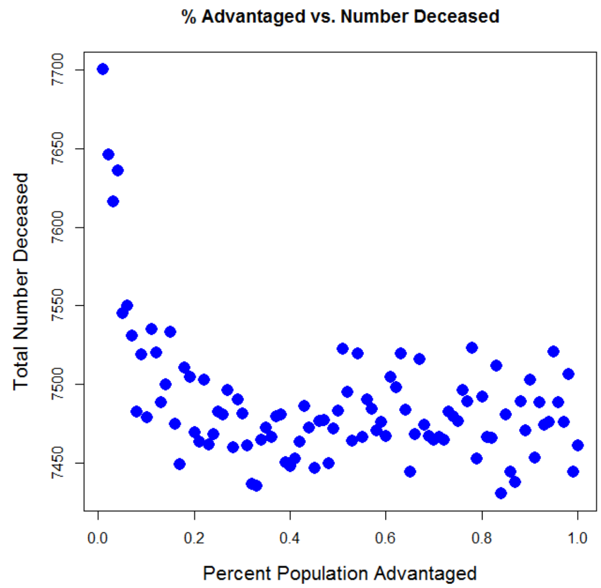
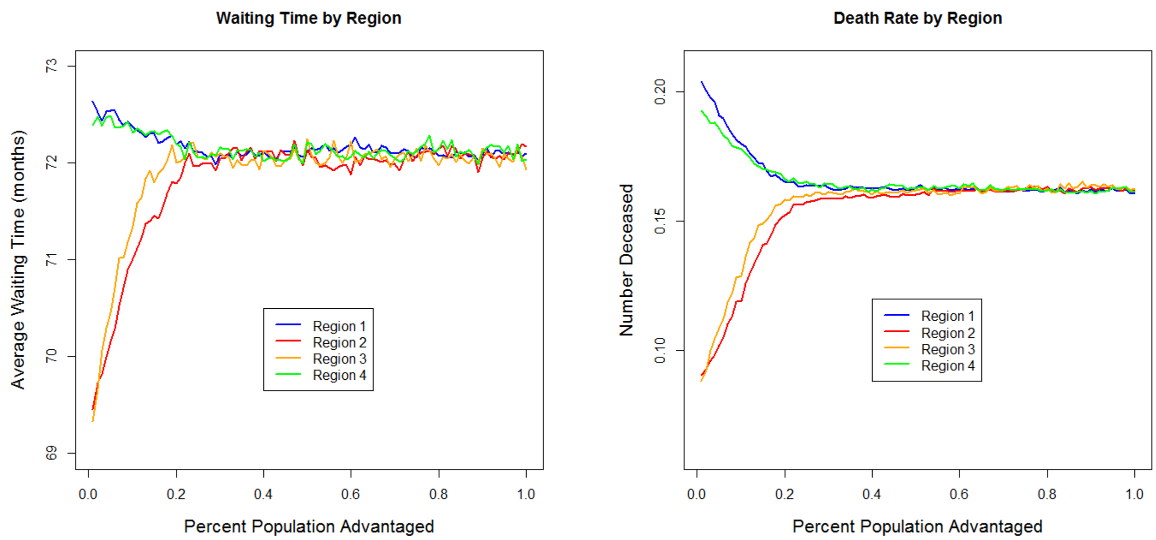


Figure 6: The number of patients transitioning to Deceased as Advantaged population increases.

The seemingly negative result of a longer national waiting list and longer average waiting time is accompanied by the counter-intuitive outcome of fewer Deceased patients overall. Fewer patients dying early on while waiting for a transplant result in a higher survival rate and therefore more people waiting for a transplant. Since the death rate is lower, the surviving patients waiting for a transplant is much higher, increasing the waiting list time. Figure 6 shows the average number of patients who transitioned to the Deceased state plotted against the percentage of the population that is Advantaged. Note again the majority of the impact occurs when only a small percentage of the population is Advantaged. With more than 20% of the population being Advantaged, the number of Deceased patients levels off.

The reason for using an agent-based approach for this model was to analyze not only the system level impact, but also the local level impact of having Advantaged patients present in the model. In light of the result that fewer deaths occur once some portion of the population are Advantaged, we analyzed the same metrics in the individual regions. Figure 7a shows how the average wait time for patients is not realized uniformly over all four regions. Instead, the majority of the increase in wait time comes from Regions 2 and 3, while Regions 1 and 4 showed slight decreases. This suggests that Regions 2 and 3 had favorable queue lengths and transplant rates that attracted the Advantaged patients to choose them as an alternate listing. Figure 7b shows that a similar pattern holds for the number of Deceased patients. As more Advantaged patients are attracted to Regions 2 and 3 the increased wait time means that more patients exceed their lifespan in those queues and die before receiving a transplant. Referring back to the statistics for DSAs these regions are calibrated to represent, these two areas had the absolute highest rate of donated organs per new patient arrivals. Since these two regions have such high donor rates, there is significant advantage to be gained from choosing them as an alternate listing.

Our final results examine the fairness of allowing Advantaged patients to list in multiple DSAs. One method for assessing fairness is to test whether Advantaged patients are disproportionately represented among those receiving transplants and those avoiding death. That is, if Advantaged patients constitute 20% of the population they should receive at most 20% of the transplants and make up 20% of the total deaths. In a fair system, the difference between the Advantaged patient transplant rate and the percentage



(a) (b)

Figure 7: (a) Wait time by region as Advantage population increases. (b) Death rate by region as Advantage population increases.

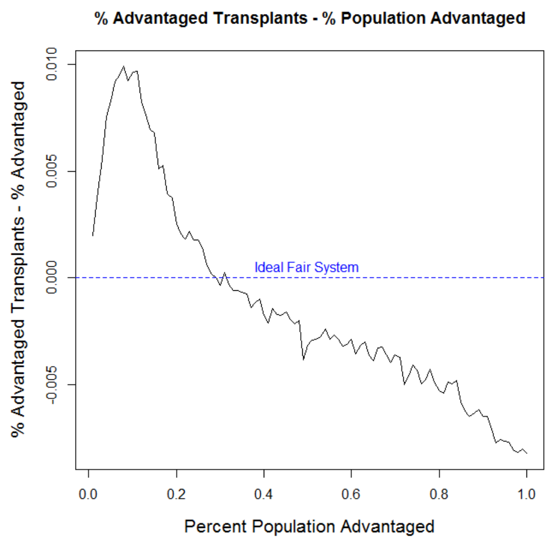
of Advantaged patients in the population should be zero. Similarly, the difference between the percentage of Advantaged patient deaths and the percentage of Advantaged patients in the population should also be zero. Figure 8a plots the difference for the Advantaged patient transplant rate and Figure 8b plots the difference for the Advantaged patient death rate. When the Advantaged population is less than roughly 30% of the total population, the Advantaged patients receive a disproportionate number of the available organs. Additionally, the Advantaged population always represents disproportionately fewer deaths, the most pronounced occurring when they make up less than 30% of the total population.

5 CONCLUSIONS

Our model of the national transplant list concurs with the allocation policies in effect in the United States allowing multiple transplant registrations outside a patient's primary region. Our results agree with earlier research that assert the policy of multiple registrations does not adversely affect the transplant list at the national level. Indeed, our results show only a slight increase in wait times and queue length, while simultaneously showing a decrease in the overall death rate of transplant patients.

Upon closer inspection, by allowing advantaged patients to register with multiple Donor Service Areas, there are disadvantages for patients at the local regional level. As shown in Figure 7b, when a small portion of the population is considered to be advantaged, patients with a primary listing in the smaller regions tend to have higher death rates compared to other regions. So although the national death rates are lowered overall, waiting lists with better donor programs attract the advantaged population and the locals in these areas are potentially harmed more than the national average reveals. The outcomes of our model suggest that the multiple listing policy should be studied more closely and on a regional level rather than on the national level. We contend that a model such as ours can be used to investigate whether certain policies unfairly disadvantage smaller communities that may become target areas for a domestic form of transplant tourism.

We employed the agent-based modeling paradigm when designing our model to enable incremental additions to the simulation and analysis it performs. As part of our future research we intend to make the population of patients considerably more heterogeneous to determine if additional disparities exist between



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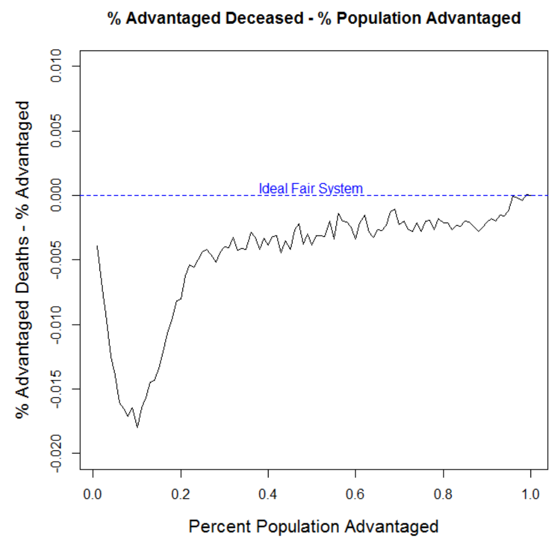

(b)

Figure 8: (a) The relative fairness in receipt of transplants. (b) The relative fairness in death rates.

aggregate measures and more specific ones. Similar upgrades will be added to better define what it means to be "advantaged," and more advanced decision-making algorithms can be added to the patients' behavior. We also intend to expand the number of regions to analyze whether the phenomena observed here scale accordingly when all 58 DSAs are considered. Given the results of our analysis, we contend that increased scrutiny at all levels of the transplant process are needed to accurately determine the true impact of certain policy decisions.

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AUTHOR BIOGRAPHIES

CHRISTINE HARVEY is a Modeling and Simulation Engineer at the MITRE Corporation where she specializes in data analysis and high performance computing in simulation. Her research interests include HPC in simulation, Agent Based Modeling, and Big Data Analysis particularity in the field of Healthcare. She completed her Masters in Computational Science from Stockton University in 2013 and is currently working on her PhD in Computational Science and Informatics at George Mason University. Her email address is ceharvey@mitre.org.

JAMES R. THOMPSON currently works at MITRE Corporation in Washington, D.C. He is a member of INFORMS, and his research interests are focused on stochastic modeling techniques, including agent-based simulation, large-scale discrete-event simulation, and system dynamics as applied to problems of policy making and decision analysis in the context of government, economics, and healthcare. His email address is jrthompson@mitre.org.