# Does Broader Sharing Improve Patient Outcomes? Analysis of The Share 35 Liver Allocation Policy

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**Problem definition:** This paper studies the deceased donor liver allocation policies in the United States (U.S.). The liver allocation policy has been through three major modifications in the last eight years, yet the issue of geographic inequity persists. Broader sharing of organs is believed to mitigate geographic inequity, and the recent policies are moving in that direction in principle.

**Methodology/results:** In this study, we develop a patient's dynamic choice model to analyze her strategic response to a policy change. First, we study the impact of the Share 35 policy, a variant of broader sharing introduced in 2013, on behavior change of transplant centers, geographic equity, and efficiency (transplant quality, offer refusals, survival benefit from a transplant, and organ travel distance). We find that sicker patients became more selective in accepting organs under the Share 35 policy. Second, we study the current Acuity Circles policy and conclude that it would result in lower efficiency (more offer refusals and lower transplant benefit) than the previous Share 35 policy. Finally, we show that broader sharing in its current form may not be the best strategy to balance geographic equity and efficiency. The intuition is that by indistinctively enlarging the pool of supply locations from where patients can get the offers, they tend to become selective, resulting in more offer rejections and less efficiency. We illustrate that a policy that equalizes supply (deceased-donors) to demand (waiting list patients) ratios across the geographies is better than broader sharing in achieving geographic equity at the lowest trade-off on the efficiency metrics.

**Managerial implications:** The key message to the policymakers is that they should move away from the "one-size-fits-all" approach and focus on matching supply and demand to develop organ allocation policies that score well both in terms of efficiency as well as geographic equity.

*Key words*: liver allocation, healthcare policy, geographic disparity, structural estimation, dynamic optimization

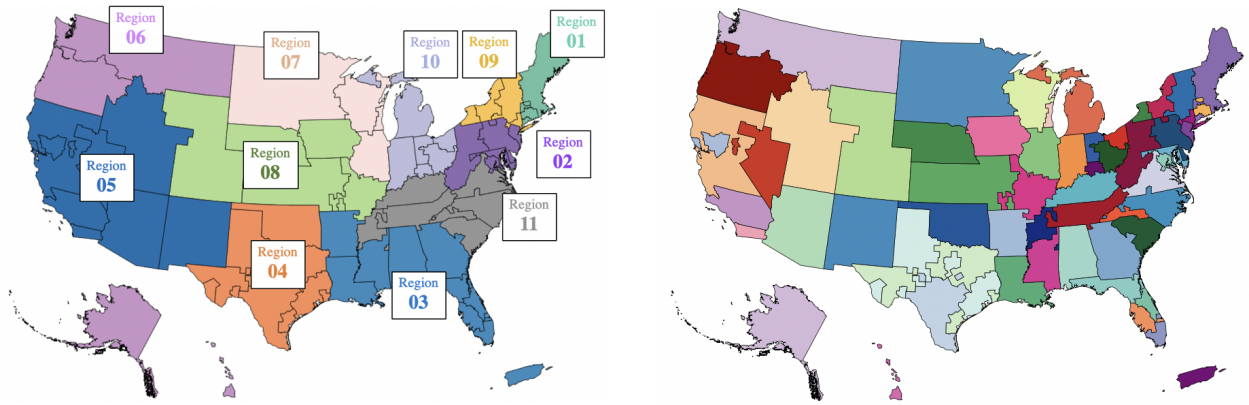


**Figure 1** **The U.S. is divided in to 11 regions (left) comprising of 58 DSAs (right).**

# 1. Introduction

## 1.1. Background

In the United States (U.S.), on average three people die every day awaiting a liver transplant for a total of 1,202 lives lost in 2019. While 12,941 patients were added to the waiting list in 2019, only 8,896 patients received liver transplantation. Liver transplantation is the only treatment option for patients with end-stage liver disease when other medical therapies have failed. The deceased donation has been contributing to greater than 95% of liver donations in the last 15 years in the U.S. Unlike living donation that can be arranged privately by a patient-donor pair, deceased-donor organs are considered *national* resources by law. The U.S. is divided into 11 geographical regions (Figure 1), which consists of 58 Donation Service Areas (DSAs). A DSA based allocation policy was in place for thirty years (from 1989 to Feb. 4, 2020) that recently got replaced by the Acuity Circles policy (Section 2.2). The medical urgency, used to rank the patients for an organ offer, is quantitatively measured by the Model for End-Stage Liver Disease (MELD) score. (Pediatric End-Stage Liver Disease (PELD) severity score, a measure calculated slightly differently, is used for patients $\leq 12$ years old.) MELD score reflects the probability of death within three months and ranges from 6 to 40; a higher score indicates greater mortality risk (Freeman et al. 2002). More serious patients are assigned Status 1A (for adults) and 1B (for non-adults), and their number is fewer than 50 nationwide at any time.

The U.S. government created the Organ Procurement and Transplantation Network (OPTN) in 1984 to coordinate a nationwide transplant system and optimize the usage of the limited resource of donor organs for transplants. Since 1986, the United Network for Organ Sharing (UNOS), a non-profit private organization has overseen the operations of the OPTN. A key regulatory framework that guides organ transplantation is the "Final Rule" that was adopted in 1998 by the Department of Health and Human Services (HHS) to establish a more detailed framework for the structure and operations of the OPTN (HHS 1998). The Final Rule requires that policies shall not be based on

| Candidate UNOS status at transplant | Number functioning (Alive) | Survival rate |
|---|---|---|
| MELD/PELD 6-14 | 759 | 89.8 |
| MELD/PELD 15-29 | 12538 | 90.2 |
| MELD/PELD 30-34 | 3492 | 89.3 |
| MELD/PELD $\geq$35 | 5283 | 87.0 |
| Status 1A | 934 | 83.8 |
| Status 1B | 377 | 89.0 |

**Table 1 One year Kaplan-Meier graft survival rate based on 2012-2015 transplants. Follow-up done till December 18, 2020.**

the candidate's place of residence or place of listing, except to the extent required by the other requirements of the Rule. Geographic inequity in access to liver transplantation across DSAs is well documented in the literature (see Yeh et al. 2011). In 2012, the OPTN board adopted a strategic plan that included reducing geographic disparities in access to transplantation. Hughes (2015) provide an excellent summary of the laws enacted to improve liver allocation policies in the U.S.

### 1.2. Motivation

In June 2013, the Share 35 policy was introduced, with the intent of reducing waiting list mortality and addressing the geographic disparity across the DSAs. It allowed broader sharing of organs to high MELD patients beyond the local DSA (where the organ was recovered). The summary statistics show that while the waiting list mortality rate (the number of patients who died on the waiting list divided by the number of new patients joining the waiting list) decreased from 12.0% in the pre-Share 35 era to 9.4% in the Share 35 era, the median waiting time to transplant increased by 5% (and its standard deviation across the regions increased by 28%). The survival rates of the transplanted patients in Table 1 from 2012 to 2015 indicate that lower MELD candidates have better outcomes. Therefore, a patient would want to get transplanted earlier in their disease progression. However, if an allocation policy prioritizes sicker patients, then it may be worth waiting longer to receive preferential access to better-quality organs. There is an inherent trade-off a patient faces, transplant early (i.e., at a lower MELD score) with a lower quality organ or wait longer (i.e., achieve a higher MELD score) for a better quality organ. Therefore, it is not clear if the Share 35 policy resulted in an overall improvement in terms of patients' outcomes. To access a new proposal and predict its impact, SRTR's Liver Simulated Allocation Model (LSAM) is used by the transplant community. One of its main shortcomings is that it cannot account for behavior change due to a new policy. It assumes the same organ acceptance probability function, irrespective of policy or geography, or organ access. Goel et al. (2018) compared the LSAM predictions due to Share 35 policy with that of observed. They found that LSAM overestimated the increase in the transplant

rates for MELD/PELD $\geq 35$ candidates (46% predicted versus 36% observed), and underestimated the decrease in the transplant rates for MELD/PELD 30-34 candidates (1% predicted versus 33% observed). Prior research (Su and Zenios 2005) has also shown that ignoring patient's choice leads to overestimating the efficiencies. To sum up, the impact of the Share 35 policy is not straightforward to conclude. Our first *research question* is to study the impact of the Share 35 policy on patients' outcomes.

Despite implementing broader sharing of organs in a region for candidates with MELD scores $\geq 35$ in 2013; geographic inequities remained in the system. The U.S. Scientific Registry of Transplant Recipients (SRTR) Liver Transplant Waiting List Outcomes Tool (that is built on historical data from 2017 to 2019) shows that for waitlist candidates in Los Angeles with MELD score in the range 25-29, only 15% received a transplant within 90 days, while for candidates in Indianapolis (with MELD scores in the range 25-29), 72% received a transplant within 90 days. The highest reported median MELD score was 39, in Los Angeles, California (DSA: CAOP), and the lowest 20 in Indianapolis, Indiana (DSA: INOP) (Kim et al. 2018). In July 2018, six waiting list patients in New York, California, and Massachusetts filed a lawsuit (Cruz et al v. U.S. Dept. of Health and Human Services, S.D.N.Y 18-CV-06371) against the Health Resources and Services Administration (HRSA), an agency of the HHS. The lawsuit points out the wide geographic variability in the median MELD scores, in candidates for deceased-donor transplants, arguing that place of residence largely determines the chances of one's survival in the current policy. HRSA has already been under pressure over the last two decades to address geographic disparity (Hughes 2015), and the lawsuit precipitated a change from the Share 35 allocation policy to the Acuity Circles policy. In the previous DSA based allocation policy (due to rigid boundaries) it was possible for an organ to be offered to a less sicker candidate at a further transplant center over a more sicker candidate at a closer transplant center. The Acuity Circles policy eliminated this possibility which was the genesis of several lawsuits against the previous DSA based policy. Our second *research question* is to study whether the current Acuity Circles policy is moving the outcomes in the right direction?

Managing the trade-off between equity and efficiency has been a very active area for researchers (see Section 3) and policymakers. The liver allocation system in the U.S. has been through three policy modifications in the last eight years. Recent policies are moving towards broader sharing in principle. To give some perspective, the Pre-Share 35 policy allowed sharing of organs mainly within the DSA (average distance between the donor hospital and the transplant center (TC) pairs within the same DSA is 66 nautical miles (NM)); the Share 35 policy allowed sharing of organs to the regional level for sicker patients (average distance between the donor hospital and the TC pairs within the same region is 262 NM); the current Acuity Circles policy allows sharing of organs till 500 NM for sicker patients; and the future policy framework aims to further increase this distance.

Our third and final *research question* is to investigate if there is a better alternative than broader sharing of organs as currently implemented. Overall, our study uniquely fills the gap of evaluating the impact of an earlier policy and using the insights to propose a new one.

### 1.3. Contributions

In this paper, we build a structural model and provide a framework to analyze a patient's strategic response to a policy change. Our model is based on more than 40 medical characteristics of patients and donors and we use techniques to make the analysis computationally tractable. Our paper makes the following contributions to the literature (see Section 7.1 for geographic equity metrics, and Section 7.2 for efficiency metrics): 1. We perform a comparative study of the Pre-Share 35 and Share 35 policies and demonstrate the heterogeneity in the change in behavior of patients as a function of their region and MELD scores. We find that sicker patients benefited and became more selective in their behavior, however, there was heterogeneity in behavior change across geographies in less sick patients. Overall, the Share 35 policy was effective in reducing the geographic disparity than its predecessor policy. 2. The Acuity Circles policy was implemented in February 2020 to "improve" upon the "Share 35" policy. To the best of our knowledge, ours is the first work to study the Acuity Circles policy using the endogenous patient's choice model. We conclude that compared to the Share 35 policy, the Acuity Circles policy performs very similar in geographic equity metrics, but would result in more offer refusals and lower transplant benefit. 3. We illustrate that broader sharing in its current form may not be the best strategy to balance geographic equity and efficiency. The intuition is that by indistinctively enlarging the pool of supply locations from where patients can get the offers, they tend to become more selective, resulting in more offer rejections and less efficiency. We suggest an alternative approach, one that equalizes the supply (deceased-donors) to demand (waiting list patients) ratios across the geographies by selectively increasing the sharing radius around the donor hospitals, and show that it has the highest efficiency among the policies studied while achieving a similar level of geographic equity.

The structure of the rest of this paper is as follows. In the next section, we give a brief overview of the liver allocation system in the U.S. Section 3 reviews the relevant literature. Section 4 describes the data, summary statistics, and few model-free pieces of evidence of behavior change. Section 5 presents our optimization model. Section 6 describes our estimation procedure, and the results. We compare various allocation policies in Section 7. Finally, we summarize and conclude in Section 8.

## 2. Liver Allocation Policy

UNOS supervises the transplantation network in the U.S. Its primary responsibilities are to manage the national transplant waiting list, match organs from deceased-donors to candidates, establish medical criteria for allocating organs, facilitate organ distribution, frame equitable policies, etc.

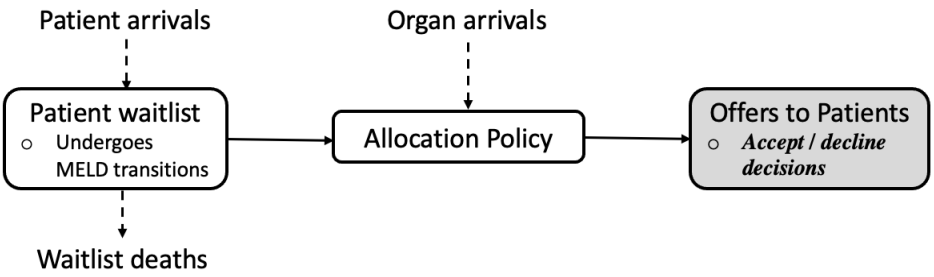


**Figure 2** **Flowchart of deceased-donor organ allocation process in the U.S.**

Some of the main UNOS members are the 142 liver transplant centers (TCs) and Organ Procurement Organizations (OPOs) in the 58 DSAs. The OPO coordinates the local procurement of deceased-donor organs and allocation in a DSA.

Figure 2 shows the flowchart of deceased-donor liver allocation for transplantation. Each TC evaluates patients and adds candidates to the waitlist. The medical data about the candidates are shared with UNOS. This pooled data of candidates across all transplant hospitals is constantly updated when new candidates get added and existing candidates are either removed or their medical conditions (e.g. MELD scores) are updated. When a deceased-donor organ becomes available, the OPO sends medical data about the organ donor to UNOS. Subsequently, the UNOS matching system compares the donor information with the candidate pool to rank the candidates for the organ offer as per the allocation policy. Upon receiving an offer, the transplant surgeon or physician, in consultation with the candidate decides whether to accept the offer. The only clinically approved preservation method in the case of liver is simple cold storage (see Lee and Mangino 2009, for details). Since an organ loses viability due to a lack of oxygen, a liver has to be discarded after around 12 hours in general.

Now, we describe the allocation policies that we consider in this study.

| Sequence # | Pre-Share 35 | Share 35 |
|---|---|---|
| 1 | Status 1 (local) | Status 1 (local) |
| 2 | Status 1 (regional) | Status 1 (regional) |
| 3 | MELD $\geq$15 (local) | MELD $\geq$35 (local and regional, with preference to local candidates at each MELD) |
| 4 | MELD $\geq$15 (regional) | MELD $\geq$15 (local) |
| 5 | MELD $<$15 (local) | MELD $\geq$15 (regional) |
| 6 | MELD $<$15 (regional) | Status 1 (national) |
| 7 | Status 1 (national) | MELD $\geq$ 15 (national) |
| 8 | MELD $\leq$40 (national) | MELD $<$15 (local) |
| 9 | - | MELD $<$15 (regional) |
| 10 | - | MELD $<$15 (national) |

**Table 2** **Comparison of deceased adult donor allocation policies. Local (regional) refers to donor and candidate belonging to the same DSA (region), and national in case of different regions.**

### 2.1. Previous Policies

The first objective scoring system adopted by the OPTN/UNOS was the Child-Turcotte-Pugh (CTP) score, in 1998. However, the score was not effective in discriminating the severity of illness (Smith et al. 2012). Since February 2002, MELD has been used in the allocation policies to quantify urgency level. Table 2 compares the policy in place before and after June 2013 (until February 4, 2020) for adult donors. We refer to the policy before June 2013 as a Pre-Share 35 policy. The Share 35 policy brought the following two changes: increased the priority of regional patients with MELD $\geq$35, and prioritized national patients over low MELD ($<$15) local/regional patients. Since it led to the prioritization of patients registered outside the DSA, and region; the Share 35 policy can be seen as a broader sharing policy. In the above policies, the hierarchy of offer priority is on the basis of MELD and sharing type (local/regional/national).

### 2.2. Current Policy: Acuity Circles

In the Acuity Circles policy, the distance of the donor hospital and candidate's TC is also considered in addition to the MELD score. This policy progressively shares organs in circles of radius 150 NM, 250 NM, and 500 NM around the donor hospital, with the following hierarchy: (1) Status 1 candidates at the TCs within 500 NM; (2) candidates with MELD $\geq$37 within 150 NM, then 250 NM, then 500 NM; (3) candidates with MELD $\geq$33 within 150 NM, then 250 NM, then 500 NM; (4) candidates with MELD $\geq$29 within 150 NM, then 250 NM, then 500 NM; (5) candidates with MELD $\geq$15 within 150 NM, then 250 NM, then 500 NM, then nationally; (6) candidates with MELD$<$ 15 within 150 NM, then 250 NM, then 500 NM, and then nationally. This is a "one-size-fits-all" policy because it does not account for the organ arrival rate, the candidate waiting list, nor the distances of the TCs from a donor hospital.

### 2.3. s/d Match Policy

We use the optimization framework proposed in Akshat et al. (2021) and apply the *maximin* principle to design heterogeneous radii circles that maximize the minimum value of the supply to demand (s/d) ratio across all the TCs. The s/d match policy adheres to the Final Rule and the principles adopted by the UNOS board in 2018 for all the future organ policies. We set the minimum and maximum radius of the circles around the donor hospitals to be 150 NM and 500 NM (referring to the innermost and the outermost radii used in the Acuity Circles policy; and thus the Acuity Circles policy can be seen as a broader sharing analogue of the s/d Match policy) as an illustration. Based on the setup considered in Section 7, the optimized set of circles results in the minimum (maximum) s/d ratio (at the TC level) to be 0.58 (0.83). In contrast, if we consider 500 NM circles around every donor hospital, the s/d ratio range is 0.45-1.14. (We note that a tighter s/d range can be obtained by changing the maximum radius value. See Appendix F for details

on s/d range and performance measures when we allow the maximum radius around the donor hospital to be 600 NM.)

### 2.4. National Sharing Policy

As the name suggests, the candidates are first ranked based on their MELD scores, irrespective of their location in the U.S. In case of a tie (i.e., conditional on the MELD), local candidates are preferred over regional, and regional over candidates outside the region (Feng et al. (2006) document the increased risk of graft failure from local to regional, and from regional to national sharing). Therefore, we try to mitigate (although not eliminate entirely) the role of one's location through this policy. We note that this policy might involve long-distance travel and may not be an appealing and practical idea since it may increase organ discard chances.

## 3. Related Research

There are mainly three streams of literature relevant to our study: 1. Proposals to address the geographic disparity, 2. Efficiency-equity trade-off, and 3. Dynamic optimization modeling in organ transplantation.

Redistricting has been proposed by many researchers in the operations community to address the issue of geographic inequity. Redistricting is a problem that occurs frequently in multiple domains (e.g., political redistricting, school redistricting, and sales territory assignment) where a finite, denumerable set of non-overlapping geographical units are aggregated into regions/districts subject to some criteria. Hess et al. (1965) and Garfinkel and Nemhauser (1970) introduced the use of optimization techniques for political redistricting. Stahl et al. (2005) consider geographical equity as measured using intraregional transplant rates in their objective function along with efficiency (measured by total intraregional transplants) but they restrict their regions to contain up to eight DSAs due to computational challenges. Extending their work, Demirci et al. (2012) developed a branch-and-price algorithm to incorporate a larger set of potential regions and explored the efficient frontier in a trade-off between efficiency and geographical equity. Gentry et al. (2015) used optimization to reorganize DSAs into regions/districts to reduce geographical disparity. Working closely with the liver committee of UNOS, they proposed eight-district and four-district (reorganized DSA) maps. The proposed maps were under active consideration by UNOS from 2015 to 2017, but ultimately after significant debate and public comment were not adopted. Kilambi and Mehrotra (2017) introduced the neighborhood framework in organ allocation as a way to provide for broader sharing and improve geographic equity. Each DSA has its own neighborhood, which consists of a unique set of other DSAs (or neighbors) to which it shares its organs. Rectifying the shortcomings in the supply to demand ratio measure used by Kilambi and Mehrotra (2017),

Akshat et al. (2021) proposed heterogeneous circles around the donor hospitals to create an equitable geographic distribution by developing a scalable set-partitioning optimization model. Ata et al. (2017) used fluid approximation and game theory to show that multilisting (a patient lists at more than one TC (potentially in other DSA or region) so that he/she can get organ offers from multiple places) can reduce geographical disparity in kidney allocation. However, fewer than 2% of patients (on April 14, 2021, the OPTN website shows less than 181 out of 11,868 candidates on the waiting list are multiple listed) waiting for liver transplant multiple list. Moreover, multilisting would not make the system fair, rather it would instead create disparity based on a candidate's economic means. Bertsimas et al. (2020) suggest the use of tradeoff curves for the assessment of the three organ distribution frameworks identified by the UNOS. Running a massive number of simulations for the three distribution frameworks[1], they plot tradeoff curves of efficiency (measured as average travel distance) versus fairness (measured as deaths or variance of median MELD at transplant). For a given value of the efficiency metric, the tradeoff curve then identifies the policy with the greatest fairness. Most of the above studies rely on LSAM to assess the performance of their proposals, owing to the reliance on it by the policymakers. LSAM is a sophisticated patient-level simulation that handles MELD scores and models candidate accept or decline decisions (Thompson et al. 2004). However, it ignores the heterogeneity in patients' organ acceptance behavior and its dependence on the policy.

Zenios et al. (2000) study the trade-off between clinical efficiency (measured as Quality Adjusted Life Years (QALY)) and equity (types of patients defined based on their demographics) in kidney allocation problem using a fluid model, ignoring patients' choices. They propose a heuristic dynamic index policy to maximize the multi-criteria objective function. Su and Zenios (2005) use a sequential assignment model (of $n$ transplant patients and $n$ kidneys) to investigate the impact of patient's choice in kidney allocation system. They focus on a social planner's objective of maximizing the overall social welfare and conclude that ignoring patient's choice leads to overestimating the efficiencies in the policies they studied. Bertsimas et al. (2012) study the $\alpha$-fairness scheme (see Atkinson 1970) to trade off efficiency and fairness. Their measure of efficiency is the sum total of utilities and they do not focus on geographic disparity. Su and Zenios (2006) find that introducing information asymmetry (transplantation system does not know the post-transplant outcome, which is known to the patient) in the allocation policy achieves an overall outcome in the middle of the efficiency-equity spectrum. Bertsimas et al. (2013) proposed a method to design a point-based kidney allocation system, where policymakers can select the fairness constraints and the method maximizes the medical efficiency (captured using life-year gained from transplant). However, they

[1] https://optn.transplant.hrsa.gov/media/2565/geography_publiccomment_201808.pdf

test policies assuming an exogenous organ acceptance model for patients. Arikan et al. (2018) use a probit model to elicit differences in the intent for organ (kidney) procurement at the level of DSAs between marginal quality organs and the rest. They conclude that geographically broader sharing of the bottom 15% quality kidneys can help in enhancing the kidney supply.

Other papers (Washburn et al. 2016, Goldberg et al. 2017) have studied the effect of Share 35 policy, albeit using a very simplistic methodology like logistic regression that is not appropriate for studying dynamic optimization problem setting (more in Section 4.3). Zhang (2010) is the closest paper to ours in terms of methodology. Their focus is on studying the presence of observational learning in the behavior of patients in the deceased-donor kidney allocation process. Agarwal et al. (2021) and Ata et al. (2020) study deceased-donor kidney allocation policies using structural models. Besides the difference in context (liver versus kidney), there are three key differences between these two papers and ours. First, in addition to transplantation, dialysis is also a treatment option for kidney failure. Second, these two papers assume patients' health transitions to be deterministic, whereas we model the stochastic transition of MELD scores. And third, the liver allocation policy evolution presents a unique opportunity to study the impact of broader sharing on the patients' outcomes. Furthermore, Agarwal et al. (2021) do not study geographic disparity. Alagoz et al. (2007) use a discrete-time, infinite-horizon discounted Markov decision process model to study the patient's decision to accept an offer or wait. They find that the optimal policy is typically of control-limit type. However, they assume a fixed cost of waiting and our model uses a richer set of variables to model utility and waiting cost. With regard to living donation, Alagoz et al. (2004) study the problem of optimal timing of living-donor transplant. They assume that the patient cannot receive an organ from a deceased donor, and ignore the risk to living donors. Ergin et al. (2020) model liver exchange as a market-design problem where they account for risk to donors and compatibility issues. We focus on deceased donation in this study, and our findings are likely to remain unaffected by the recent promising developments in living donation.

# 4. Data and Evidence

## 4.1. Data

This study used data from the Scientific Registry of Transplant Recipients (SRTR). The SRTR data system includes data on all donors, wait-listed candidates, and transplant recipients in the U.S., submitted by the members of the Organ Procurement and Transplantation Network (OPTN). The Health Resources and Services Administration (HRSA), U.S. Department of Health and Human Services provides oversight to the activities of the OPTN and SRTR contractors. The four main datasets used in the study are candidates' information at the time of registration, the transition of their MELD scores while waiting, donor information, and the candidates' decisions for organ offers.

We use around 16 years (January 2003 to February 2019) of data on transitions of candidates' MELD to estimate the MELD transition matrix. We use nine years (2010 to 2018) of candidate and donor information in our analysis. This covers both the pre-Share 35 and Share 35 policy eras. We restrict our analysis of deceased-donor organs from adult donors and to adult candidates (allocation policies are different for donors <18 years). Since we are interested in analyzing geographic disparity across policies, we use data from all the 11 regions. In the next subsection, we provide summary statistics of a few key variables in the data.

### 4.2. Summary Statistics

Table 3 reports the summary statistics of various patients, donors, and transplant attributes that we use in the model. We see that the new patients' age, MELD at listing, and life support status remain almost the same in the pre-and Share 35 policy eras. There is a slight difference in the distribution of the medical condition between the two time periods. The donors' age, race distribution, and donation after circulatory death (DCD) status do not change much, however, there is a difference in the cause of death distribution between the two time periods. Thus, it is important to control for donor characteristics in the model. After Share 35 implementation, on average, the offers were accepted later in the queue, and interestingly, the cold ischemia time (CIT), the time between the organ recovery and the transplantation, decreased (Gentry et al. (2014) investigated the relationships between estimated transport time, distance, and CIT. They concluded that estimated transport time for livers comprised only 21% of CIT and explained only 14.7% of the variance of CIT. So, the impact of broader sharing on CIT is not very clear). Comparing sharing type of the transplants, the Share 35 policy resulted in greater (lower) proportion of regional (local) sharing.

Figure 3 compares the MELD at the time of offer and at transplant (of candidates who accepted the offer) between Pre-Share 35 and Share 35 policies using the box plots. Consistent with the Share 35 policy that prioritizes the sicker patients, the MELD at offer has increased. The MELD at transplant also increased slightly suggesting that a greater number of sicker patients got transplanted, thereby avoiding deaths. However, the relative increase in MELD at transplant is smaller than MELD at offer suggesting more offer refusals. One may wonder if the refusals are due to lower quality organs being offered, or if the candidates became more selective in their behavior. We find no significant differences in the organ quality of the declined offers between the two policy eras (see Appendix A), and it is likely that the declines are due to behavior change. Offer declines tend to increase the time to transplant for an organ thereby deteriorating the organ quality (and its utility from transplantation). To summarize, while the Share 35 policy seems to save lives, it may lead to a decrease in transplant quality (in terms of graft survival probability) due to more offer rejections. Therefore, it is not obvious whether the Share 35 policy has resulted in an overall benefit to patients.

| Characteristic | Pre-Share 35 (January 2010-June 2013) | Post-Share 35 (July 2013-December 2018) |
|---|---|---|
| New patients | | |
| Age (in years): Mean/SD | 54.9/10.3 | 55.8/11.0 |
| MELD (at listing): Mean/SD | 19.3/9.2 | 19.7/9.8 |
| Life support status: | | |
| Yes | 4% | 5% |
| No | 96% | 95% |
| Medical condition: | | |
| Intensive care unit (ICU) | 8% | 3% |
| Hospitalized | 12% | 4% |
| Not hospitalized | 80% | 93% |
| Donors | | |
| Age (in years): Mean/SD | 44.3/15.2 | 43.6/14.9 |
| Race: | | |
| White | 80% | 80% |
| Black | 17% | 16% |
| Others | 3% | 4% |
| Cause of death: | | |
| Anoxia | 26% | 38% |
| Cerebrovascular accident (CVA) | 40% | 31% |
| Others | 34% | 30% |
| Donation after circulatory death: | | |
| Yes | 13% | 17% |
| No | 87% | 83% |
| Fraction of discards | 0.252 | 0.250 |
| Match | | |
| Position at acceptance: Mean/SD | 10.6/38.0 | 15.2/42.5 |
| Cold Ischemia Time (of accepted offers): Mean/SD | 6.3/3.0 | 6.0/2.5 |
| Sharing type (of accepted offers): | | |
| Local | 78% | 65% |
| Regional | 20% | 31% |
| National | 3% | 4% |

**Table 3 Summary statistics of patient, donor and transplant characteristics.**

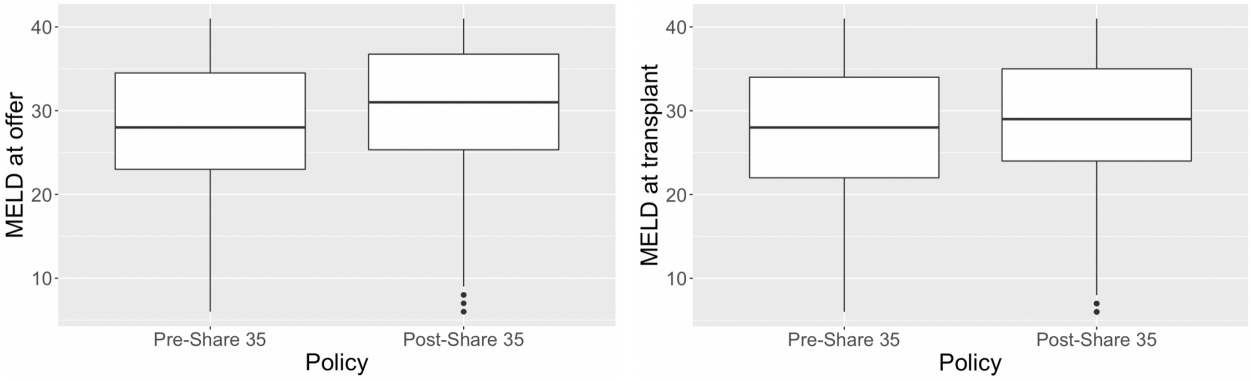


**Figure 3 Comparison of MELD at offer and at transplant between policies using box plots (Status 1A are assigned MELD score 41).**

In Figure 4, for every MELD class, we plot the mean position at which the candidates in that MELD class received the offers. We see a clear dip in offer positions post Share 35 to MELD $\geq$35

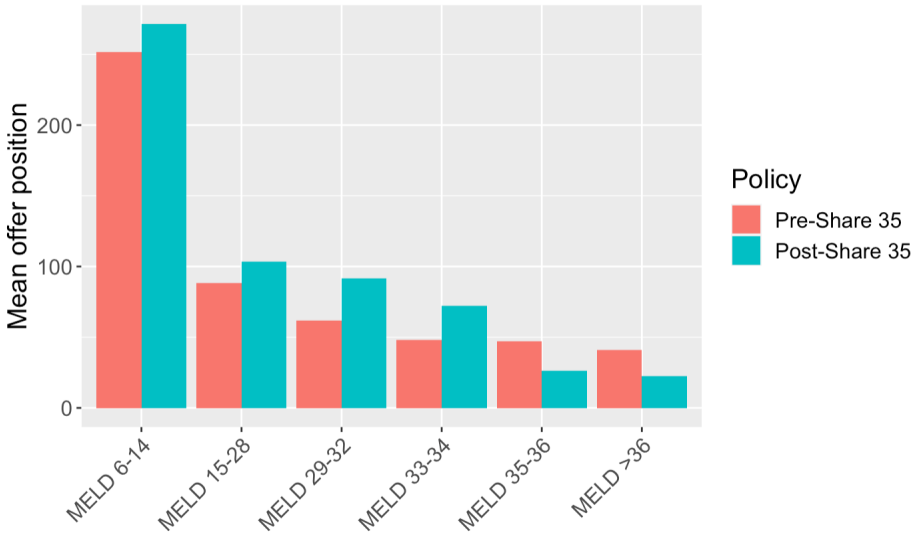


**Figure 4** **Comparison of positions at which offers were made to patients at different MELD scores between policies (Status 1A are assigned MELD score 41).**

candidates, suggesting that more high MELD patients were at the top of the offer list. The observation is consistent with what one would expect with the Share 35 policy; organ access increased (decreased) to candidates with MELD $\geq$35 (MELD $<$35) in general.

We plot the year-wise trend of new patients joining the waiting list (demand) and deceased-donors (supply) in Figure 5. The gap between supply and demand has been persisting. Supply has been increasing, for example, it increased 30% from 2010 to 2018, while demand does not show a clear trend. To study the impact of the Share 35 policy, it is important to delineate the effect of increased supply and demand changes from the pre-Share 35 to the Share 35 policy eras.

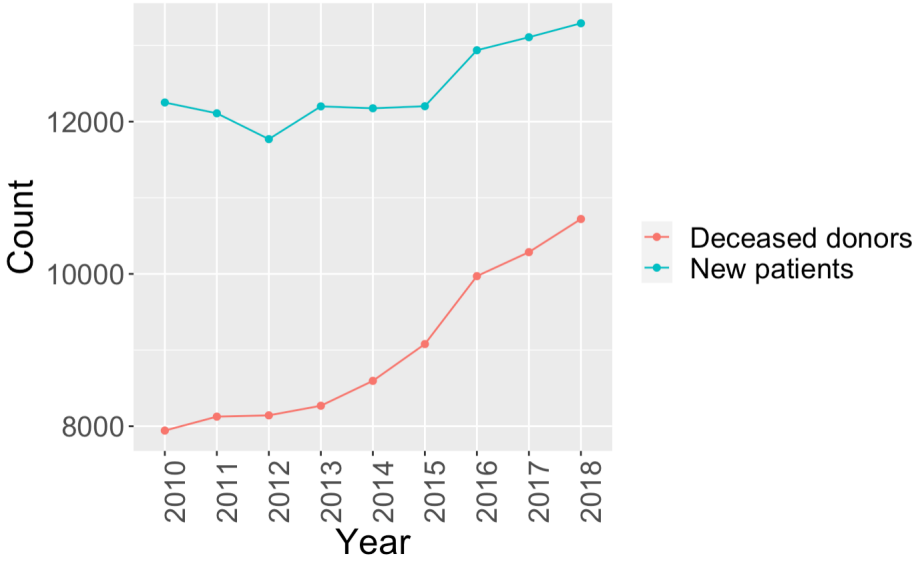


**Figure 5** **Supply and demand trends over time.**

Of all the offers, 93.3% were made to patient-donor pairs of identical blood types and only 2.4% and 4.3% were made to compatible and incompatible pairs, respectively. Therefore, to keep our model simpler and tractable, we do not consider blood type compatibility.

### 4.3. Model-Free Evidence

In this section, we present a few preliminary pieces of evidence of behavior change. First, we run a logistic regression with accept/decline as the dependent variable and add an indicator variable for policy change, a focal parameter. The sickness level of the patient is likely to play a role in her decision, therefore we use MELD classes as explanatory variables. We also add other patient-level controls like age, life support status, and medical condition. Further, we classify an organ based on the donor's age, race, cause of death, and if the donation was after circulatory death, and thus we control for organ quality in the regression. The medical literature (Schaubel et al. 2009, Feng et al. 2006) guides our selection of the above explanatory variables. In Table 4, we report the results of the regression model. The estimate of the indicator variable, $\mathbb{1}_{\{Policy:Pre-Share35\}}$ is positive and statistically significant, suggesting that the candidates were more likely to accept an offer in the Pre-Share 35 policy era. However, logistic regression assumes that the expected utility of the outside option (corresponds to a declined offer) is the same and does not depend on the explanatory variables (patient's characteristics), which is not true in this dynamic optimization problem setting where future opportunities are a function of the current state. For example, a sicker patient might get priority and thus have greater access to higher quality organs in the future.

We also observe heterogeneity in behavior change of candidates based on their MELD scores. Conditional on candidates with MELD $<35$ (MELD $\geq 35$), the average MELD at offer acceptance increased (decreased) by 0.68 (0.43). Next, we use a simple measure to calculate the acceptance probability (ratio of the number of offers accepted and the number of offers received). In Table 7,

| **Parameters** | Estimates |
|---|---|
| Intercept | -5.3063*** |
| MELD 15-28 | 2.3635*** |
| MELD 29-32 | 2.8308*** |
| MELD 33-34 | 2.9424*** |
| MELD 35-36 | 3.6693*** |
| MELD >36 | 3.9579*** |
| $\mathbb{1}_{\{Policy:Pre-Share35\}}$ | 0.1864*** |
| Candidate controls: Yes | |
| Donor controls: Yes | |
| No. of parameters: 59 | |
| AIC = 362,269 | |
| No. of observations = 939,302 | |

$^{***}P < 0.0001$

**Table 4 Estimation results of the logistic regression.**

we report the change in acceptance probabilities as a function of MELD at different regions (and further contrast with respect to the structural model findings in Section 6.4).

## 5. Patient's Dynamic Choice Model

In this section, we describe the choice model of a patient. When offered an organ, she evaluates the utility (in terms of her survival chances) derived from that organ and decides to either accept it and undergo transplantation or decline it and wait for the next offer (anticipating a better one). A patient, in consultation with a transplant surgeon, evaluates an offer (the SRTR data system does not contain surgeon-level information). While waiting, her health state will evolve stochastically, affecting her priority for future offers. As per the allocation policy in the U.S., there is no implication of a patient's declining an offer on her future offers. In the next subsection, we formally introduce our model. Table 5 describes the notation used in the formulation.

### 5.1. Patient's Dynamic Optimization Problem

We model the patient's problem as a discrete-time infinite-horizon dynamic optimization problem where she faces the trade-off between accepting the current offer and waiting for future offers. We consider the Markov perfect equilibrium and patients account for only payoff-relevant variables, compositely represented by $S_{it}$, in their decision making.

Upon accepting an offer, a patient receives an expected utility of $EU(S_{it})$ and is removed from the waiting list (and we assume that she never joins again). $EU(S_{it})$ captures the expected present discounted payoff from accepting an offer (in state $S_{it}$). If a patient declines the offer, then she incurs an immediate waiting cost (as modeled in Section 5.1.3) and expects to receive some utility in the future (as modeled in Section 6.1.1). Formally, the Bellman equation for patient $i$'s dynamic optimization problem at time $t$ is

$$V(S_{it}) = \max \left\{ EU(S_{it}), -EW(S_{it}) + \delta \sum_{S_{i,t+1}} \mathcal{P}(S_{i,t+1}|S_{it}, d_{it}=0).V(S_{i,t+1}) \right\}. \tag{1}$$

Now, we will describe the payoff and state transition probability functions.

**5.1.1. Utility Function.** We consider a linear functional form for modeling utility associated with a candidate-donor pair. For a pair, we estimate the graft survival probability using the SRTR Risk Adjustment Model[2], which is based on a total of 41 predictors that include the candidate's and donor's medical attributes, and CIT. Using post-transplant outcome in the utility is in line with extant literature (Su and Zenios 2006). Moreover, we believe that a patient would be interested in maximizing her eventual survival outcome (post-transplantation) without incorporating her

[2] `https://www.srtr.org/reports-tools/posttransplant-outcomes/` accessed on $12^{th}$ July 2020. See Appendix G for details.

| Notation | Description |
|---|---|
| $i$ | Patient |
| $t = 1, ..., \infty$ | Organ arrival time (in days) |
| $\delta$ | Daily discount factor |
| **Payoff-relevant variables** | |
| Candidate specific variables: | |
| $MELD_{it}$ | MELD score of the patient $i$ at time $t$ |
| $Rec\_age_{it}$ | Candidate $i$'s age group at time $t$ |
| $Rec\_life\_support_{it}$ | Candidate $i$'s life support status ('Yes' or 'No') at time $t$ |
| $Rec\_med\_cond_{it}$ | Candidate $i$'s medical condition ('ICU': Intensive Care Unit, 'H': Hospitalized, or 'NH': Not Hospitalized) at time $t$ |
| Organ specific variables: | |
| $Don\_age_{it}$ | Age of the donor whose organ is offered to candidate $i$ at time $t$ |
| $Don\_race_{it}$ | Race of the donor whose organ is offered to candidate $i$ at time $t$ |
| $Don\_cod_{it}$ | Cause of death of the donor whose organ is offered to candidate $i$ at time $t$ |
| $Don\_dcd_{it}$ | Indicates donation after circulatory death ('Yes' or 'No') of the donor whose organ is offered to candidate $i$ at time $t$ |
| Joint candidate-donor variables: | |
| $GS_{it}$ | One-year graft survival probability |
| $Sharing\_type_{it}$ | Denotes if the organ offer (with respect to patient $i$'s DSA) at time $t$ is classified as $local, regional$, or $national$ sharing |
| $X_{it}$ | $(1, GS_{it}, Sharing\_type_{it})$ |
| $Y_{it}$ | $(Rec\_age_{it}, Rec\_life\_support_{it}, Rec\_med\_cond_{it})$ |
| $Q_{it}$ | $(Don\_age_{it}, Don\_race_{it}, Don\_cod_{it}, Don\_dcd_{it})$ |
| $S_{it}$ | $(MELD_{it}, Rec\_age_{it}, Rec\_life\_support_{it}, Rec\_med\_cond_{it}, Q_{it}, GS_{it}, Sharing\_type_{it})$ |
| $\mathcal{P}(S_{i,t+1}\|S_{it})$ | Transition probability of candidate $i$'s state from $t$ to $t+1$ |
| **Payoff functions** | |
| $U_{it}(S_{it})$ | Utility to candidate $i$ upon accepting an offer at time $t$ |
| $W_{it}(S_{it})$ | One period candidate $i$'s waiting cost at time $t$ |
| $V(S_{it})$ | Patient's maximum expected present discounted value associated with state $S_{it}$ |
| **Decision variable** | |
| $d_{it}$ | 1 if candidate $i$ accepts the offer at time $t$, and 0 otherwise |

**Table 5 Model Notation**

survival chance without a transplant. The CIT is realized and observed only for transplants that took place, so we use the median value (=6.9 hours) in the graft survival probability function and include $Sharing\_type$ variables to capture the effect of the elapsed time between organ recovery and transplantation on the (prospective) transplant quality. We model the utility of transplantation to be derived from the one-year graft survival probability and $Sharing\_type$, which captures the effect of CIT. The utility to patient $i$ at time $t$ is given by:

$$U_{it}(S_{it}) = \begin{cases} X_{it}\beta + \epsilon_{it}, & \text{if the candidate } i \text{ accepts the organ at time } t, \\ \epsilon_{it}. & \text{if no offer is made at time } t. \end{cases} \tag{2}$$

$X_{it}$ is observable to both patient $i$ and the econometrician, and it includes the intercept term. $\beta$ is the associated utility parameter vector. $\epsilon_{it}$ denotes the idiosyncratic utility shock experienced by patient $i$ while evaluating the offer at time $t$. It represents the random factors (playing a role in the decision making) that are unobserved to the econometrician like weather conditions, momentary inconveniences to the patient, surgery-related factors, randomness involved in survival probability assessment, etc. $\epsilon_{it}$ is assumed to follow an independent and identically distributed (i.i.d.) Gumbel distribution across patients and offers. We subtract $E(\epsilon_{it})$, a constant, from the utility so that the expected utility upon accepting an offer is given by:

$$EU(S_{it}) = X_{it}\beta \tag{3}$$

**5.1.2. State Transition Probability.** The health condition of a patient evolves stochastically and is a major determinant of her priority in a queue in the organ allocation policies studied. The state transition probability is written as:

$$\begin{aligned}\mathcal{P}(S_{i,t+1}|S_{it}, d_{it}=0) = \mathcal{P}(&MELD_{i,t+1}, Rec\_age_{i,t+1}, Rec\_life\_support_{i,t+1}, Rec\_med\_cond_{i,t+1},\\ &Q_{i,t+1}, GS_{i,t+1}, Sharing\_type_{i,t+1}|MELD_{it}, Rec\_age_{it}, Rec\_life\_support_{it},\\ &Rec\_med\_cond_{it}, Q_{it}, GS_{it}, Sharing\_type_{it}, d_{it}=0)\end{aligned} \tag{4}$$

Since the priority of a candidate on the offer list does not depend on past offers, by dropping history on the previous time period's offer, the transition probability can be rewritten as:

$$\begin{aligned}\mathcal{P}(S_{i,t+1}|S_{it}, d_{it}=0) = \mathcal{P}(&MELD_{i,t+1}, Rec\_age_{i,t+1}, Rec\_life\_support_{i,t+1}, Rec\_med\_cond_{i,t+1},\\ &Q_{i,t+1}, GS_{i,t+1}, Sharing\_type_{i,t+1}|MELD_{it}, Rec\_age_{it}, Rec\_life\_support_{it},\\ &Rec\_med\_cond_{it}, d_{it}=0)\end{aligned} \tag{5}$$

We assume that the MELD state transition is the same for all age groups, life support statuses, and medical conditions (the pooling of various patient types enables the estimation of the MELD state transition matrix with greater confidence than estimating multiple (18 in our case, see Section 6.3) matrices for different patient types). *Death* is an absorbing state. Next, when an organ arrives, the allocation policy does not depend on the candidates' age, life support status, and medical condition, thus only MELD plays a role in determining organ offer probabilities in a policy. These allow us to simplify the transition probability as:

$$\begin{aligned}\mathcal{P}(S_{i,t+1}|S_{it}, d_{it}=0) = \mathcal{P}(&MELD_{i,t+1}|MELD_{it}, d_{it}=0).\mathcal{P}(Q_{i,t+1}|MELD_{i,t+1}, d_{it}=0).\\ &\mathcal{P}(Rec\_age_{i,t+1}, Rec\_life\_support_{i,t+1}, Rec\_med\_cond_{i,t+1}, GS_{i,t+1}, Sharing\_type_{i,t+1}|\\ &MELD_{i,t+1}, Q_{i,t+1}, MELD_{it}, Rec\_age_{it}, Rec\_life\_support_{it}, Rec\_med\_cond_{it}, d_{it}=0)\end{aligned} \tag{6}$$

We estimate $\mathcal{P}(MELD_{i,t+1}|MELD_{it}, d_{it}=0)$ from the data on MELD transitions. To estimate $\mathcal{P}(Q_{i,t+1}|MELD_{i,t+1}, d_{it}=0)$, we adopt an approach identical to Alagoz et al. (2007):

$$\mathcal{P}(Q_{i,t+1}|MELD_{i,t+1}, d_{it}=0) = \frac{\sum_i \#\text{ of offers of type } Q_{i,t+1} \text{ candidate } i \text{ received at } MELD_{i,t+1}}{\sum_i \#\text{ of days candidate } i \text{ waited at } MELD_{i,t+1}} \tag{7}$$

It is possible that a candidate does not receive an offer on a given day. We add *no_offer* to $Q_{it}$ (calculated as per equation 7) and $Sharing\_type_{it}$ (if $Q_{it} = no\_offer$, $Sharing\_type_{it}$=*no_offer* and vice versa).

The *Sharing_type* depends on the candidate's MELD and organ characteristics. Low-quality organs tend to get declined more often and are likely to be shared nationally. Sicker patients get higher priority therefore, they are likely to receive local/regional offers more often. Next, the graft survival probability, $GS$ depends on a total of 41 predictors, each taking a set of values. Including them in the structural model will cause a state space explosion and impede transition probability matrix estimation. Following the extant literature (Gowrisankaran and Rysman 2012) on *logit inclusive value*, we simplify the evolution of those 41 medical attributes using the evolution of $GS$. We estimate the graft survival as a function of $S_{it} - \{GS_{it}\}$. Using data on all offers corresponding to $S_{it} - \{GS_{it}\}$, we average the calculated graft survival probabilities of the offers to estimate $GS_{it}$ (*Sharing_type*, part of $S_{it}$ would not affect graft survival probability since we use a constant value of CIT in its calculation; thus we ignore *Sharing_type* variable from $S_{it}$ to pool the offers). Only the MELD of the patient evolves over time. The data does not have patients' transition of life support and medical condition. The patients differing in age group, life support status and medical condition can be thought of different patients types. These assumptions allow us to simplify the transition probability to:

$$\begin{aligned}
\mathcal{P}(S_{i,t+1}|S_{it}, d_{it}=0) = \mathcal{P}(MELD_{i,t+1}|MELD_{it}, d_{it}=0).\mathcal{P}(Q_{i,t+1}|MELD_{i,t+1}, d_{it}=0).\\
\mathcal{P}(GS_{i,t+1}|MELD_{i,t+1}, Rec_age_{i,t+1}, Rec_life_support_{i,t+1}, Rec_med_cond_{i,t+1}, Q_{i,t+1}, d_{it}=0).\\
\mathcal{P}(Sharing_type_{i,t+1}|MELD_{i,t+1}, Q_{i,t+1}, d_{it}=0).\\
\mathbb{1}_{\{Rec_age_{i,t+1}=Rec_age_{it}, Rec_life_support_{i,t+1}=Rec_life_support_{it}, Rec_med_cond_{i,t+1}=Rec_med_cond_{it}\}},
\end{aligned} \tag{8}$$

where $\mathcal{P}(Sharing\_type_{i,t+1}|MELD_{i,t+1}, Q_{i,t+1}, d_{it}=0)$ is estimated as:

$$\frac{\sum_i \#\text{ of offers of type } Q_{i,t+1} \text{ received at } MELD_{i,t+1} \text{ that have } Sharing\_type_{i,t+1}}{\sum_i \#\text{ of offers of type } Q_{i,t+1} \text{ received at } MELD_{i,t+1}} \tag{9}$$

The MELD transition matrix, and $GS_{it}$ are estimated based on the data of the entire U.S. However, $\mathcal{P}(Q_{i,t+1}|MELD_{i,t+1}, d_{it}=0)$ and $\mathcal{P}(Sharing\_type_{i,t+1}|MELD_{i,t+1}, Q_{i,t+1}, d_{it}=0)$ are estimated for every DSA separately (while evaluating a policy that uses TC instead of DSA, we estimate the quantities for every TC). This is because DSAs might differ in organ offer and *Sharing_type* probabilities in the pre-Share 35 and Share 35 policy eras.

**5.1.3. Waiting Cost Function.** A candidate incurs a waiting cost if she declines the offer, or does not receive one at $t$. To model her waiting cost, we use variables like age, life support status, and medical condition, represented by $Y_{it}$. Since $Death$ is an undesirable and terminal state, we add the term $\mathbb{1}_{\{MELD_{it}=Death\}}$ to the waiting cost function and a patient incurs a one time expected cost of $\frac{1}{1-\delta} \times \omega_d$ upon $Death$. Formally,

$$W_{it}(S_{it}) = \mathbb{1}_{\{MELD_{it}=Death\}}\omega_d + \mathbb{1}_{\{MELD_{it}\neq Death\}}Y_{it}\omega + \epsilon_{i0t}, \tag{10}$$

where $\epsilon_{i0t}$ is an independent and identically distributed (i.i.d.) Gumbel distribution across patients and times. We subtract $E(\epsilon_{i0t})$, a constant, from the function so that the expected waiting cost is given by:

$$EW(S_{it}) = \mathbb{1}_{\{MELD_{it}=Death\}}\omega_d + \mathbb{1}_{\{MELD_{it}\neq Death\}}Y_{it}\omega \tag{11}$$

**5.1.4. Offer Acceptance Probability.** It follows from the i.i.d. Gumbel assumption of the idiosyncratic shocks in the payoff functions, and the fact that the difference of two Gumbel variables is distributed logistic, the logit choice probability of accepting an offer is:

$$P(\text{accepting an offer}|S_{it}) = \frac{e^{EU(S_{it})}}{e^{EU(S_{it})} + e^{-EW(S_{it})+\delta\sum_{S_{i,t+1}}\mathcal{P}(S_{i,t+1}|S_{it},d_{it}=0).V(S_{i,t+1})}}, \tag{12}$$

where $EU(.)$ and $EW(.)$ represent expected utility and waiting cost, respectively.

## 6. Model Estimation

In this section, we will describe the estimation procedure, parameter identification, and results. Our estimation framework closely follows Zhang (2010).

### 6.1. Estimation Procedure

We estimate the model using the nested fixed point algorithm (Rust 1987). First, given a set of parameter values, an "inner" algorithm computes the value function, $EV(S_{it})$, then the log-likelihood function is calculated using the parameter values and the value function vector. An "outer" algorithm chooses the next set of parameters, to maximize the log-likelihood function.

**6.1.1. Value Function.** The value function, denoted by $EV(S_{it})$, is defined as the total future value that candidate $i$ expects to receive when she waits (declines or does not receive an offer) at time $t$. It depends on the candidate's health state, state transition matrix, and future opportunities, but not the offered (if any) organ characteristics.

$$EV(S_{it}) = \sum_{S_{i,t+1}} \mathcal{P}(S_{i,t+1}|S_{it}, d_{it}=0).V(S_{i,t+1}) \tag{13}$$

Substituting equation (13) into equation (1), we get:

$$V(S_{it}) = \max\{EU(S_{it}), -EW(S_{it}) + \delta EV(S_{it})\} \tag{14}$$

From Rust (1987), we can rewrite the value function as follows:

$$EV(S_{it}) = \sum_{S_{i,t+1}} \mathcal{P}(S_{i,t+1}|S_{it}, d_{it} = 0) \ln\left[e^{EU(S_{i,t+1})} + e^{-EW(S_{i,t+1})+\delta EV(S_{i,t+1})}\right], \tag{15}$$

where the second term under summation corresponds to the expected payoff when in state $S_{i,t+1}$.

The state space (described in section 6.3) in our setting is discrete. Let $K$ be the dimension of the state space, and $\Pi$ be a $K \times K$ Markov transition matrix of the state elements calculated using equation (8). The value function can be concisely represented as:

$$EV(.) = \Pi. \ln\left[e^{EU(.)} + e^{-EW(.)+\delta EV(.)}\right], \tag{16}$$

where $EV(.), EU(.)$, and $EW(.)$ are all $K \times 1$ vectors. This non-linear system of equations can be solved iteratively using a fixed-point algorithm.

**6.1.2. Log-Likelihood Function.** We use the maximum likelihood estimation approach to estimate the structural model parameters. The derivation and final expression of the log-likelihood function are in Appendix D. We maximize the overall log-likelihood function, equation (21), to estimate the parameters ($\beta$, $\omega_d$ and $\omega$).

### 6.2. Identification

Now we discuss the identification strategy. The utility parameters ($\beta$) consist of coefficients for $GS_{it}$ and $Sharing\_type_{it}$. The waiting cost parameters ($\omega_d$ and $\omega$) consist of cost incurred upon death (determined by the estimate of $\mathbb{1}_{\{MELD_{it}=Death\}}$) and the estimates of $Rec\_age_{it}$, $Rec\_life\_support_{it}$ and $Rec\_med\_cond_{it}$. The estimate of $GS_{it}$ is identified by the exogeneous variation of candidates' MELD scores, which creates variation in $GS_{it}$, in the data. The offers vary in sharing types (local, regional or national) after controlling for candidate and donor specific state variables. The differences in candidates' acceptance behavior helps in identifying the estimates of $Sharing\_type_{it}$.

The candidates might die if they keep declining the offers and continue waiting. The MELD transition matrix, $\mathcal{P}(MELD_{i,t+1}|MELD_{it}, d_{it} = 0)$ enables us to identify $\omega_d$. In the data, we have candidates of various age groups, life support statuses, and medical conditions. The variations in their offer acceptance behaviors facilitate the identification of $\omega$. We assume the daily discount factor, $\delta = 0.99$ in our estimation. Our value of $\delta$ is in line with that of Zhang (2010) who uses a discount factor of 0.99 for every six days (equivalent to a daily discount factor of 0.991).

| **Parameters** | Estimate | Standard Error |
|---|---|---|
| Utility Function: | | |
| Intercept | -21.7803 | 0.3145 |
| Sharing type: Regional | -1.0348 | 0.0113 |
| Sharing type: National | -2.3328 | 0.0243 |
| Graft survival probability (GS) | 19.5200 | 0.3353 |
| | | |
| Waiting Cost Function: | | |
| Death ($\omega_d$) | 0.1160 | 0.0007 |
| Candidate age group: R2 (45-65 years) | 0.0057 | 0.0002 |
| Candidate age group: R3 ($\geq$65 years) | 0.0061 | 0.0003 |
| Candidate life support: Yes | 0.0134 | 0.0008 |
| Candidate medical condition: H | 0.0114 | 0.0004 |
| Candidate medical condition: ICU | 0.0229 | 0.0008 |
| | | |
| No. of observations = 939,302 | | |
| Log-likelihood = -173,630.9 | | |

**Table 6 Estimation results of the structural model.**

### 6.3. Parameters and Results

Before we present the estimates, we expand on some of the state variables. We discretize *Rec_age* into three groups: R1: $< 45$ years, R2: $(45-65)$ years and R3: $\geq 65$ years, *Don_age* into four groups: $(18-39)$ years, $(40-49)$ years, $(50-59)$ years and $\geq 60$ years, *Don_race* into 'White' and 'Others' categories, and *Don_cod* into 'Anoxia', 'Cerebrovascular accident (CVA)' and 'Others' categories. The discretization and parameter selection are primarily motivated by the medical literature (Schaubel et al. 2009, Feng et al. 2006). We categorize MELD scores into six classes: MELD 6-14, MELD 15-28, MELD 29-32, MELD 33-34, MELD 35-36, and MELD >36, and add the terminal *Death* state. This creates a $7 \times 7$ MELD transition matrix (Appendix C). The above classification of MELD score provides sufficient granularity to evaluate Pre-/Share 35 and Acuity Circles policies. Overall, there are 18 patient types, 49 organ types, 15,678 elements in the state space, and every geographical unit (DSA or TC, depending on allocation policy) has its unique $K \times K$ Markov transition matrix where $K = 15{,}678$. Table 6 reports the estimates of the structural model.[3]

The estimates of $Sharing\_type : Regional$ and $Sharing\_type : National$ (with respect to $Sharing\_type : Local$) are negative, and national sharing is associated with the least utility. This is reasonable given that local organs are generally associated with fewer prior refusals, and the organs outside the region are associated with a higher number of prior refusals, thus are of lower quality and less desirable. In fact, Feng et al. (2006) got similar estimates (0.105 for regional sharing and 0.244 for national sharing, with respect to local sharing) in their estimation of donor risk index

[3] We used Julia 1.5.3 and KNITRO solver to estimate our model on a 3.2 GHz 6-Core Intel Core i7 MAC with 32 GB RAM. Due to the size of the problem, it took around two weeks to solve the model.

(DRI), a measure of the riskiness of graft failure associated with a donor organ. The estimate of graft survival probability is positive, consistent with the fact that organs that provide better survival are more desirable. *Death* is associated with a positive estimate and translates to a candidate incurring a one-time expected cost of $\frac{1}{1-\delta} \times \omega_d$ (=11.6) upon death. We observe that the waiting cost increases with age (most likely due to a decrease in well-being and chances of comorbidities), and thus the older patients are more likely to accept an offer. Patients, who are on life support incur more waiting cost than their counterparts. Compared to the patients who are not hospitalized, hospitalized patients incur more costs, and ICU patients incur double the cost compared to the hospitalized patients. A higher waiting cost means a greater urgency for accepting an offer. The above waiting cost estimates are in line with the hazard ratios that Schaubel et al. (2009) report using Cox regression (Cox 1972).

### 6.4. Comparison of Pre- and Post-Share 35 Policy Eras

In this subsection, we investigate if the behavior of a candidate is different between the pre-Share 35 and Share 35 policy eras. Only the second term in the denominator of equation (12) might vary between the two time periods. Specifically, only $EV(.)$, the value function denoting the future discounted value upon waiting, might differ in the two policy eras due to potential changes in organ offer probabilities, among others.

We compare the candidates as a function of their MELD class, region-wise. Since the probability of an offer acceptance depends on the state ($S_{it}$) the candidate is in, we weigh the states to come up with a single number for each MELD class and region. For each MELD class (in a region), the weights assigned to the corresponding states (associated with that MELD class) reflect the empirical probabilities (estimated using the data) of being in those states. In Table 7, we report the weighted change in candidate's offer acceptance probabilities from the pre-Share 35 to the Share 35 policy eras using our structural model. We see that high MELD candidates (MELD 35-36 and MELD >36) in all regions (except region 9) became less aggressive in the Share 35 policy era as their acceptance probabilities decreased. Given that the Share 35 policy prioritized sicker candidates in a geographically broader sense allowing access outside their DSAs, they can afford to be selective. Interestingly, the high MELD classes in Region 9 became aggressive in the Share 35 policy era. Region 9 had the lowest ratio (0.51) of the number of deceased donors to the number of new patients joining the waiting list among all the regions (2010 to 2018). Probably, the Share 35 policy increased competition among the already organ deficient DSAs (in Region 9), which led to an increase in aggressive behavior at even higher MELD categories in Region 9 in the Share 35 policy era.

For lower MELD classes, we observe heterogeneity (across regions) in their behavior change. For example, MELD 6-14 candidates experienced a negative effect and became more aggressive in more

| Region | MELD class | | | | | |
|---|---|---|---|---|---|---|
| | MELD 6-14 | MELD 15-28 | MELD 29-32 | MELD 33-34 | MELD 35-36 | MELD >36 |
| Using structural model: | | | | | | |
| Region 1 | 0% | -0.2% | -0.4% | -0.7% | -1.4% | -1.6% |
| Region 2 | 0.2% | -0.1% | -0.5% | -1% | -4.6% | -7.4% |
| Region 3 | 0.2% | 0.1% | 0.3% | -0.3% | -4.2% | -6.5% |
| Region 4 | -0.2% | -0.6% | -1.4% | -2.7% | -7.4% | -10.5% |
| Region 5 | -0.1% | -0.4% | -0.9% | -1.4% | -3.4% | -6.6% |
| Region 6 | 0.1% | -0.1% | -0.5% | -2% | -4.7% | -7.3% |
| Region 7 | -0.2% | -0.5% | -1.2% | -2.3% | -5.7% | -8.4% |
| Region 8 | 0.1% | 0% | 0.4% | 0.4% | -1.4% | -2.8% |
| Region 9 | 0.2% | 0.1% | 0.3% | 0.3% | 0.8% | 1.7% |
| Region 10 | 0% | -0.2% | -1% | -2% | -5.6% | -9% |
| Region 11 | 0.1% | -0.1% | -0.2% | -0.8% | -5.5% | -8.7% |
| Using summary statistics: | | | | | | |
| Region 1 | -0.2% | -2.3% | -6.4% | -8.4% | -3.7% | -3.2% |
| Region 2 | 0.9% | -1.1% | -4.5% | -7.2% | -5.1% | -5.4% |
| Region 3 | 2.6% | -0.4% | -9.8% | -15.3% | -3.8% | -10.2% |
| Region 4 | 0.4% | -4% | -15.6% | -19.6% | -13.7% | -7.3% |
| Region 5 | 0.5% | -0.9% | -5.1% | -9% | -13.4% | -10.1% |
| Region 6 | 0% | -6.3% | -16.8% | -29.5% | -27.6% | -19.5% |
| Region 7 | -0.4% | -5.6% | -9.1% | -13.1% | -12.2% | -10.6% |
| Region 8 | 0.2% | -1.9% | -16.2% | -17.4% | 3.3% | -3.5% |
| Region 9 | 0.8% | -0.3% | -4.8% | -8.5% | -6.4% | -9.4% |
| Region 10 | 6.4% | -6.5% | -12.6% | -10.9% | -9.4% | -3.1% |
| Region 11 | 1.3% | -4.9% | -15.8% | -16.8% | -9% | -2.5% |

**Table 7 Comparison of change in offer acceptance probabilities as a function of MELD score from pre-Share 35 to Share 35 policy eras.**

than half of the regions (Regions: 2, 3, 6, 8, 9, 11). It turns out that these regions were associated with relatively higher organ supply. The average supply (number of deceased donors) to demand (number of new patients joining the waiting list) ratio, based on 2010 to 2018 time period, in these regions was 0.82, compared to 0.67 in the rest of the regions. Since the Share 35 policy increased the priority of the national patients over low MELD (<15) local/regional patients, the low MELD patients in the regions with higher organ supply became aggressive in response to potentially losing access to organs that were now offered to candidates outside their respective regions.

To highlight the importance of using the structural model in our problem setting, we report the corresponding numbers (lower half in Table 7) if we had simply calculated the acceptance probability as the ratio of the number of offers accepted and the number of offers received. They would have led to misleading conclusions. The structural model accounts for not just offer probabilities, but also the expected utilities associated with those offers in calculating the offer acceptance probabilities (see equation 12).

## 7. Counterfactual Study

The value function, $EV(.)$, depends on allocation policy, exogeneous organ, and demand arrivals, and together they determine the offer probabilities. To delineate the effect of allocation policy from

other factors like changes in patient and organ arrival processes, we simulate various policies using the common data on organ and patient arrivals. In our simulation setup, we have 5,000 patients and 3,600 donors arriving at different points in time.

Recent studies (Ata et al. 2020, Agarwal et al. 2021) have widely used the iterative simulation approach to estimate the new equilibrium organ offer probabilities in a counterfactual study. Instead of a simulation-based iterative approach, we derive analytical expressions to calculate quantities like the number of offers, transplants, deaths, etc. We use these in an iterative framework (see Appendix B for details including simulation setup) to compute the equilibrium organ offer probabilities in an allocation policy. The benefit of using the analytical expressions is that it avoids randomness due to candidates' accept/decline decisions and their MELD transitions, which helps in achieving a faster convergence with tighter tolerance limits.

We now discuss the various performance metrics to measure geographic equity and efficiency and compare between the following policies of interest: (1) Pre-Share 35, (2) Share 35, (3) Acuity Circles, (4) s/d Match, and (5) National Sharing. For performance metrics whose analytical computations are cumbersome, we simulate the organ allocation policy 50 times (using its equilibrium organ offer probabilities) and report the *average*. Performance metrics based on analytical computations are reported as an *expected* quantity.

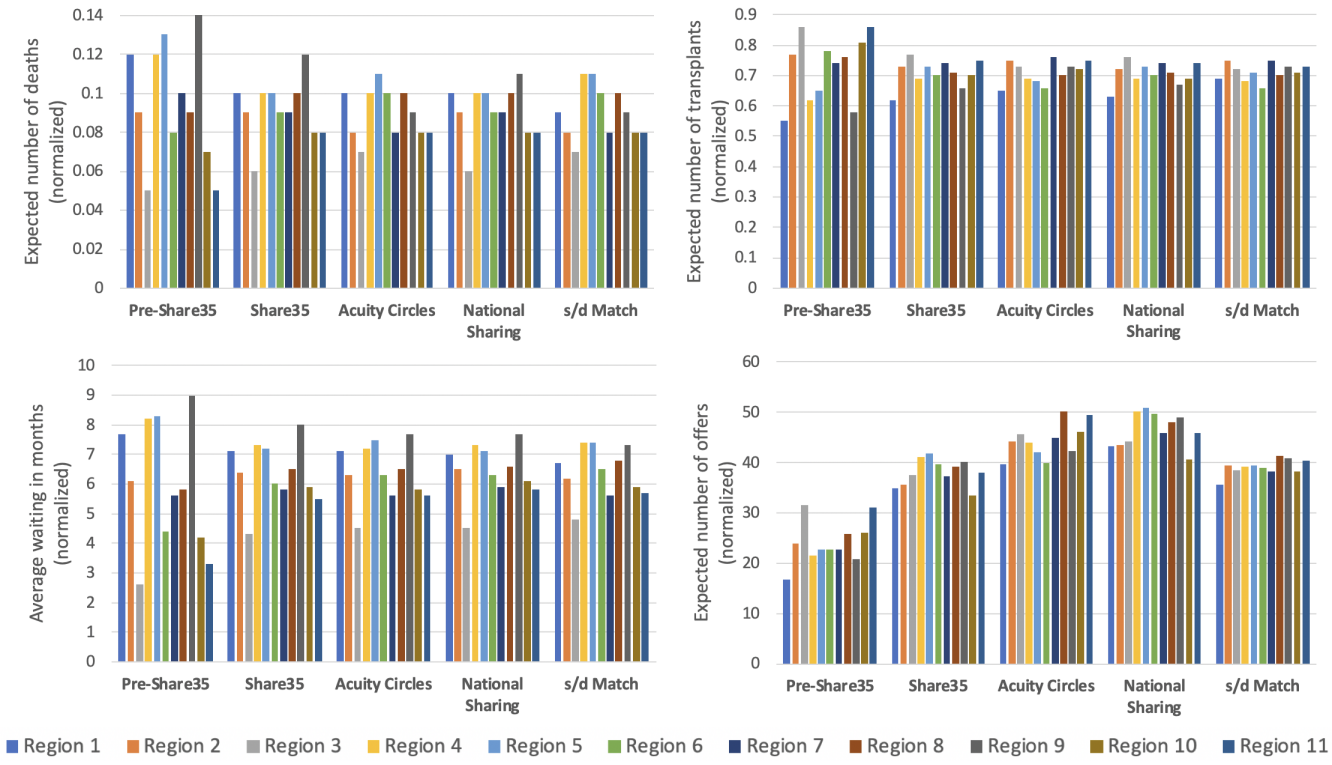


**Figure 6** **Comparison of various geographical equity measures between policies.**

### 7.1. Geographic equity

We compare the expected number of deaths, the expected number of transplants, average waiting time in months (that a patient spends on the waiting list till transplantation, death or the end of simulation), and the expected number of offers across the regions and between various allocation policies in Figure 6. We report the values after normalizing them by the waiting list volumes in their respective regions. We see that not all regions benefit from the introduction of the Share 35 policy (compared to the Pre-Share 35 policy). For example, region 11 gets adversely impacted: the number of deaths and waiting time increased, and the number of transplants decreased. To gain more insights, we performed a simple correlation study (at the level of regions) between the reduction in the number of deaths (normalized by the waiting list volume) and the supply to demand ratios (deceased donors in a region constitute the supply and total patients joining the waiting list in that region constitute the demand). We observed a strong negative correlation coefficient ($r = -0.91$; $P < 0.001$) suggesting that the benefit in terms of life savings due to the Share 35 policy is higher for regions with lower supply to demand ratios. This is reflective of the change brought due to the Share 35 policy that prioritized MELD $\geq$15 national patients before MELD $<$15 local or regional patients (see Table 2). A similar correlation study between the increase in the chances of receiving a transplant (from Pre-Share 35 to Share 35 policy) and the supply to demand ratios revealed a strong negative correlation coefficient ($r = -0.89$; $P < 0.001$). The reduction in the expected waiting period was also negatively correlated ($r = -0.93$; $P < 0.001$) with the supply to demand ratios. Along the same lines, the increase in the expected offers was negatively correlated ($r = -0.68$; $P = 0.021$) with the supply to demand ratios. Overall, they suggest that the benefit due to the Share 35 policy is higher for regions with lower supply to demand ratios. Compared to the Pre-Share 35 policy, other policies (Share 35, Acuity Circles, National Sharing, and s/d Match) increase geographic equity (as indicated by the decrease in variability in performance metrics across the regions). In Table 8, we report the standard deviations, calculated across the regions, for different geographic equity metrics and allocation policies. The Pre-Share 35 (s/d Match) policy has the highest (lowest) variability across all the performance measures.

On an aggregate basis, we find that out of a total of 5,000 patients in our study, the Pre-Share 35 policy resulted in 499.0 expected number of deaths, the Share 35 policy resulted in 463.2 deaths,

| **Geographic equity metrics (normalized)** | Standard deviation across the regions | | | | |
|---|---|---|---|---|---|
| | Pre-Share 35 | Share 35 | Acuity Circles | National Sharing | s/d Match |
| Deaths | 0.031 | 0.015 | 0.013 | 0.014 | 0.013 |
| Transplants | 0.109 | 0.043 | 0.038 | 0.037 | 0.028 |
| Waiting (in months) | 2.164 | 1.024 | 0.964 | 0.878 | 0.801 |
| Offers | 4.350 | 2.626 | 3.413 | 3.364 | 1.553 |

**Table 8 Comparison of the standard deviation of various geographic equity measures between policies.**

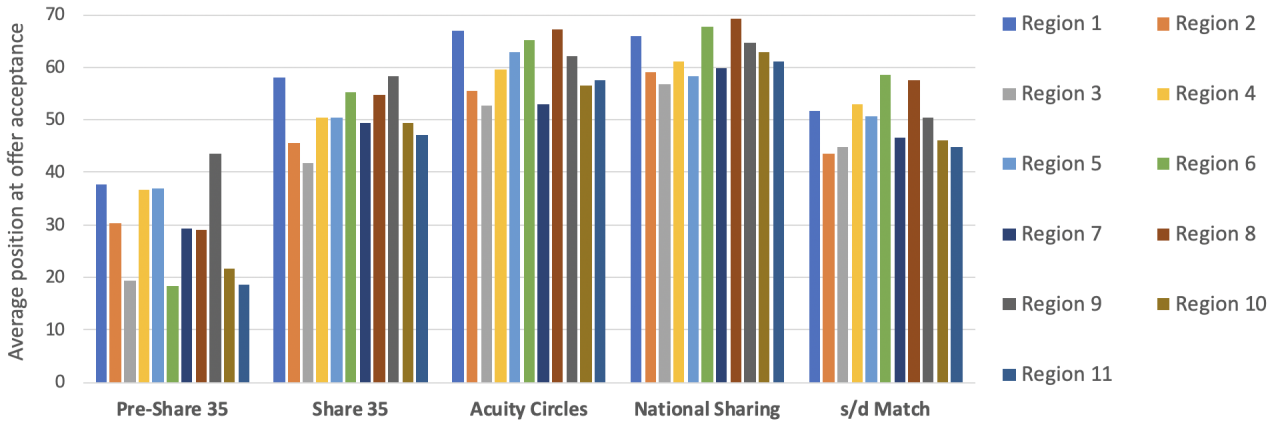


**Figure 7** **Comparison of position at offer acceptance between policies.**

the Acuity Circles policy resulted in 462.2 deaths, the s/d Match policy resulted in 459.9 deaths, and the National Sharing policy resulted in the least number of 454.1 deaths. Out of a total of 3,600 organs, the Pre-Share 35 policy resulted in 3575.4 expected number of transplants, the Share 35 policy resulted in 3570.4 transplants, the Acuity Circles policy resulted in 3564.3 (lowest) transplants, the s/d Match policy resulted in 3570.8 transplants, and the National Sharing policy resulted in 3564.6 transplants.

### 7.2. Efficiency

We capture efficiency using four performance metrics: position in the queue at offer acceptance, the utility derived from transplantation, increase in patient's survival probability (calculated at the end of one year) due to transplant, and distance traveled by the organ.

In Figure 7, we compare the average position at which a candidate accepts an offer across the regions and between various allocation policies. The three policies (Pre-Share 35, Share 35, and National Sharing) are in increasing order of broader sharing. The Pre-Share 35 policy prioritizes the local patients, the Share 35 policy allows more regional and national sharing than its predecessor policy while the National Sharing policy does not consider geography conditional on the MELD of the patient. The Acuity Circles policy can be seen as a broader sharing analogue of the s/d Match policy (since the latter allows the radius around a donor hospital to be less than 500 NM). We observe that as sharing becomes broader, the position at acceptance and offer refusals increase as a consequence. This is consistent with the takeaway drawn from comparing MELD at offer and MELD at transplant that the Share 35 resulted in higher offer refusals (see Figure 3).

Since utility on its own has no physical interpretation, we report the fractional change in the average utility from transplantation with respect to the Pre-Share 35 policy in Figure 8. We see that all the policies are associated with lower transplant utility (as compared to Pre-Share 35). We also observe that as the position at offer acceptance increases, the transplant utility decreases.

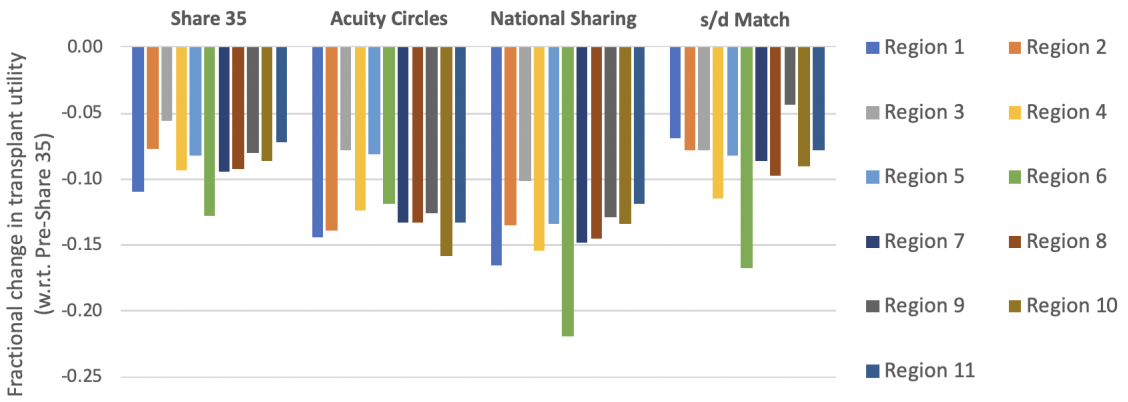


**Figure 8** **Comparison of fractional change in utility from transplant (with respect to Pre-Share 35) between policies.**

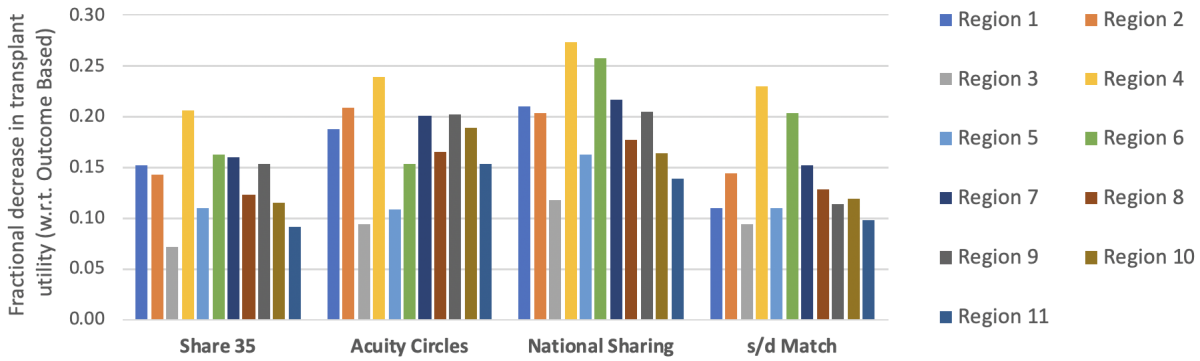


**Figure 9** **Cost of fairness (with respect to Outcome Based) of various policies.**

This is reasonable since offer refusals will tend to deteriorate the quality of the organ and thus transplant utility.

We simulate a new policy, Outcome Based, where the candidates are sequenced in decreasing order of the prospective expected utility derived from transplantation. It sets a benchmark for the best outcomes that can be expected of an allocation policy. We then estimate the cost of fairness (fractional decrease in transplant utility with respect to the Outcome Based policy) in Figure 9. The Share 35, and the s/d Match policies have the least cost (13% decrease in transplant utility with a significant increase in geographic equity with respect to the Outcome Based policy) while the Acuity Circles and the National Sharing policies result in 17% and 19% decrements, respectively.

We calculate the increase in a patient's survival probability due to a transplant as the difference between the probability of graft survival, and probability of a patient's survival without a transplant, both measured at the end of one year. See Appendix E for methodological details. We simulate a new policy, Survival Benefit, where the candidates are sequenced in decreasing order of the increment in patient's survival probability due to the transplant. It sets a benchmark for the greatest benefits that can be expected of an allocation policy. In Figure 10, we report the average

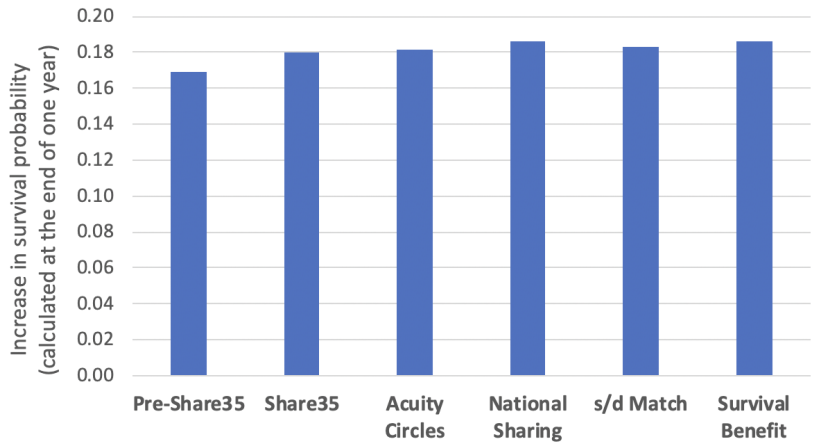


**Figure 10** **Comparison of average increase in survival probability due to transplantation between policies.**

| | Pre-Share 35 | Share 35 | Acuity Circles | National Sharing | s/d Match |
|---|---|---|---|---|---|
| Mean | 240 | 390 | 357 | 503 | 360 |
| 1st quartile | 46 | 59 | 56 | 71 | 52 |
| Median | 114 | 176 | 197 | 279 | 180 |
| 3rd quartile | 282 | 528 | 435 | 760 | 417 |

**Table 9** **Comparison of travel distance (in NM) between policies.**

increase in survival probability due to a transplant in different policy regimes. We see that the Survival Benefit and the National Sharing policies result in the highest benefits (survival probability increases by 0.186 on average), followed by the s/d Match (0.183), the Acuity Circles (0.181), the Share 35 (0.180), and the Pre-Share 35 (0.169) policies.

Table 9 compares the travel distance between the policies (we exclude the observations associated with the donor hospitals and transplant centers situated at HIOP (DSA in Hawaii) and PRLL (DSA in Puerto Rico) from the analysis). The distance between any two DSAs $i$ and $j$, is calculated as the mean of the transplant-volume-weighted distance between donor hospitals in DSA $i$ and transplant center in DSA $j$, and the reverse. We see that the National Sharing policy results in the largest travel distance, and the Pre-Share 35 policy results in the smallest travel distance. This is reasonable since they are the two extremes of the broader sharing level. The s/d Match policy is marginally better than the Acuity Circles policy and outperforms the Share 35 policy (in all but median travel distance).

Overall, the s/d Match policy that is based on equalizing the s/d ratios by selectively increasing the sharing of donor organs has the lowest trade-off on the efficiency metrics (compared to the Pre-Share 35 policy) to address the issue of geographic inequity. In fact when a larger radius is allowed around a donor hospital, s/d ratios are much closer at the transplant centers (i.e., equalized better) and the efficiency metrics are further improved. Please see Appendix F for details.

## 8. Conclusions

We develop a structural model that endogenizes the forward-looking behavior of the patients with the allocation policy. We formulate the problem as a discrete-time infinite-horizon dynamic optimization model and use a rich set of patient and donor medical attributes without losing the tractability of the model.

First, we study the impact of the Share 35 liver allocation policy (introduced in June 2013) on the patients' behavior. We find that the Share 35 policy induced selective behavior, and benefited high MELD (sicker) patients, with mixed results in low MELD patients across the regions. We also find that the Share 35 policy was effective in reducing geographic disparity in metrics like the number of deaths, access to transplants, waiting time, and organ offers. We observe that the benefit due to the Share 35 policy was strongly correlated with the supply (deceased-donors) to demand (new patients) ratios in the regions. Regions with lower supply to demand ratios reaped greater benefits. However, the Share 35 policy resulted in more offer refusals and lower average utility from the transplantations. The intuition is that the Share 35 policy prioritized sicker patients, who became more selective in their behavior due to an increase in organ access, thus resulting in more organ refusals. Although, the Share 35 policy alleviates geographic disparity compared to the Pre-Share 35 policy, its rigid DSA based geographical boundaries resulted in organ allocations that were not legally defensible (i.e., an organ being offered to a less sicker patient further away).

Recent policies are moving towards broader sharing in principle. The current, "one-size-fits-all" Acuity Circles policy performs very similarly to the Share 35 policy under geographic equity metrics. However, it leads to even lower efficiency (more offer refusals and less utility from transplantation). We illustrate that broader sharing in its current form *may not be the best strategy to balance geographic equity and efficiency*. Rather a customized approach (equalizing the supply to demand ratios across the geographies) through the s/d Match policy performs best in addressing the issue of geographic inequity while sacrificing the least efficiency (compared to the Pre-Share 35 policy). This policy selectively enhances radii around donor hospitals, increasing broader sharing as necessary to equalize supply and demand. We *strongly recommend that policymakers move away from a "one-size-fits-all" approach to broader sharing and instead develop broader sharing in a framework that matches supply and demand*. Such a policy has the greatest potential to score well both in terms of efficiency as well as geographic equity!

Previous policy proposals have been assessed using LSAM that uses the same probability acceptance function for candidates and does not consider whether a candidate is residing in an organ-rich/deficient location. Our study provides a framework for researchers and policymakers to incorporate patient's potential behavior change in the assessment of a new policy proposal, which influences their acceptance probability. There is a considerable push in the transplant community

about using the continuous scoring framework (a distribution framework in active consideration by the UNOS).[4] An interesting and potentially impactful future study would be to model policy parameters in a continuous scoring framework that equalizes the supply to demand ratios across the transplant centers.

We limit our study to focus only on geographic inequity (as motivated by the prior lawsuits) and do not consider other kinds of disparities, like race, gender, socio-economic factors, organ size and, blood type. Developing a model to incorporate and mitigate these additional disparities (if any) can be an interesting future direction of research.

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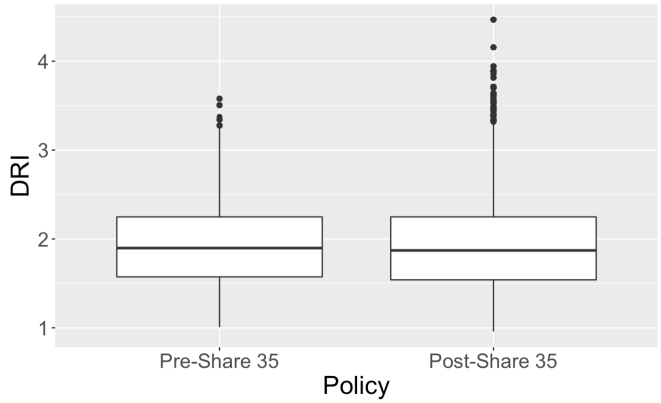


**Figure 11 Comparison of organ quality of declined offers between pre- and Share 35 policy eras using donor risk index (DRI).**

## Appendix A: Comparing Organ Quality of Declined Offers

We use the metric, donor risk index (DRI), proposed by Feng et al. (2006) to evaluate the quality of organs that were declined. This index measures the quality of an organ using demographic factors (age, race, height), cause and type of donor death, sharing type (local/regional/national), and CIT. A higher DRI is associated with a greater risk of graft failure. Since CIT is observed only for accepted offers, we use the median value(=6.9 hours) in our calculation. In Figure 11, we compare the box plots of DRI between pre-and Share 35 policy eras. We see that there are no significant differences in the distributions of organ quality.

## Appendix B: Iterative Method for Estimating Equilibrium

We simulate different organ allocation policies on a daily basis over two years ($t = 1, ..., 730$). The common inputs across the policies are the sampled organ and candidate arrivals, the MELD transition matrix, and the estimates from the structural model. We randomly sample 5,000 patients and 3,600 donors from the 11 regions, and they arrive at different points in time. Every organ is offered to a maximum of 500 candidates (which is close to $99^{th}$ percentile in the actual dataset) before getting discarded. We let 34% of the patients be on the waiting list at $t = 1$, and the distribution of the initial MELD of the arriving patients is representative of the actual data. We consider two patient groups ({($Rec\_age$:<45 years, $Rec\_life\_support$='No', $Rec\_med\_cond$='NH'), ($Rec\_age$: 45-65 years, $Rec\_life\_support$='No', $Rec\_med\_cond$='NH')} that constitutes 83% of the patient population in the UNOS data) and 48 organ types in the simulation study. Different patient groups may have different probabilities of acceptances for the same organ due to differences in expected utilities (derived from the transplant) and waiting costs. The equilibrium behavior of each group will depend on the presence of the others, and by considering two groups in our study, we capture their interactions in the equilibrium offer acceptance probabilities.

The steps (followed by the pseudo algorithm) to estimate steady-state equilibrium (for each allocation policy) using the iterative method are:

1. Start with the organ offer and sharing type probabilities: $\mathcal{P}^{(k)}(Q_{it}|MELD_{it})$ and $\mathcal{P}^{(k)}(Sharing\_type_{it}|MELD_{it}, Q_{it})$. This enables us to calculate the state transition matrix, $\Pi^{(k)}$. Using the "inner" algorithm of the nested fixed point algorithm, estimate $EV^{(k)}(.)$. When $k = 0$, we start with arbitrary values of the above quantities. Skip the next step if $k = 0$.

2. If $||EV^{(k)}(.) - EV^{(k-1)}(.)||_\infty < \varepsilon_1$, stop, else go to the next step. We use $\varepsilon_1 = 10^{-5}$.

3. Calculate the probability of acceptance: $P^{(k)}(d_{it} = 1|S_{it}) = \frac{e^{EU(S_{it})}}{e^{EU(S_{it})} + e^{-EW(S_{it}) + \delta EV^{(k)}(S_{it})}}$.

4. **Policy simulation**:[5] For an allocation policy, we analytically calculate the expected number of offers, the expected number of transplants, and the expected waiting period by any time $t$. Using analytical expressions avoids the randomness introduced due to candidates' accept/decline decisions and their MELD transitions, which helps in achieving a faster convergence with tighter tolerance limits. First, we create a table of states for every geography (DSA or TC) and tabulate the count of patients in those states. Each state has its probability of acceptance. A patient's state might transition to other states (geography of the patient does not change). At different points in time, new patients join the waiting list, donors arrive, some patients receive offers, get transplanted, and leave the system. To analytically calculate the expected number of offers received and transplants (to patients in various MELD classes and geographies) due to an organ arriving at time $t$, we sum the finite geometric series sequentially, in the order (determined by the allocation policy) in which offers are made to the various groups of patients. The transplanted patients are removed from the waiting list. Using the MELD transition matrix, we calculate the expected number of patients transitioning to different MELD categories at time $t+1$ and update the waiting list. New patients who join the waiting list at time $t+1$ are added. If no donor arrives at time $t+1$, only the MELD transitions occur.

We can track the expected number of patients on the waiting list, the number of offers received, and the number of transplants at different $t$. This enables us to calculate the quantities of interest to us, which are organ offer and sharing type probabilities: $\mathcal{P}^{(k)}(Q_{it}|MELD_{it})$ and $\mathcal{P}^{(k)}(Sharing\_type_{it}|MELD_{it}, Q_{it})$ in the $k^{th}$ step of the iterative method.

5. Update $k$ to $k+1$. Go to Step 1.

Each iteration took around 25 hours for policies that use TC as the geographic unit (and around 9 hours for DSA based policies), and we were able to achieve convergence within 10 iterations for every policy. For the Acuity Circles policy, we define 'local' sharing if the distance between the donor hospital and the TC is <66 NM (average of the distance between the donor hospital and TC pairs that are in the same DSA), 'regional' sharing if the distance is ≥66 NM and <262 NM (average of the distance between the donor hospital and TC pairs that are in the same region), and 'national' otherwise.

[5] Although we do not use any random numbers, we refer to this step as policy simulation since we use the above-mentioned common inputs for every allocation policy.

| | MELD class | | | | | | |
|---|---|---|---|---|---|---|---|
| | MELD 6-14 | MELD 15-28 | MELD 29-32 | MELD 33-34 | MELD 35-36 | MELD >36 | Death |
| MELD 6-14 | 0.9958 | 0.0036 | 0.0002 | 0.0001 | 0.0000 | 0.0000 | 0.0003 |
| MELD 15-28 | 0.0049 | 0.9922 | 0.0016 | 0.0002 | 0.0001 | 0.0002 | 0.0008 |
| MELD 29-32 | 0.0041 | 0.0120 | 0.9693 | 0.0082 | 0.0022 | 0.0020 | 0.0021 |
| MELD 33-34 | 0.0042 | 0.0070 | 0.0092 | 0.9508 | 0.0166 | 0.0086 | 0.0036 |
| MELD 35-36 | 0.0062 | 0.0112 | 0.0114 | 0.0114 | 0.8809 | 0.0688 | 0.0102 |
| MELD >36 | 0.0098 | 0.0123 | 0.0051 | 0.0036 | 0.0059 | 0.9335 | 0.0299 |
| Death | 0 | 0 | 0 | 0 | 0 | 0 | 1 |

**Table 10 MELD transition matrix.**

**Algorithm 1** Steady State Equilibrium

**Input:** Candidate and organ characteristics, allocation policy, structural parameters $(\beta, \omega_d, \omega)$, MELD transition matrix. Let $t$ be the arrival time of an organ.

**Output:** $EV^*(S_{it}), \mathcal{P}^*(Q_{it}|MELD_{it}), \mathcal{P}^*(Sharing\_type_{it}|MELD_{it}, Q_{it})$.

Initialize $k$=0 and beliefs $EV^k(S_{it}), \mathcal{P}^k(Q_{it}|MELD_{it})$, and $\mathcal{P}^k(Sharing\_type_{it}|MELD_{it}, Q_{it})$ for all possible values of $S_{it}, Q_{it}, MELD_{it}$ and $Sharing\_type_{it}$.

**repeat**

$\Pi^k \leftarrow$ Compute state transition matrix (see equation 8)

Initialize $m = 0$ and $EV^m(.)$

**repeat**

$EV^m(.) \leftarrow \Pi^k . \ln\left[e^{EU(.)} + e^{-EW(.)+\delta EV^m(.)}\right]$

$m \leftarrow m + 1$

**until** $m \geq 1, \left\|EV^m(.) - \Pi . \ln\left[e^{EU(.)} + e^{-EW(.)+\delta EV^m(.)}\right]\right\|_\infty < 10^{-9}$;

$EV^k(.) \leftarrow EV^m(.)$

$p^k_{acpt}(S_{it}) := P^k(d_{it} = 1|S_{it}) \leftarrow$ Compute offer acceptance probabilities $\forall S_{it}$ (see equation 17)

$\mathcal{P}^k(Q_{it}|MELD_{it}), \mathcal{P}^k(Sharing\_type_{it}|MELD_{it}, Q_{it}) \leftarrow$ Policy Simulation $(p^k_{acpt}(.))$

$k \leftarrow k + 1$

**until** $k > 1, \left\|EV^k(.) - EV^{k-1}(.)\right\|_\infty < 10^{-5}$;

$EV^*(S_{it}) \leftarrow EV^k(S_{it}), \mathcal{P}^*(Q_{it}|MELD_{it}) \leftarrow \mathcal{P}^k(Q_{it}|MELD_{it})$,
$\mathcal{P}^*(Sharing\_type_{it}|MELD_{it}, Q_{it}) \leftarrow \mathcal{P}^k(Sharing\_type_{it}|MELD_{it}, Q_{it})$

## Appendix C: MELD Transition Matrix

Table 10 reports the MELD transition matrix as estimated from the data (January 2003 to February 2019).

## Appendix D: Log-Likelihood Function

When an offer is made, the probability of accepting an offer, given by equation (12), can be rewritten as

$$P(d_{it} = 1|S_{it}) = \frac{e^{EU(S_{it})}}{e^{EU(S_{it})} + e^{-EW(S_{it})+\delta EV(S_{it})}}, \tag{17}$$

Taking log both sides,

$$\ln\left(P(d_{it} = 1|S_{it})\right) = \ln\left[e^{EU(S_{it})}\right] - \ln\left[e^{EU(S_{it})} + e^{-EW(S_{it})+\delta EV(S_{it})}\right] \tag{18}$$

Also,

$$\ln\left(P(d_{it}=0|S_{it})\right)=\ln\left[e^{-EW(S_{it})+\delta EV(S_{it})}\right]-\ln\left[e^{EU(S_{it})}+e^{-EW(S_{it})+\delta EV(S_{it})}\right] \tag{19}$$

The log-likelihood of a candidate's observed decision is:

$$\left\{\ln\left(P(d_{it}=1|S_{it})\right)\right\}^{d_{it}}.\left\{\ln\left(P(d_{it}=0|S_{it})\right)\right\}^{(1-d_{it})} \tag{20}$$

Grouping over all patients' decisions, the log-likelihood function is:

$$\begin{aligned}
&\sum_{i,t}\left(\mathbb{1}_{\{d_{it}=1\}}\ln\left(P\left(d_{it}=1|S_{it}\right)\right)+\mathbb{1}_{\{d_{it}=0\}}\ln\left(P\left(d_{it}=0|S_{it}\right)\right)\right)\\
&=\sum_{S_{it}}\left(n_{accept}^{S_{it}}.\ln\left(P\left(d_{it}=1|S_{it}\right)\right)+n_{decline}^{S_{it}}.\ln\left(P\left(d_{it}=0|S_{it}\right)\right)\right)\\
&=\sum_{S_{it}}n_{accept}^{S_{it}}\left(EU(S_{it})-ln[e^{EU(S_{it})}+e^{-EW(S_{it})+\delta EV(S_{it})}]\right)+\\
&n_{decline}^{S_{it}}\left(-EW(S_{it})+\delta EV(S_{it})-ln[e^{EU(S_{it})}+e^{-EW(S_{it})+\delta EV(S_{it})}]\right)\\
&=\sum_{S_{it}}n_{accept}^{S_{it}}EU(S_{it})+n_{decline}^{S_{it}}(-EW(S_{it})+\delta EV(S_{it}))-\\
&\left(n_{accept}^{S_{it}}+n_{decline}^{S_{it}}\right).(ln[e^{EU(S_{it})}+e^{-EW(S_{it})+\delta EV(S_{it})}])
\end{aligned} \tag{21}$$

Every candidate $i$ has her associated state $S_{it}$ at time $t$, therefore, we can sum over the elements in the state space, accounting for the number of candidates in those states (instead of summing over the candidates and times when they made the decisions). The first equality follows from this fact, where $n_{accept}^{S_{it}}$ and $n_{decline}^{S_{it}}$ denote the number of candidates who accepted, and declined the offers when in state $S_{it}$, respectively.

## Appendix E: Survival Benefit due to a Transplant

We estimate the survival benefit due to a transplant as the difference between the probability of graft survival and the probability of a patient's survival without a transplant, both calculated at the end of one year. The baseline survival functions are estimated using the Kaplan-Meier curves. The estimated graft survival probability (at t=1 year) of the baseline is 0.98 (standard error = 0.05), and the patient's survival probability without a transplant of the baseline is 0.875 (standard error = 0.04). We use the Cox-proportional hazards model (Cox 1972) to estimate the hazard ratios (HR) associated with organ and patient characteristics used in our simulation study. The estimates of the HRs are reported in Table 11.

## Appendix F: s/d Match Policy (Maximum Radius = 600 NM)

When we allow the maximum radius around the donor hospital to be 600 NM, the s/d ratio (at the TC level) ranges from 0.62 to 0.73. In Table 12, we compare the geographic equity metrics between the two s/d Match policies (maximum radius equals 500 NM versus 600 NM) using the simulation setup described in Appendix B. Although we do not observe improvement in all the metrics, the expected number of deaths decreases from 459.9 (maximum radius = 500 NM) to 455.4 (maximum radius = 600 NM), and the expected number of transplants increases from 3570.8 to 3578.5.

In Figure 12, we compare the efficiency metrics like the position at offer acceptance, the fractional change in the utility from transplant (with respect to the Pre-Share 35 policy), cost of fairness (with respect to the

| Covariate | Graft survival | | Patient survival without transplant | |
|---|---|---|---|---|
| | HR | p-value | HR | p-value |
| MELD 6-14 | 1.13 | 0.02 | 0.45 | <2E-16 |
| MELD 29-32 | 0.91 | 0.02 | 3.63 | <2E-16 |
| MELD 33-34 | 0.75 | 2.87E-05 | 4.49 | <2E-16 |
| MELD 35-36 | 0.92 | 0.23 | 5.97 | <2E-16 |
| MELD >36 | 1.04 | 0.24 | 11.24 | <2E-16 |
| Candidate age group: R1 (<45 years) | 1.51 | <2E-16 | 0.63 | <2E-16 |
| Candidate age group: R3 (≥65 years) | 0.65 | <2E-16 | 1.28 | <2E-16 |
| Candidate life support: Yes | 1.09 | 0.09 | 2.67 | <2E-16 |
| Candidate medical condition: H | 1.18 | 1.69E-06 | 1.65 | <2E-16 |
| Candidate medical condition: ICU | 1.09 | 0.08 | 2.07 | <2E-16 |
| Donor age group: (40 to 49 years) | 1.35 | <2E-16 | - | - |
| Donor age group: (50 to 59 years) | 1.58 | <2E-16 | - | - |
| Donor age group: (≥60 years) | 1.78 | <2E-16 | - | - |
| Donor race: Other | 1.08 | 2.03E-03 | - | - |
| Donor cause of death: Anoxia | 0.84 | 4.56E-07 | - | - |
| Donor cause of death: CVA | 1.10 | 1.17E-03 | - | - |
| Donor DCD: Yes | 1.56 | 2.59E-11 | - | - |
| Sharing type: Regional | 1.00 | 0.96 | - | - |
| Sharing type: National | 1.34 | 1.98E-13 | - | - |

**Table 11 Survival model estimates.**

| Geographic equity metrics (normalized) | Standard deviation across the regions | |
|---|---|---|
| | s/d Match (500 NM) | s/d Match (600 NM) |
| Deaths | 0.013 | 0.013 |
| Transplants | 0.028 | 0.034 |
| Waiting (in months) | 0.801 | 0.793 |
| Offers | 1.553 | 1.994 |

**Table 12 Comparison of the standard deviation of various geographic equity measures between s/d Match policies.**

| | s/d Match (500 NM) | s/d Match (600 NM) |
|---|---|---|
| Mean | 360 | 337 |
| 1st quartile | 52 | 60 |
| Median | 180 | 206 |
| 3rd quartile | 417 | 427 |

**Table 13 Comparison of travel distance (in NM) between the two s/d Match policies.**

Outcome Based policy) between the two s/d Match policies (maximum radius equals 500 NM versus 600 NM). We see that the bigger radius policy results in greater efficiency. The average increase in a patient's survival probability due to a transplant is also slightly higher (0.185 versus 0.183) in the bigger radius s/d Match policy. Table 13 compares the distance traveled by the organ between the two s/d Match policies. While the mean distance is lower in the bigger radius policy, the other measures are marginally higher. Overall, if the broader sharing is done to match the supply and demand (like increasing the maximum radius from 500 NM to 600 NM), it may not adversely impact the efficiency metrics!

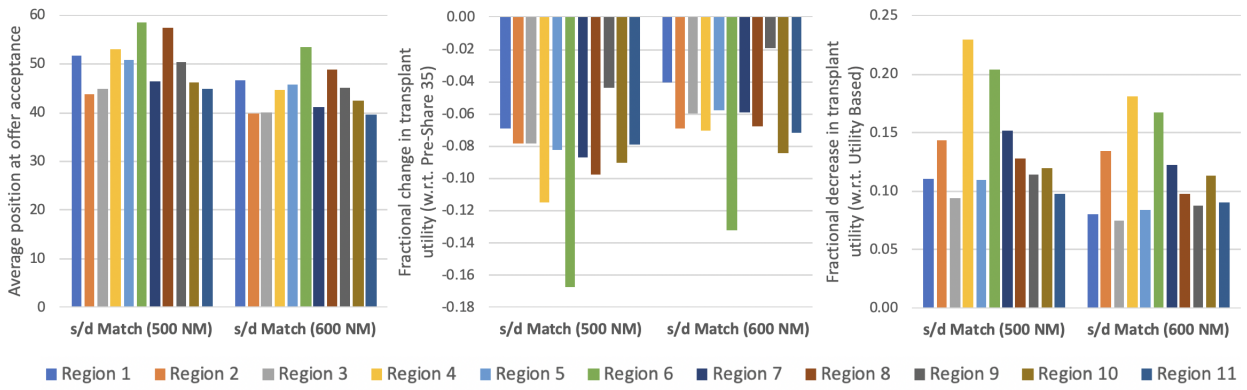


**Figure 12 Comparison of position at offer acceptance, fractional change in utility from transplant (with respect to Pre-Share 35), cost of fairness (with respect to Outcome Based) between the two s/d Match policies.**

## Appendix G: Graft Survival Model

We use the SRTR's post-transplant outcome model (Cox proportional hazards model) to estimate the probability of a graft's survival at the end of one year. The coefficients for each level of the risk adjusters present in the model are in Table 14.

| Predictor | Level | Coefficient |
|---|---|---|
| Candidate diabetes status/type at onset | None | -0.096386781 |
| Candidate diabetes status/type at onset | Type I or Type II | 0 |
| Candidate diabetes status/type at onset | Type Other/Unknown | 0.161080656 |
| Candidate diabetes status/type at onset | Missing | -0.096386781 |
| Candidate last albumin (used for MELD) | Apply to $< 2.2$ (Left LS) | 0.332645169 |
| Candidate last albumin (used for MELD) | Apply to $< 3.2$ (Left LS) | 0.102299655 |
| Candidate last albumin (used for MELD) | Apply to $< 3.8$ (Left LS) | 0.007908774 |
| Candidate last albumin (used for MELD) | Missing | 0 |
| Candidate last bilirubin (used for MELD) | Apply to $> 20$ (Right LS) | 0.000427117 |
| Candidate last bilirubin (used for MELD) | Apply to $> 30$ (Right LS) | 0.002070944 |
| Candidate last bilirubin (used for MELD) | Apply to $> 35$ (Right LS) | 0.016810742 |
| Candidate last bilirubin (used for MELD) | Missing | 0 |
| Candidate last encephalopathy (used for MELD) | None | -0.030820106 |
| Candidate last encephalopathy (used for MELD) | One to Two | 0 |
| Candidate last encephalopathy (used for MELD) | Three to Four | 0.183998674 |
| Candidate last encephalopathy (used for MELD) | Missing | -0.030820106 |
| Candidate last log(INR) (used for MELD) | Apply to $< 0.1$ (Left LS) | 0.4326963 |
| Candidate last log(INR) (used for MELD) | Apply to $< 0.8$ (Left LS) | 0.10044248 |
| Candidate last log(INR) (used for MELD) | Missing | 0 |
| Candidate last serum creatinine mg/dl (used for MELD) | Apply to $< 2$ (Left LS) | -0.083381344 |
| Candidate last serum creatinine mg/dl (used for MELD) | Apply to $< 4.5$ (Left LS) | -0.024756461 |
| Candidate last serum creatinine mg/dl (used for MELD) | Apply to $> 1$ (Right LS) | 0.003353918 |
| Candidate last serum creatinine mg/dl (used for MELD) | Missing | -0.232748885 |

| | | |
|---|---|---|
| Candidate last serum sodium (used for MELD) | Apply to > 144 (Right LS) | 0.092133301 |
| Candidate last serum sodium (used for MELD) | Missing | 0 |
| Candidate race | Asian | 0 |
| Candidate race | Black | 0.121230608 |
| Candidate race | Multiracial or Native American or Pacific Islander | 0 |
| Candidate race | White | -0.021981029 |
| Candidate race | Missing | -0.021981029 |
| Donor other drug use | Current | -0.03899045 |
| Donor other drug use | Former or Never | 0 |
| Donor other drug use | Missing | -0.03899045 |
| Recipient primary diagnosis at transplant | Acute Hepatic Necrosis | -0.003581187 |
| Recipient primary diagnosis at transplant | Biliary Atresia or Cholestatic Liver Disease/Cirrhosis | 0 |
| Recipient primary diagnosis at transplant | Malignant Neoplasms | 0 |
| Recipient primary diagnosis at transplant | Metabolic Diseases | 0.024135465 |
| Recipient primary diagnosis at transplant | Non-Cholestatic Cirrhosis or Other | 0 |
| Recipient primary diagnosis at transplant | Missing | -0.003581187 |
| Donor blood type | A or B | 0 |
| Donor blood type | AB | -0.135953984 |
| Donor blood type | O | 0.014130646 |
| Donor blood type | Missing | -0.135953984 |
| Donor age | Apply to > 50 (Right LS) | 0.001989411 |
| Donor age | Apply to > 70 (Right LS) | 0.027578938 |
| Donor age | Missing | 0 |
| Donor BUN | Apply to < 30 (Left LS) | -0.0000944 |
| Donor BUN | Apply to > 50 (Right LS) | 0.004159177 |
| Donor BUN | Missing | -0.002361233 |
| Donor cause of death | Anoxia or CNS Tumor or Head Trauma or Other or Missing | 0 |
| Donor cause of death | Cerebrovascular/Stroke | 0.122976036 |
| Donor circumstances of death | Death from Natural Causes or Homicide or MVA or Non-MVA or Other or | 0 |
| Donor circumstances of death | Suicide or Missing | -0.068517865 |
| Donor hematocrit | Apply to < 32 (Left LS) | 0.00180525 |
| Donor hematocrit | Apply to < 34 (Left LS) | 0.005421537 |
| Donor hematocrit | Missing | 0 |
| Donor height | Apply to < 160 (Left LS) | 0.000908374 |
| Donor height | Apply to > 185 (Right LS) | -0.007762809 |
| Donor height | Missing | -0.062102472 |
| Donor history of diabetes | No or Missing | 0 |
| Donor history of diabetes | Yes | 0.204194163 |
| Donor Macro Vesicular Fat Percent | 11 to 30 Percent | 0 |
| Donor Macro Vesicular Fat Percent | More than 30 Percent | 0.122816874 |
| Donor Macro Vesicular Fat Percent | Zero to 10 Percent or Not Available | -0.258465441 |
| Donor Macro Vesicular Fat Percent | Missing | -0.258465441 |
| Donor DCD | DCD Controlled | 0.52945535 |
| Donor DCD | DCD Not Controlled or Not DCD or Missing | 0 |
| Donor race | Asian | 0.254080967 |
| Donor race | Black or Multiracial or Native American or Pacific Islander | 0 |
| Donor race | White or Missing | -0.009892702 |
| Donor / Recipient Height Ratio | Apply to < 0.88 (Left LS) | 3.361045926 |

| | | |
|---|---|---|
| Donor / Recipient Height Ratio | Apply to $< 0.94$ (Left LS) | 0.114699434 |
| Donor / Recipient Height Ratio | Missing | 0 |
| Donor / Recipient Weight Ratio | Apply to $< 0.6$ (Left LS) | 1.739206256 |
| Donor / Recipient Weight Ratio | Apply to $> 1.5$ (Right LS) | 0.153246956 |
| Donor / Recipient Weight Ratio | Missing | 0 |
| Donor transfusion count | Greater Than One | 0 |
| Donor transfusion count | Zero or Missing | -0.009330057 |
| Donor weight | Apply to $< 75$ (Left LS) | 0.00119626 |
| Donor weight | Missing | 0 |
| Recipient BMI | Apply to $< 24$ (Left LS) | 0.0000353 |
| Recipient BMI | Apply to $< 26$ (Left LS) | 0.004311064 |
| Recipient BMI | Apply to $> 34$ (Right LS) | 0.0303621 |
| Recipient BMI | Missing | 0 |
| Recipient cold ischemia time | Apply to $< 9.5$ (Left LS) | -0.006968378 |
| Recipient cold ischemia time | Apply to $> 5$ (Right LS) | 0.000358078 |
| Recipient cold ischemia time | Apply to $> 5.5$ (Right LS) | 0.041714117 |
| Recipient cold ischemia time | Apply to $> 6$ (Right LS) | 0.001339226 |
| Recipient cold ischemia time | Missing | -0.051878179 |
| Recipient life support: other | No or Missing | 0 |
| Recipient life support: other | Yes | 0.067490329 |
| Recipient medical condition | Hospitalized not in ICU | 0 |
| Recipient medical condition | Intensive Care | 0.325106345 |
| Recipient medical condition | Not Hospitalized or Missing | -0.109419236 |
| Recipient portal vein thrombosis | No or Missing | 0 |
| Recipient portal vein thrombosis | Yes | 0.145174868 |
| Recipient previous abdominal surgery | No or Missing | -0.011036936 |
| Recipient previous abdominal surgery | Yes | 0 |
| Recipient previous heart transplant | No or Missing | 0 |
| Recipient previous heart transplant | Yes | 0.705420862 |
| Recipient previous kidney transplant | No or Missing | 0 |
| Recipient previous kidney transplant | Yes | 0.049886271 |
| Recipient previous liver transplant | No or Missing | 0 |
| Recipient previous liver transplant | Yes | 0.196039071 |
| Recipient previous pancreas transplant | No | 0 |
| Recipient previous pancreas transplant | Yes or Missing | -0.418820048 |
| Recipient previous solid organ transplant | No or Missing | 0 |
| Recipient previous solid organ transplant | Yes | 0.356903904 |
| Recipient life support: ventilator | No or Missing | 0 |
| Recipient life support: ventilator | Yes | 0.363596097 |
| Recipient age | Apply to $> 35$ (Right LS) | 0.008107016 |
| Recipient age | Apply to $> 40$ (Right LS) | 0.002033827 |
| Recipient age | Apply to $> 55$ (Right LS) | 0.000409195 |
| Recipient age | Missing | 0 |

Table 14: Risk adjusters in the SRTR's Cox proportional hazards model.