Electronic Companion

EC.1. Summary Statistics

Table EC.1 reports the summary statistics of various patients, donors, and transplant attributes used in the model. We see that the new patients' age, MELD score at listing, and life support status remain almost the same in the Pre-Share 35 and Share 35 policy eras. There is a slight difference in the distribution of the medical condition between the two periods. The distributions of a donor's age, race, and donation after circulatory death (DCD) status do not change much. However, there is a difference in the distribution of cause of death between the two periods. Thus, it is important to control for the donor characteristics in the model. The fractions of the donations after circulatory death and discards do not change much. After the Share 35 implementation, on average, offers were accepted later in the queue. Comparing the transplant sharing types, the Share 35 policy resulted in a greater (lower) proportion of regional (local) sharing. Interestingly, CIT decreased on average (although the coefficient of variation is more than 40%). One might expect the CIT to increase with broader sharing. However, CIT does not follow a linear relationship with distance (due to switching of the mode of transport, e.g., from driving to flying for a longer distance). In addition, non-transport factors play a significant role in determining CIT. See Gentry et al. (2014) for a detailed discussion on modeling CIT.

Of all the offers, 93.3% were made to the 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 simple and tractable, we do not consider blood type compatibility.

In Table EC.2, we report the candidate's organ-offer acceptance probabilities in the Share 35 policy era, and compare them with the Pre-Share 35 policy era in parentheses. We used a straightforward metric to calculate the acceptance probability (ratio of the number of offers accepted and the number of offers received). We see cases of both an increase and decrease in their acceptance probabilities (e.g., MELD 6-14 category in Region 10 saw a 6% increase, whereas MELD 33-34 category in Region 6 saw a 26% decrease).

EC.2. Comparing the Organ Quality of Declined Offers

We use the metric, the donor risk index (DRI), proposed by Feng et al. (2006) to evaluate the quality of declined offers. 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. Because CIT is observed only for accepted offers, we use the median value (=6.9 hours) in our calculation. In Figure EC.1, we compare the box plots of the DRI between the Pre-Share 35 and Share 35 policy eras. We see that there is no significant difference in the distributions of organ quality.

Characteristic	Pre-Share 35 (January 2010-June 2013)	Share 35 (July 2013-December 2018)
Patients		
Age (in years): Mean/SD	54.9/10.3	55.8/11.0
MELD score (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 EC.1 Summary statistics of patient, donor, and transplant characteristics.

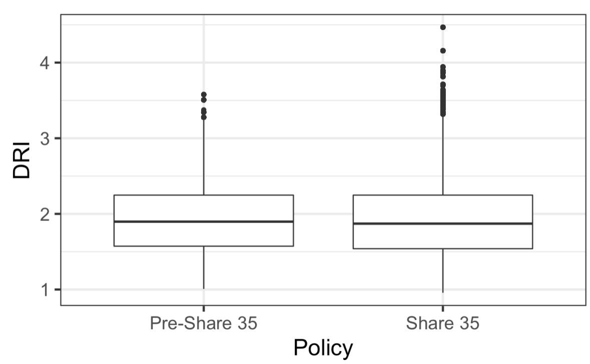

Figure EC.1 Comparison of the organ quality of declined offers between the Pre-Share 35 and Share 35 policy eras using the donor risk index (DRI). No significant difference in the distributions of organ quality is observed.

	MELD 6-14	MELD 15-28	MELD 29-32	MELD 33-34	MELD 35-36	MELD >36
Region 1	4.8% (1.5%)	4.5% (-2.8%)	6.1% (-7.6%)	13.9% (-10.4%)	26% (1.5%)	29.5% (-2.3%)
Region 2	1% (0.9%)	2.8% (-1.5%)	8% (-6.1%)	9.1% (-7.8%)	17% (-3%)	22.3% (-3.6%)
Region 3	3.4% (1%)	12.1% (-0.1%)	23.6% (-11.1%)	26.4% (-15%)	37.6% (1.9%)	36.9% (-8.6%)
Region 4	0.7% (0.4%)	2.5% (-4.3%)	9.2% (-18%)	16.8% (-21.3%)	25% (-11.7%)	32% (-4.9%)
Region 5	1.2% (0.9%)	2.1% (-0.8%)	3.4% (-7.3%)	5.1% (-10.9%)	10.9% (-13.4%)	23.7% (-9%)
Region 6	0% (0%)	6.1% (-6.3%)	14.9% (-17.7%)	20.4% (-25.9%)	27.2% (-24.8%)	28.6% (-17.1%)
Region 7	1% (-0.3%)	3.4% (-6.4%)	9.7% (-9.9%)	14.5% (-14%)	22.4% (-10.5%)	27.8% (-8.9%)
Region 8	0.5% (0.2%)	7.5% (-2.1%)	16.8% (-19.6%)	20.8% (-19.3%)	34.5% (4.2%)	38.3% (-3.4%)
Region 9	0.9% (0.8%)	1.4% (-0.3%)	2.6% (-5.1%)	6.4% (-9.6%)	14.1% (-6.9%)	25.6% (-11%)
Region 10	8.3% (6.2%)	10.7% (-5.2%)	20.6% (-12.9%)	20.3% (-10.6%)	34.6% (-8.5%)	40.3% (0.6%)
Region 11	1.5% (1.3%)	8.7% (-5.2%)	21.4% (-18%)	24.6% (-15.9%)	42.4% (-6.2%)	45% (0.8%)

Table EC.2 Organ-offer acceptance probabilities (in the Share 35 policy era) as a function of the MELD category. Parentheses report the change, compared to the Pre-Share 35 policy era. Values are calculated using summary statistics.

EC.3. Details on Logit Inclusive Value

In a dynamic model, agents (patients, in our case) form beliefs about future states based on the evolution of elements in the state space. If the number of elements is large, it can make the model very complex. To make the problem tractable, we approximate the evolution of the space space using a lower dimensional Markov process (see Gowrisankaran and Rysman 2012). In other words, agents are considered boundedly rational, and they use fewer elements to form predictions about the future.

In our context, the graft survival probability is calculated using the SRTR Risk Adjustment Model,[10] which is based on a total of 41 predictors (Z_{it}) that include the candidate's and donor's medical attributes, and CIT. Including all the 41 predictors in the state space will result in a curse of dimensionality. Following the extant literature (Gowrisankaran and Rysman 2012) on the *logit inclusive value*, we simplify the evolution of those 41 medical attributes using the evolution of lower-dimensional GS_{it}.

We model GS_{it} as a function of the MELD category ($MELD_{it}$), age group (Rec_age_{it}), life support status ($Rec\_life\_support_{it}$), medical condition ($Rec\_med\_cond_{it}$), and organ type (Q_{it}). For every combination of the (values taken by the) above variables, we first filter the offers. For this subset of offers, we use the values of all the 41 predictors[11] to calculate the graft survival probability (using the SRTR Risk Adjustment Model) for each offer in the subset. The average of the graft survival probabilities is the value of GS_{it}. In other words, we group the offers by $(MELD_{it}, Rec\_age_{it}, Rec\_life\_support_{it}, Rec\_med\_cond_{it}, Q_{it})$, and GS_{it} is the average of the graft survival probabilities obtained on these offers. Thus, GS_{it} is always ≤ 1. We approximate the evolution of 41-dimensional Z_{it} with the evolution of GS_{it}, which is lower-dimensional. As

[10] `https://www.srtr.org/reports-tools/posttransplant-outcomes/` accessed on July 12, 2020.

[11] We use a constant value of CIT (=6.9 hours) in our model. We do not model GS_{it} to depend on $Sharing\_type_{it}$ because $Sharing\_type_{it}$ is already a part of the utility function, and Z_{it} does not contain $Sharing\_type_{it}$ variable.

a sanity check, we regress GS_{it} with the MELD category, age group, life support status, medical condition, and organ type in Table EC.4. We find that the signs and the relative ordering of the regression estimates are as expected.

EC.4. State Transition Probability

A patient's health condition 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:

$$\begin{aligned}\mathcal{P}(S_{i,t+1}|S_{it}, d_{it}=0) = \mathcal{P}(&\mathit{MELD}_{i,t+1}, \mathit{Rec\_age}_{i,t+1}, \mathit{Rec\_life\_support}_{i,t+1}, \mathit{Rec\_med\_cond}_{i,t+1},\\ &Q_{i,t+1}, Z_{i,t+1}, \mathit{Sharing\_type}_{i,t+1}|\mathit{MELD}_{it}, \mathit{Rec\_age}_{it}, \mathit{Rec\_life\_support}_{it},\\ &\mathit{Rec\_med\_cond}_{it}, Q_{it}, Z_{it}, \mathit{Sharing\_type}_{it}, d_{it}=0)\end{aligned} \tag{EC.1}$$

Because the priority of a candidate on the offer list does not depend on past offers, by dropping the history of the previous period's offer (i.e., Q_{it} and $\mathit{Sharing\_type}_{it}$), the transition probability can be rewritten as:

$$\begin{aligned}\mathcal{P}(S_{i,t+1}|S_{it}, d_{it}=0) = \mathcal{P}(&\mathit{MELD}_{i,t+1}, \mathit{Rec\_age}_{i,t+1}, \mathit{Rec\_life\_support}_{i,t+1}, \mathit{Rec\_med\_cond}_{i,t+1},\\ &Q_{i,t+1}, Z_{i,t+1}, \mathit{Sharing\_type}_{i,t+1}|\mathit{MELD}_{it}, \mathit{Rec\_age}_{it}, \mathit{Rec\_life\_support}_{it},\\ &\mathit{Rec\_med\_cond}_{it}, Z_{it}, d_{it}=0)\end{aligned} \tag{EC.2}$$

We assume that the MELD category 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 category transition matrix with greater confidence than estimating multiple (18 in our case) matrices for different patient types). *Death* is an absorbing state. Next, when an organ arrives, the allocation policy does not depend on the candidate's age, life support status, or medical condition. Thus, only MELD category plays a role in determining the organ offer probabilities, $\mathcal{P}(Q)$, in a policy. These allow us to simplify the transition probability as:

$$\begin{aligned}\mathcal{P}(S_{i,t+1}|S_{it}, d_{it}=0) = &\mathcal{P}(\mathit{MELD}_{i,t+1}|\mathit{MELD}_{it}, d_{it}=0) \times \mathcal{P}(Q_{i,t+1}|MELD_{i,t+1}, d_{it}=0)\times\\ &\mathcal{P}(\mathit{Rec\_age}_{i,t+1}, \mathit{Rec\_life\_support}_{i,t+1}, \mathit{Rec\_med\_cond}_{i,t+1}, Z_{i,t+1}, \mathit{Sharing\_type}_{i,t+1}|\\ &\mathit{MELD}_{i,t+1}, Q_{i,t+1}, \mathit{MELD}_{it}, \mathit{Rec\_age}_{it}, \mathit{Rec\_life\_support}_{it}, \mathit{Rec\_med\_cond}_{it}, Z_{it}, d_{it}=0)\end{aligned} \tag{EC.3}$$

We estimate $\mathcal{P}(\mathit{MELD}_{i,t+1}|\mathit{MELD}_{it}, d_{it}=0)$ from the data (January 2003 to February 2019) on MELD score transitions (Table EC.3). To estimate $\mathcal{P}(Q_{i,t+1}|\mathit{MELD}_{i,t+1}, d_{it}=0)$, we adopt an approach identical to Alagoz et al. (2007):

$$\mathcal{P}(Q_{i,t+1}|\mathit{MELD}_{i,t+1}, d_{it}=0) = \frac{\sum_i \text{\# of offers of type } Q_{i,t+1} \text{ candidate } i \text{ received at } \mathit{MELD}_{i,t+1}}{\sum_i \text{\# of days candidate } i \text{ waited at } \mathit{MELD}_{i,t+1}} \tag{EC.4}$$

	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 EC.3 MELD category transition matrix.

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 EC.4) and $\textit{Sharing\_type}_{it}$ (if $Q_{it} = \textit{no\_offer}$, $\textit{Sharing\_type}_{it}$=*no_offer*, and vice versa).

Now, we are left with modeling the evolution of $\textit{Sharing\_type}_{it}$, Z_{it}, $\textit{Rec\_age}_{it}$, $\textit{Rec\_life\_support}_{it}$, and $\textit{Rec\_med\_cond}_{it}$. The sharing-type probability depends on the candidate's MELD category and organ characteristics. Low-quality organs are usually 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. We calculate the sharing-type probability as per equation EC.6. Next, Z_{it} consists of 41 predictors, each of which takes a set of values. Including them in the structural model will cause a state space explosion and impede the transition probability matrix estimation. We use the *logit inclusive value* technique to simplify the evolution of 41 predictors using the transition of lower-dimensional GS_{it} (see EC.3). We replace Z_{it} (and $Z_{i,t+1}$) with GS_{it} (and $GS_{i,t+1}$) in the state transition probability expression (equation EC.3). A patient predicts the value of $GS_{i,t+1}$ based on $(\textit{MELD}_{i,t+1}, \textit{Rec\_age}_{i,t+1}, \textit{Rec\_life\_support}_{i,t+1}, \textit{Rec\_med\_cond}_{i,t+1}, Q_{i,t+1})$. Next, the data do not include the patient's transition of life support or medical condition. Only the MELD score of the patient evolves over time. Patients differing in age group, life support status, and medical condition can be thought of as different patient types. These assumptions allow us to simplify the transition probability to:

$$\begin{aligned}\mathcal{P}(S_{i,t+1}|S_{it}, d_{it}=0) = \mathcal{P}(\textit{MELD}_{i,t+1}|\textit{MELD}_{it}, d_{it}=0) \times \mathcal{P}(Q_{i,t+1}|\textit{MELD}_{i,t+1}, d_{it}=0)\times \\ \mathcal{P}(GS_{i,t+1}|\textit{MELD}_{i,t+1}, \textit{Rec\_age}_{i,t+1}, \textit{Rec\_life\_support}_{i,t+1}, \textit{Rec\_med\_cond}_{i,t+1}, Q_{i,t+1}, d_{it}=0)\times \\ \mathcal{P}(\textit{Sharing\_type}_{i,t+1}|MELD_{i,t+1}, Q_{i,t+1}, d_{it}=0)\times \\ \mathbb{1}_{\{\textit{Rec\_age}_{i,t+1}=\textit{Rec\_age}_{it}, \textit{Rec\_life\_support}_{i,t+1}=\textit{Rec\_life\_support}_{it}, \textit{Rec\_med\_cond}_{i,t+1}=\textit{Rec\_med\_cond}_{it}\}},\end{aligned} \tag{EC.5}$$

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

$$\frac{\sum_i \text{\# of offers of type } Q_{i,t+1} \text{ received at } \textit{MELD}_{i,t+1} \text{ that have } \textit{Sharing\_type}_{i,t+1}}{\sum_i \text{\# of offers of type } Q_{i,t+1} \text{ received at } \textit{MELD}_{i,t+1}} \tag{EC.6}$$

The MELD category transition matrix and GS_{it} are estimated once based on the data of the entire U.S. However, the estimation of $\mathcal{P}(Q_{i,t+1}|\textit{MELD}_{i,t+1}, d_{it}=0)$ and $\mathcal{P}(\textit{Sharing\_type}_{i,t+1}|\textit{MELD}_{i,t+1}, Q_{i,t+1}, d_{it}=0)$ are done for every DSA-policy era pair separately (when evaluating a policy that uses TC instead of DSA, we estimate the quantities for every TC). This is because the organ offer and sharing-type probabilities might differ across the DSAs and, in the Pre-Share 35 and Share 35 policy eras.

EC.5. Log-Likelihood Function

When an offer is made, the probability of accepting an offer, equation 6, can be rewritten as:

$$P(d_{it}=1|S_{it}) = \frac{e^{EU(S_{it})}}{e^{EU(S_{it})}+e^{-EW(S_{it})+\delta EV(S_{it})}} \tag{EC.7}$$

Taking the log of both sides,

$$\ln\left(P(d_{it}=1|S_{it})\right) = \ln\left[e^{EU(S_{it})}\right] - \ln\left[e^{EU(S_{it})}+e^{-EW(S_{it})+\delta EV(S_{it})}\right] \tag{EC.8}$$

$$\text{Also,} \quad \ln\left(P(d_{it}=0|S_{it})\right) = \ln\left[e^{-EW(S_{it})+\delta EV(S_{it})}\right] - \ln\left[e^{EU(S_{it})}+e^{-EW(S_{it})+\delta EV(S_{it})}\right] \tag{EC.9}$$

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

$$\{\ln\left(P(d_{it}=1|S_{it})\right)\}^{d_{it}} \times \{\ln\left(P(d_{it}=0|S_{it})\right)\}^{(1-d_{it})} \tag{EC.10}$$

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

$$\begin{aligned}
&\sum_{i,t}\left(\mathbb{1}_{\{d_{it}=1\}}\ln\left(P\left(d_{it}=1|S_{it}\right)\right)+\mathbb{1}_{\{d_{it}=0\}}\ln\left(P\left(d_{it}=0|S_{it}\right)\right)\right) \\
&=\sum_{S_{it}}\left(n_{accept}^{S_{it}}\ln\left(P\left(d_{it}=1|S_{it}\right)\right)+n_{decline}^{S_{it}}\ln\left(P\left(d_{it}=0|S_{it}\right)\right)\right) \\
&=\sum_{S_{it}}n_{accept}^{S_{it}}\left(EU(S_{it})-ln[e^{EU(S_{it})}+e^{-EW(S_{it})+\delta EV(S_{it})}]\right)+ \\
&n_{decline}^{S_{it}}\left(-EW(S_{it})+\delta EV(S_{it})-ln[e^{EU(S_{it})}+e^{-EW(S_{it})+\delta EV(S_{it})}]\right) \\
&=\sum_{S_{it}}n_{accept}^{S_{it}}EU(S_{it})+n_{decline}^{S_{it}}(-EW(S_{it})+\delta EV(S_{it}))- \\
&(n_{accept}^{S_{it}}+n_{decline}^{S_{it}})\times(ln[e^{EU(S_{it})}+e^{-EW(S_{it})+\delta EV(S_{it})}])
\end{aligned} \tag{EC.11}$$

Every candidate i has an 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 time periods 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 in state S_{it}, respectively.

EC.6. Details on Identification of β_{GS}

We want to check whether the variables (on which we rely to identify GS_{it}, and whose variation we observe in the data) are correlated with GS_{it} or not. In Table EC.4, we regress GS_{it} with the MELD category, age group, life support status, medical condition, and organ type. We find that most of the regression estimates are statistically significant, and 55% of the variability in GS_{it} is explained by the independent variables used in the regression. Thus, we can identify GS_{it} in the structural model through the variation of these independent variables in the observed data.

Independent variable	Estimate
Intercept	0.9582***
MELD 15-28	0.0028
MELD 29-32	-0.0058*
MELD 33-34	-0.008**
MELD 35-36	-0.0127***
MELD >36	-0.0203***
Candidate age group: R2 (45-65 years)	-0.0211***
Candidate age group: R3 (≥65 years)	-0.0268***
Candidate life support: Yes	-0.0492***
Candidate medical condition: H	-0.0182***
Candidate medical condition: ICU	-0.0649***
Donor controls: Yes	
No. of parameters: 58	
(Adjusted) R-squared = (0.5438) 0.5518	
No. of observations = 3,264	

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Table EC.4 Estimation results of regressing GS.

EC.7. Relaxing the Assumption of a Fixed Value of CIT

In our main model, we assume a fixed value of CIT and endogenize *sharing_type* (which captures the effect of CIT) with the allocation policy. As a robustness check, we relax the assumption and build a CIT prediction model (a linear regression model). We need a prediction model because CIT is only observed for accepted offers, and not for declined offers. We then used the predicted CIT values (instead of a fixed value of 6.9 hours) in calculating the one-year graft survival probability. In Table EC.5, we compare the structural model estimates (when we use fixed CIT versus the predicted CIT). We find that there's only a slight change in the estimates of the utility and waiting cost functions parameters. The estimates of the parameters associated with regional and national sharing are closer to zero in the predicted CIT model than the fixed CIT model. This is because some of the disutilities (associated with regional/national sharing) are captured by the higher CIT in the predicted CIT model. Although the log-likelihood value is slightly better in the latter case, we prefer to use the fixed CIT model in our main analysis due to the following reasons: 1) Nonavailability of the key variables (mode of organ transport) for predicting CIT; 2) In counterfactual studies, we would need to predict CIT. Because we are less confident in the CIT prediction model, the prediction inaccuracies will make the policy evaluation less reliable; and 3) The measurement error in CIT (due to using a predicted value) will be passed over to the structural model.

EC.8. Iterative Method for Estimating the Equilibrium

We simulate different organ allocation policies. The common inputs across the policies are the sampled organ and candidate arrivals, the MELD category transition matrix, and the estimates from the structural model. We randomly sample 5,000 patients and 3,600 donors from the 11 regions, which arrive at different points in time ($t = 1, ..., 730$). Every organ is offered to a maximum of 500 candidates (which is close to the 99^{th} percentile in the actual dataset) before being discarded. We let 34% of the patients be on the

Variable	Parameter	Fixed CIT Estimate (SE)	Predicted CIT Estimate (SE)
Utility Function:			
Intercept	β_0	-21.7803 (0.3145)	-22.5536 (0.3257)
Sharing type: Regional	$\beta_{Sharing}$	-1.0348 (0.0113)	-0.9655 (0.0114)
Sharing type: National		-2.3328 (0.0243)	-2.0680 (0.0247)
Graft survival probability (GS)	β_{GS}	19.5200 (0.3353)	20.3111 (0.3468)
Waiting Cost Function:			
Death	ω_d	0.1160 (0.0007)	0.1153 (0.0007)
Candidate age group: R2 (45-65 years)	ω_{Age}	0.0057 (0.0002)	0.0058 (0.0002)
Candidate age group: R3 ($\geq$65 years)		0.0061 (0.0003)	0.0063 (0.0003)
Candidate life support: Yes	ω_{LS}	0.0134 (0.0008)	0.0130 (0.0008)
Candidate medical condition: H	ω_{MC}	0.0114 (0.0004)	0.0115 (0.0004)
Candidate medical condition: ICU		0.0229 (0.0008)	0.0232 (0.0008)
No. of observations		890,402	890,402
Log-likelihood		-173,630.9	-173,579.2

Table EC.5 Comparison of the estimation results of the structural models (when CIT is fixed versus predicted). The estimates are qualitatively the same.

waiting list at $t = 1$, and the initial MELD score distribution of the patients is representative of the actual data. We consider two patient groups ({(*Rec_age*:<45 years, *Rec_life_support*='No', *Rec_med_cond*='NH') and (*Rec_age*: $(45 - 65)$ years, *Rec_life_support*='No', *Rec_med_cond*='NH')}, which constitute 83% of the patient population in the UNOS data) and 48 organ types in the simulation study. Various patient groups may have different probabilities of acceptance for the same organ due to differences in the expected utilities (derived from the transplant) and waiting costs. The equilibrium behavior of each group will depend on the presence of the others; further, by considering two groups in our study, we capture their interactions in the equilibrium organ-offer acceptance probabilities. The steps to estimate the steady state equilibrium (for each allocation policy) using the iterative method are as follows:

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, or 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: For an allocation policy, we analytically calculate the expected number of offers, expected number of transplants, and expected waiting period by any time t. Using analytical expressions avoids the randomness introduced due to candidates' accept/decline decisions and their MELD score transitions, which helps achieve faster convergence with tighter tolerance limits. First, we create a table of states for every geography (TC or DSA) and tabulate the patient counts in those states. Each state has its own probability of acceptance. A patient's state might transition to other states (the patient's geography

does not change). At different points in time, new patients join the waiting list, and donors arrive; some patients receive offers, get a transplant, and leave the system. To analytically calculate the expected number of offers received and transplants (to patients in various MELD categories 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 the offers were made to the various patient groups. The patients who received transplants are removed from the waiting list. Using the MELD category 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 category transitions occur. We can track the expected number of patients on the waiting list, number of offers received, and number of transplants at different instances of t. Finally, we calculate the quantities of interest to us, which are the organ offer and sharing-type probabilities: $\mathcal{P}^{(k)}(Q_{it}|\mathit{MELD}_{it})$ and $\mathcal{P}^{(k)}(\mathit{Sharing\_type}_{it}|\mathit{MELD}_{it}, Q_{it})$ in the k^{th} step of the iterative method.

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

Algorithm 1 Steady State Equilibrium

Input: Candidate and organ characteristics, allocation policy, structural parameters (β_0, β_{GS}, β_{Sharing}, ω_d, ω_{Age}, ω_{LS}, ω_{MC}), MELD category transition matrix. Let t be the arrival time of an organ.

Output: $EV^*(S_{it}), \mathcal{P}^*(Q_{it}|\mathit{MELD}_{it}), \mathcal{P}^*(\mathit{Sharing\_type}_{it}|\mathit{MELD}_{it}, Q_{it})$.

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

repeat

  $\Pi^k \leftarrow$ Compute state transition matrix (see equation EC.5)

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

  repeat

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

    $m \leftarrow m+1$

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

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

  $p^k_{acpt}(S_{it}) := P^k(d_{it} = 1|S_{it}) \leftarrow$ Compute offer acceptance probabilities $\forall S_{it}$ (see equation EC.7)

  $\mathcal{P}^k(Q_{it}|\mathit{MELD}_{it}), \mathcal{P}^k(\mathit{Sharing\_type}_{it}|\mathit{MELD}_{it}, Q_{it}) \leftarrow$ Policy Simulation ($p^k_{acpt}(.)$)

  $k \leftarrow k+1$

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

$EV^*(S_{it}) \leftarrow EV^k(S_{it}), \mathcal{P}^*(Q_{it}|\mathit{MELD}_{it}) \leftarrow \mathcal{P}^k(Q_{it}|\mathit{MELD}_{it})$,
$\mathcal{P}^*(\mathit{Sharing\_type}_{it}|\mathit{MELD}_{it}, Q_{it}) \leftarrow \mathcal{P}^k(\mathit{Sharing\_type}_{it}|\mathit{MELD}_{it}, Q_{it})$

Each iteration took approximately 25 hours for policies using the TC as the geographic unit (and approximately nine 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 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 in the same region), and 'national' otherwise.

EC.9. Numerical Study to Derive Insights from the Structural Model

The allocation policies essentially differ in the utility of waiting or the future prospects of being offered an organ (through the expected future value, $EV(S_{it})$). The objective of this exercise is to generate insights about how a patient would react to the possibility of a transplant based on her health status and her future prospect of being offered an organ. This, in turn, depends on the organ offer probability, which depends on the supply and demand at the various DSAs and the allocation policy in place. For this reason, we study the effect of a change in supply and demand on a patient's organ-offer acceptance probability.

We simulate the organ and candidate arrivals for a two-year time period ($t = 1, ..., 730$). We use a stylized setup of two regions and three DSAs (Region A: DSA 1 and DSA 2; Region B: DSA 3), each with a single TC, in our numerical study. We let 34% of the patients be on the waiting list at $t = 1$, and the initial MELD score distribution of the patients is representative of the actual data. We only consider a single patient type (*Rec_age*: $(45 - 65)$ years, *Rec_life_support*='No', *Rec_med_cond*='NH'), and a single organ type (*Don_age*: $(18 - 39)$ years, *Don_race* = 'White', *Don_cod* = 'Others', *Don_dcd* = 'No'). They represent the most frequent patient and organ types.

We study a total of five settings of demand and supply across the DSAs (Set 1,..., Set 5; see Table 5). The organ and the candidate's arrival times are random; we run 20 iterations for each setting. The steady state equilibrium organ-offer acceptance probabilities are estimated using Algorithm 1 in EC.8. We consider two organ allocation policies: Share 35 and Acuity Circles. The insights, as we will see, are similar.

Discussion of Insights

In Table 5, we report the probability of offer acceptance (95% confidence interval) as a function of a patient's MELD category and DSA. We select Set 1 as the baseline scenario: a similar supply and demand volume (in aggregate) is there at Region A and Region B, and at DSA 1 and DSA 2. We then change either the demand or s/d ratio, one at a time. We conduct an intra-set analysis (discuss the results of each set on its own), and an inter-set analysis (compare a set with the baseline setting, Set 1). Before we proceed, it is useful to do a quick sanity check. The two DSAs in Region A have similar characteristics in Set 1, Set 3 and Set 5. Therefore, the probability of offer acceptance should also be the same for a patient in DSA 1 and DSA 2 (for a given MELD category and a given set). The results are consistent with our expectation, i.e., the confidence intervals overlap. We note that there are more observations for lower-MELD categories; therefore, the confidence interval is smaller for lower-MELD categories. The absolute numbers are less important than their relative ordering with MELD categories. In the ensuing discussion, for brevity, we combine the range of MELD scores when referring to multiple MELD categories whose MELD scores are contiguous (e.g., MELD 29-34 categories refers to the MELD 29-32 and MELD 33-34 categories).

Set 1 (baseline setting): The aggregate s/d ratio is the same for Regions A and B. One may expect that the probability of offer acceptance should also be the same. However, sharing within Region B is all local, whereas sharing within Region A will be a mix of local and regional. Therefore, the behavior of Region B patients might be different from their counterparts in Region A.

We find that DSA 3 patients are more selective than DSA 1 and 2 patients. This selective nature is more prominent in middle-MELD categories (such as MELD 29-34 categories). For a lower-MELD category patient to receive an organ offer, it has to be declined by the higher-MELD category patients of both the regions. Thus, we do not see a significant difference between the organ-offer acceptance probabilities between the two regions in lower-MELD category patients. Higher-MELD (MELD score $\geq$35) category patients do not have significant difference in organ access, in this stylized model, due to broader sharing under both the Share 35 and Acuity Circles policies.

Set 2 (and its comparison with Set 1): In Set 2, we decrease the supply at DSA 2 such that the new s/d ratio in DSA 2 becomes 0.5 (from 0.7). The DSA 2 patients have a higher probability of offer acceptance than DSA 1 patients due to reduced organ access. This aggressive behavior is especially seen at lower MELD scores (the impact of difference in the s/d ratio is attenuated at higher MELD scores due to the prioritization of higher-MELD patients through broader sharing).

Upon comparing with Set 1, we see that DSA 2 patients react by increasing their probability of offer acceptance (especially at MELD 6-32 categories). We also observe that a decrease in supply at DSA 2 affects other DSAs as well. DSA 1 patients became aggressive (than Set 1), especially at MELD 6-28 categories. DSA 3 patients were less impacted than DSA 1 patients, and we did not see a significant change in their probability of offer acceptance (compared to Set 1).

Set 3 (and its comparison with Set 1): In Set 3, we decrease the supply at DSA 3 such that the new s/d ratio in DSA 3 becomes 0.5 (from 0.7). The DSA 3 patients have a higher probability of offer acceptance than DSA 1 and 2 patients in lower-MELD categories (i.e., MELD 6-28).

Upon comparing with Set 1, we see that DSA 3 patients react by increasing their probability of offer acceptance (especially at MELD 6-32 categories). DSA 1 and 2 patients also felt the effect, and they became more aggressive (than Set 1), especially at MELD 6-32 categories.

Set 4 (and its comparison with Set 1): In Set 4, we increase the supply and demand volume at DSA 2 by 40%. DSA 2 patients became more selective than DSA 1 patients at the MELD 15-28 category (and the MELD 29-32 category in the Share 35 policy but not in the Acuity Circles policy) due to an enlarged supply from where the patients could receive an offer.

Upon comparing with Set 1, we see that DSA 2 patients react by becoming more selective, especially at MELD 15-36 categories (except that the MELD 33-34 category did not see a significant effect in the Acuity

Circles policy). DSA 1 and DSA 3 patients also became more selective (than Set 1), especially at MELD 29-36 and MELD 29-34 categories, respectively. The selectiveness in the patient's behavior (compared to Set 1) is driven by the enlarged supply (even though demand also proportionally increased) from where the patients could receive an offer.

Set 5 (and its comparison with Set 1): In Set 5, we increase both the supply and demand volume at DSA 3 by 40% keeping the s/d ratio same as before. DSA 3 patients are more selective than DSA 1 and 2 patients at MELD 15-34 categories.

Upon comparing with Set 1, we see that DSA 3 patients react by becoming more selective, especially at MELD 15-36 categories. Again, the selectiveness in the patient's behavior (compared to Set 1) is driven by the enlarged supply (even though demand also proportionally increased) from where the patients could receive an offer. DSA 1 and 2 patients also became more selective (than Set 1), especially at MELD 29-36 categories.

To summarize, the main insights are: 1) When the s/d ratio differs between two DSAs (see DSA 1 and 2 in Set 2; DSA 2 in Set 1 and 2; and DSA 3 in Set 1 and 3), its impact (in terms of the probability of offer acceptance) is felt more by patients with lower MELD scores. The impact becomes attenuated at higher MELD scores due to the prioritization of patients with larger MELD scores through broader sharing (Share 35 and the Acuity Circles policy). If the s/d ratio decreases at a DSA (see DSA 2 in Set 1 and 2; and DSA 3 in Set 1 and 3), their patients react by becoming aggressive in organ acceptance behavior. 2) Increasing the supply and demand volume (keeping the s/d ratio the same) in a DSA leads to an enlarged supply from where the patients can receive an offer, which induces selective behavior (see DSA 3 in Set 1 and 5; and DSA 2 in Set 1 and 4). This shift is not just limited to the DSA at which a change is made; it also has a spillover effect on other DSAs.

EC.10. Details of Logistic Regression Models

In Table EC.6, we report the coefficients corresponding to various logistic regression models (RM1, RM2, and RM3) that we used in Table 6. The dependent variable in all the models is the accept/decline decision. Overall, we find the coefficients to be reasonable for predicting the acceptance of an offer.

In Figure EC.2(a), we plot the probability of offer acceptance (calculated as the fraction of offers that were accepted based on the observed data) by MELD category and use this as a reference. In Figure EC.2(b), (c), and (d), we plot the reduced-form models' predicted probabilities of offer acceptance. RM1 and RM2 do not capture a patient's change in organ-offer acceptance probability (with their MELD category), and the regime shift (from the Pre-Share 35 to Share 35 policy) in terms of a patient's behavior with regards to their organ-offer acceptance probability. RM3, which has more variables, is relatively better.

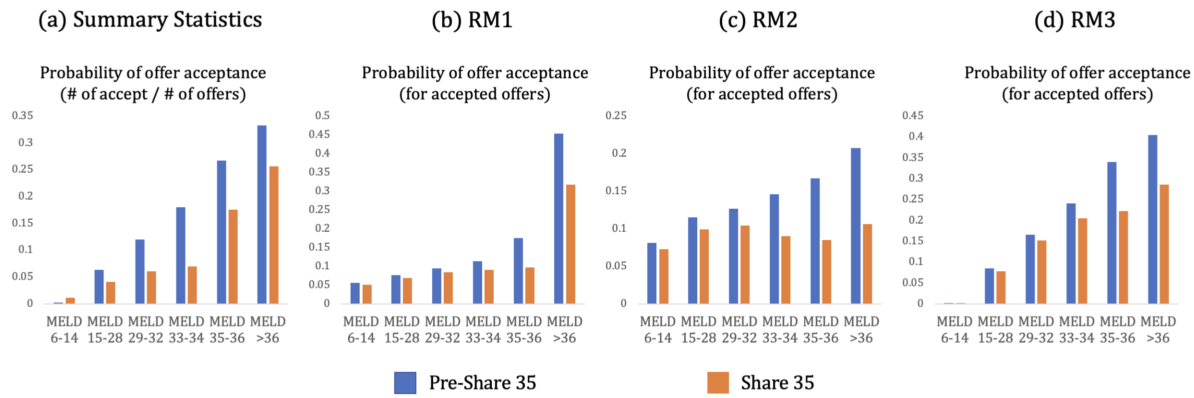

Figure EC.2 Out-of-sample comparison of reduced-form models.

EC.11. Comparison of the Pre-Share 35 and Share 35 Policy Eras using the Structural Model

In this section, we compare the organ-offer acceptance probabilities of a patient between the Pre-Share 35 and Share 35 policy eras. Only the second term in the denominator of equation EC.7 might vary between the two time periods. Specifically, only $EV(.)$, the value function denoting the future discounted value upon waiting, might differ due to factors such as the changes in organ offer probabilities, and the quality of those offers. The comparison based on equation EC.7 gives a more complete picture than a straightforward metric to calculate the acceptance probability (ratio of the number of offers accepted and the number of offers received) as used in Table EC.2. This is because the latter does not account for the quality of organ offers (it might happen that a patient is declining more often not because she became selective, but because the offers are of poorer quality).

Independent variable	RM1	RM2	RM3
Intercept	-20.659***	-16***	-5.714***
Graft survival probability (GS)	19.322***	15.136***	-
MELD 15-28	-	-	3.287***
MELD 29-32	-	-	3.987***
MELD 33-34	-	-	4.419***
MELD 35-36	-	-	4.899***
MELD >36	-	-	5.2***
P(death|MELD)	80.745***	-	-
Wait time (in years)	-	-0.423***	-
Sharing type: Regional	-1.228***	-1.224***	-1.089***
Sharing type: National	-2.105***	-1.969***	-2.38***
Candidate age group: R2 (45-65 years)	0.433***	0.278***	0.182***
Candidate age group: R3 ($\geq$65 years)	0.546***	0.356***	0.085**
Candidate life support: Yes	0.962***	1.165***	-0.058
Candidate medical condition: H	1.079***	1.278***	0.549***
Candidate medical condition: ICU	1.735***	2.398***	0.625***
Log-likelihood	-57,861.72	-58,629.47	-53,815.62
No. of observations = 277,367			

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table EC.6 Regression estimates of the reduced-form models.

	MELD 6-14	MELD 15-28	MELD 29-32	MELD 33-34	MELD 35-36	MELD >36
Region 1	4% (0%)	4.4% (-0.2%)	7.5% (-0.3%)	13.6% (-0.3%)	22.1% (-1.1%)	33.7% (-1.5%)
Region 2	3.8% (0.1%)	4.1% (-0.1%)	7% (-0.5%)	11% (-1.3%)	14.9% (-4.9%)	23.5% (-7.7%)
Region 3	3.1% (0.2%)	4.5% (0.1%)	6.6% (0.3%)	10.2% (-0.2%)	12.7% (-4.3%)	21.5% (-6.4%)
Region 4	4.6% (-0.2%)	4.7% (-0.6%)	7.7% (-1.3%)	12.9% (-2.6%)	16.9% (-7.1%)	27.2% (-10.2%)
Region 5	3.9% (-0.1%)	4.1% (-0.4%)	6.3% (-0.9%)	10.2% (-1.3%)	15.7% (-3.4%)	25.7% (-7%)
Region 6	4.2% (0.1%)	4.8% (-0.1%)	7.7% (-0.5%)	13.6% (-2.1%)	19.8% (-4.8%)	31.8% (-7.5%)
Region 7	3.6% (-0.1%)	4.1% (-0.5%)	6.8% (-1.1%)	11.9% (-2.3%)	16.5% (-6%)	27.1% (-8.8%)
Region 8	3.7% (0.1%)	4.5% (0%)	7.3% (0.4%)	11.4% (0.5%)	16.7% (-1.4%)	27.1% (-3%)
Region 9	4.6% (0.2%)	4% (0.1%)	6.3% (0.3%)	11% (0.3%)	19.9% (0.8%)	31.5% (1.7%)
Region 10	3.6% (0%)	4.5% (-0.2%)	6.8% (-1%)	9.3% (-2%)	14.5% (-5.7%)	24% (-9.3%)
Region 11	2.9% (0.1%)	4.2% (0%)	6.6% (-0.2%)	10.5% (-0.9%)	14.4% (-5.5%)	23.5% (-8.6%)

Table EC.7 Organ-offer acceptance probabilities (in the Share 35 policy era) as a function of the MELD category. Parentheses report the change compared to the Pre-Share 35 policy era. Values are calculated using the structural model (whose parameters are estimated using data from 2010 to 2018).

We compare the candidates as a function of their MELD category, region-wise. Given that the probability of an offer acceptance depends on the candidate's state (S_{it}), we weigh the states to come up with a single number for each MELD category and region. For each MELD category (in a region), the weights assigned to the corresponding states (associated with that MELD category) reflect the empirical probabilities (estimated using the data) of being in those states. In Table EC.7, we report the candidate's organ-offer acceptance probabilities in the Share 35 policy era. Parentheses report the change compared to the Pre-Share 35 policy era. We see that some estimates of the change vary significantly between the structural model (Table EC.7) and summary statistics (Table EC.2). For example, MELD 33-34 category (Region 6) values differ by 23.8%, MELD 35-36 category (Region 6) and MELD 29-32 category (Region 8) values differ by 20%, and so on. Thus, it is important to use a structural model to compare policies.

Coming back to Table EC.7, we see that high-MELD category candidates (MELD score $\geq$35) in all regions (except region 9) became more selective in the Share 35 policy era, as their acceptance probabilities decreased.[12] Given that the Share 35 policy prioritized sicker candidates in a geographically broader sense, by allowing access outside their DSAs, they can afford to be more selective. For lower-MELD categories, we observe heterogeneity (across regions) in their behavioral change. For example, MELD 6-14 category candidates experienced a negative effect and became aggressive in more than half of the regions (Regions: 2, 3, 6, 8, 9, 11). It turns out that these regions were associated with a relatively higher organ supply. The average supply (number of deceased donors)-to-demand (number of new patients joining the waiting list) ratio (based on the 2010 to 2018 time period) in these regions was 0.82, compared to 0.67 in the rest of the

[12] 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 regions (based on the 2010 to 2018 time period). It is likely that the Share 35 policy increased competition among the already organ-deficient DSAs (in Region 9), which led to an increase in aggressive behavior in even higher-MELD category patients in Region 9 in the Share 35 policy era.

Covariate	Graft survival	Patient survival without transplant
	Hazard ratio	Hazard ratio
MELD 6-14	1.13*	0.45***
MELD 29-32	0.91*	3.63***
MELD 33-34	0.75***	4.49***
MELD 35-36	0.92	5.97***
MELD >36	1.04	11.24***
Candidate age group: R1 (<45 years)	1.51***	0.63***
Candidate age group: R3 (≥65 years)	0.65***	1.28***
Candidate life support: Yes	1.09	2.67***
Candidate medical condition: H	1.18***	1.65***
Candidate medical condition: ICU	1.09	2.07***
Donor age group: (40 to 49 years)	1.35***	-
Donor age group: (50 to 59 years)	1.58***	-
Donor age group: (≥60 years)	1.78***	-
Donor race: Other	1.08**	-
Donor cause of death: Anoxia	0.84***	-
Donor cause of death: CVA	1.10**	-
Donor DCD: Yes	1.56***	-
Sharing type: Regional	1.00	-
Sharing type: National	1.34***	-

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Table EC.8 Survival model estimates.

regions. Because the Share 35 policy increased the priority of national patients over local/regional patients with a low MELD score (< 15), the low-MELD scoring patients in the regions with a higher organ supply became aggressive in response to potentially losing access to organs that were now offered to candidates outside their respective regions.

To summarize, we find that sicker patients benefited and became more selective in their behavior (i.e., their organ-offer acceptance probability decreased for the same organ in consideration) in the Share 35 policy era (compared to the Pre-Share 35 policy era). However, there was heterogeneity in the behavioral change across geographies in less sick patients.

EC.12. Survival Benefit due to a Transplant

We estimate the survival benefit due to a transplant as the difference between the graft survival probability and the patient's survival probability 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 the organ and patient characteristics used in our simulation study. The estimates of the HRs are reported in Table EC.8.

EC.13. 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 EC.9, we compare the geographic equity metrics between the two s/d

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 EC.9 Comparison of the standard deviation of geographic equity measures between s/d Match policies.

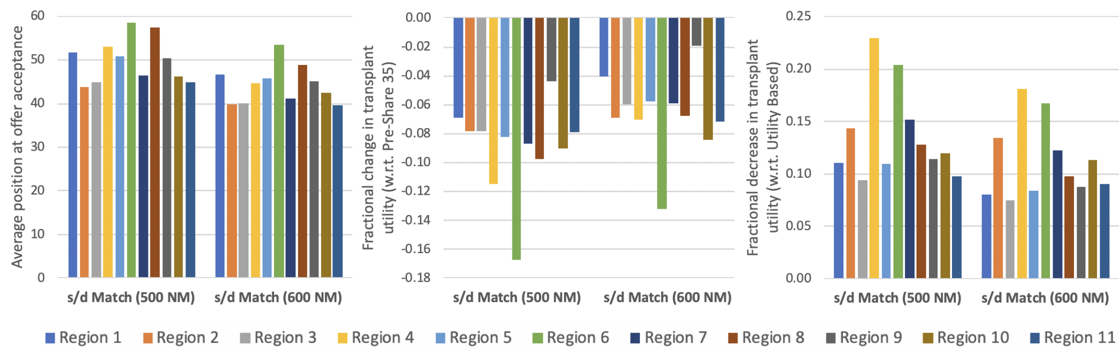

Figure EC.3 Comparison of the position at offer acceptance, fractional change in utility from the transplant (with respect to Pre-Share 35), and cost of fairness (with respect to Outcome-based) between the two s/d Match policies. The s/d Match (600 NM) policy results in greater efficiency.

	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 EC.10 Comparison of travel distance (in NM) between the two s/d Match policies.

Match policies (maximum radius equals 500 NM versus 600 NM) using the simulation setup described in EC.8. Although we do not observe improvement in all the metrics, we find that 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 3,570.8 to 3,578.5.

In Figure EC.3, we compare the efficiency metrics such as the position at offer acceptance, fractional change in the utility from the transplant (with respect to the Pre-Share 35 policy), and cost of fairness (with respect to the Outcome-based policy) between the two s/d Match policies. 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 EC.10 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 only marginally higher. In conclusion, if broader sharing is done right by matching supply and demand, it results in greater equity with minimal impact on the efficiency metrics!