Appendix for "An Empirical Framework for Sequential Assignment: The Allocation of Deceased Donor Kidneys"

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A Data Appendix

A.1 Data Description

Our data on patients, donors, transplants, and offers are based on information submitted to the Organ Procurement and Transplantation Network (OPTN) by its members. The main dataset on the waitlist is the Potential Transplant Recipient (PTR) dataset. It contains the sequences of offers made to patients on the deceased donor kidney waitlist, their decisions, and their reasons for refusal. Detailed information on patient characteristics, donor characteristics, and transplant outcomes come from the Standard Transplantation Analysis and Research (STAR) dataset. UNOS also provided supplemental information for this study, including the ordering of distinct match runs conducted for the same deceased donor; the transplant centers of donors and patients in our dataset; and dates of birth for pediatric candidates, who joined the waitlist before turning 18 years of age.

The data contain unique identifiers that allow us to link the offer and acceptance data to patient and donor characteristics. Each deceased donor has a unique identifier. Similarly, each patient registration generates a unique patient waitlist identifier. Because patients may move to different transplant centers or be registered in multiple centers simultaneously, some individual patients have multiple waitlist id's. Where appropriate, we de-duplicate offers so that each patient can receive at most one offer from each donor. The patient history file also contains a unique patient record identifier corresponding to a particular state of the patient on the waitlist, including the patient's CPRA, activity status, and pre-set screening criteria. Each offer in the PTR dataset contains the identifiers for the donor, the patient registration, and the patient history record that were used in the match run.

The PTR dataset contains all offers made to patients on the deceased donor kidney waitlist. Information include identifiers for the donor, patient, and patient history record that generated the offer; the order in which the offers were made; each patient's acceptance decision; and if the offer was not accepted, a reason for rejecting. Each offer record also contains certain characteristics of the match, including the number of tissue type mismatches.

The STAR dataset contains separate files on deceased donor characteristics, patient characteristics and transplant outcomes, and patient histories. The patient and donor characteristics from these tables are used to estimate our models of acceptance behavior, positive crossmatch probabilities, and patient departure rates. We also use these characteristics to

replicate the mechanism and determine each patient's compatibility with and priority score for each deceased donor in our sample.

A.2 Sample Selection

This section explains the selection of patients, donors, and offers used in our structural model. We consider patients who were registered in NYRT and actively waiting for a deceased donor kidney between January 1st, 2010 and December 31st, 2013. Our donor sample includes all U.S. deceased kidney donors whose organs were allocated according to the standard mechanism. Our offer sample includes valid offers from all deceased donors to NYRT patients during this period recorded in the PTR data, as well as offers that were not made because of pre-specified screening criteria. The next section discusses our replication of the offer mechanism, which we use to determine offers that were refused through these screening criteria, as well as the waiting time each patient would need to have been offered each compatible donor. The remainder of this section discusses the details of how we select our samples of donors, patients, and offers that met screening criteria.

Because NYRT patients may be offered donors from across the U.S., our procedure first constructs a nationwide sample of deceased donors, patients, and offers that meet our sample criteria. We then restrict the sample to NYRT and omit certain donors and patients who received non-standard treatment in the mechanism.

Our U.S. sample of deceased kidney donors comes from the intersection of donor identifiers in the PTR and STAR deceased donor files. Patients in our sample were active on the deceased donor kidney waitlist after 2010 and were not jointly registered for a pancreas transplant. Patient registration date and activity status are determined from the patient history file. We also exclude patients who departed the waitlist for reasons which indicate that they did not ultimately need a transplant. We exclude patients who were transplanted in another country, whose condition improved, or who could no longer be contacted. These departure reasons are recorded in the STAR patient and transplant outcome dataset.

We then determine which offers were valid and could have been accepted by and transplanted into the patient; patients' acceptance decisions; and the resulting priority score cutoffs in each match run.

We first exclude offers that are not valid. In certain cases, patients are bypassed when a donor is allocated to a specific recipient outside of the standard allocation rules. This can occur if the donor is an armed service member; if the donor specified a particular recipient (directed donation); if there is a medical emergency or expedited placement attempt; or if organ sharing among DSAs generates a "payback" in which one DSA allocates a kidney from another DSA as though it had been recovered in its own service area. There are also cases in which a patient is offered a tissue type incompatible donor, or a donor that did not meet the

patient's pre-specified screening criteria. We identify these cases using a refusal reason code provided in the PTR data. In some cases, there is also text specifying specific circumstances justifying a rejection, which we parse to identify invalid offers in cases where the refusal code does not provide a specific reason. Finally, some offers are refused due to technological constraints if the patient needs a specific organ laterality or requires multiple simultaneous organ transplants. We do not consider these cases to be genuine refusals, and omit them from the offer dataset.

Next, we created an algorithm to de-duplicate offers and acceptances within and across match runs, and to determine the true priority score cutoff for each donor in each match run. For some donors, multiple match runs are conducted, and these match runs can include offers to overlapping sets of patients. A specific kidney (e.g. the left kidney) may also be accepted in multiple match runs. Finally, a patient can have multiple offers recorded from the same donor, even in the same match run. Our algorithm assumes that later match runs take precedence over earlier ones (using the match run numbers provided by OPTN), and that the last observed match run in which an organ is placed takes that organ out of circulation for subsequent match runs. After de-duplication, there were 11,428,540 offers nationwide that met patient screening criteria. The U.S. sample contains 30,079 donors and 226,000 patients.

We then implement the sample restrictions for NYRT. We consider all patients who were registered in NYRT and had active status sometime between January 1st, 2010 and December 31st, 2013. At this stage, we exclude patients who received a transplant through non-standard allocation rules. This includes cases of medical urgency, an expedited placement attempt, a multi-organ transplant, or a military or directed donation. 68 patients were excluded because they received deceased donor kidney transplants for these reasons, leaving 9,917 patients in our NYRT sample. We also exclude the donors whose organs were placed according to these reasons, even if the organs were allocated to non-NYRT patients. The NYRT offer sample contains valid offers from the sample of deceased donors to the sample of NYRT patients. There are 1,281,024 such offers. These offers and patient acceptance decisions determine the priority score cutoff in each match run for each donor's available organs.

A.3 Replicating the Mechanism, Offer Dataset

Knowledge of the mechanism allows us to determine the set of offers that were declined through pre-set screening criteria, as well as the waiting time required for a particular patient to have access to a particular donor. These are essential for correctly modeling patient acceptance behavior and transplant opportunities under the current and counterfactual mechanisms. We wrote compute code to replicate the standard deceased donor kidney allocation rules in place between January 1st, 2010 and December 31st, 2013.

For each deceased donor and match run, the algorithm begins with all concurrent patient waitlist history records. It first determines which patients are incompatible with the donor due to their blood type and unacceptable human leukocyte antigen (HLA) antigens (if any). We use blood type and HLA equivalence tables followed by the OPTN, as well as the donor's HLA antigens and the current unacceptable antigens listed by each patient. Next, we check whether the donor met each patient's screening criteria. Finally, we determine the priority score of each patient given their CPRA, waiting time, geography, age, and number of HLA and DR mismatches with the donor. Given the priority score, we can calculate whether the patient was above the priority score cutoff for the donor. We can also determine the amount of additional waiting time (which may be infinite) after which the patient's priority score would exceed the donor's cutoff.

From the simulation, we obtain a set of offers predicted by our simulation of the mechanism. These are pairs of donors and patients where the patient met the priority score cutoff and was blood and tissue type compatible with the donor. Some of these offers met the patient's screening criteria, while others did not. Those that did should appear in the PTR data. This provides a check on the performance of our mechanism code. Table A.3 tabulates offers appearing in our filtered PTR data and those predicted by simulation. The vast majority of offers in the PTR data (93.1%) were predicted by our simulation. However, a substantial fraction of offers predicted by the simulation (29.6%) are not in our PTR offer sample.

To estimate the patient acceptance model, we take as our offer sample the union of the PTR offer dataset and the set of offers that the simulation predicts were filtered due to the patient's screening criteria but which would otherwise have appeared in the PTR data. In a final step, we de-duplicate offers at the patient level, since a patient registered at multiple centers will occasionally receive multiple offers from the same donor. The final offer sample contains 2,850,572 offers: 1,267,531 PTR offers, and 1,583,041 predicted offers that were "screened out." The PTR offers include the 88,366 offers that were not predicted by our simulation but which appear in the PTR data, and exclude the 502,239 offers predicted by the simulation but which did not appear in PTR. Offers that were screened out are interpreted as rejections since the patient deemed the donor's characteristics unacceptable.

To calculate patient value functions, we store all compatible patient and donor pairs, including patients who did not meet the donor's priority score cutoff.

A.4 Imputing Missing Donor DR Antigens

A donor's HLA antigens are needed to determine tissue type compatibility with transplant candidates as well as kidney points, which are in turn essential for replicating the mechanism. A limitation of our data is that we only observe a donor's DR antigens if one of their kidneys or pancreas was transplanted into a patient. In this case, they appear in the KIDPAN (patient/transplant) dataset. If no organs were placed, a donor's antigen information is

recorded in the deceased donor file for kidney/pancreas donors. The deceased donor file lists the donor's HLA antigens at the A and B loci, but not at the DR locus.

We either obtain or impute a donor's missing DR antigens from two sources. First, some deceased donors had a liver, lung, or part of their intestine transplanted even though their kidneys and pancreas were not transplanted. The equivalent transplant files for these additional organs are part of the STAR dataset, and we take the donor's DR antigens directly from those files.

Second, for deceased donors who had no organs transplanted, we use the reported number of DR mismatches in the PTR offer dataset to impute the donor's DR antigens. Because we observe all patients' HLA antigens, the number of DR mismatches between a donor and patient is informative about the donor's antigens. For example, if a donor-patient pair has zero DR mismatches, the patient's tissue type limits the donor's antigens to a few possibilities.[40] A two DR mismatch pair also restricts the donor's DR antigens, though less so than a zero mismatch. Since deceased donors whose organs are not transplanted are usually offered to many patients, we can combine information across all offers to make an educated guess of the donor's DR antigens.

We use the following imputation algorithm. For each donor without DR antigen information, we take all of the donor's offers in the PTR data. Based on these offers, the recorded number of DR mismatches, and the patient's DR antigens and listed unacceptable antigens, we calculate a score for each DR antigen that the donor might have. We dock one point from a DR antigen's score for each PTR offer it contradicts in the following cases:

- The offer has zero DR mismatches, and the antigen is not equivalent to one of the patient's DR antigens
- The offer has two DR mismatches, and the antigen is equivalent to one of the patient's DR antigens
- The antigen was listed as unacceptable by the patient

For each donor, we take the two DR antigens with the highest scores. Ties are broken in favor of the antigens that appear most frequently among donors for whom DR antigens are recorded.

[40] In the zero DR mismatch case, the donor may not share the patient's exact DR antigens because of HLA equivalences. Some distinct HLA proteins are equivalent in the sense that a patient with one DR antigen may desensitize it to several DR antigens. UNOS publishes HLA equivalence tables for measuring HLA mismatches, and a separate table for equivalent unacceptable antigens. Furthermore, even ignoring equivalences, a zero DR mismatch donor could be homozygous at the DR locus.

B Estimation

B.1 Normalization

In this section, we show that the model described in Section 3.3.2 yields the same decision-rules as a model in which $O_i(t) = 0$ for all t (therefore, $d_i(t) + \delta_i(t) D_i(t) = 0$ for all t) and the net present value of a transplant is $\tilde{\Gamma}_{ij}(t) = \Gamma_{ij}(t) - O_i(t)$. To do this, the next proposition establishes two results which hold for any assignment rule that does not affect the value of being on dialysis or departing without a deceased donor transplant.

Proposition 1. *Let $p_{ij}(t)$ be the conditional probability that i is assigned object j given that j arrives in period t. Let $V_i(t;p)$ be i's value of the assignment rule p. Then,*

1. For any assignment rule p, $\Gamma_{ij}(t) - V_i(t;p) = \tilde{\Gamma}_{ij}(t) - \tilde{V}_i(t;p)$, where $\tilde{\Gamma}_{ij}(t) = \Gamma_{ij}(t) - O_i(t)$ and

$$(\rho + \delta_i(t))\,\tilde{V}_i(t;p) = \lambda \int p_{ij}(t) \left(\tilde{\Gamma}_{ij}(t) - \tilde{V}_i(t;p)\right) \mathrm{d}F + \tilde{V}_i(t;p)$$

with boundary condition $\tilde{V}_i(T_i;p) = 0$.

2. For any two assignment rules p and p', $V_i(t;p) - V_i(t;p') = \tilde{V}_i(t;p) - \tilde{V}_i(t;p')$

Proof. Part 1: First, we verify that $\tilde{V}_i(t;p) = V_i(t;p) - O_i(t)$ satisfies the differential equation above. Note that

$$(\rho + \delta_i(t))\,V_i(t;p) = d_i(t) + \delta_i(t)\,D_i(t) + \lambda \int p_{ij}(t)\,(\Gamma_{ij}(t) - V_i(t;p))\,\mathrm{d}F + \dot{V}_i(t;p)\,.$$

Therefore,

$$(\rho + \delta_i(t))\,(V_i(t;p) - O_i(t)) = \lambda \int p_{ij}(t) \left(\tilde{\Gamma}_{ij}(t) - (V_i(t;p) - O_i(t))\right) \mathrm{d}F + \frac{\partial}{\partial t}\,(V_i(t;p) - O_i(t))\,.$$

Hence, $\tilde{V}_i(t;p)$ satisfies the necessary differential equation. It is straightforward to check that $V_i(T_i;p) = O_i(T_i) = D_i(T_i)$ showing that the solution with the boundary condition $\tilde{V}_i(T_i;p) = 0$ satisfies the requirements of the proposition.

Part 2: Observe that for any pair of assignment rules, p and p',

$$\begin{aligned}
V_i(t;p) - V_i(t;p') &= \lambda \int p_{ij}(t)\,(\Gamma_{ij}(t) - V_i(t;p))\,\mathrm{d}F + \dot{V}_i(t;p) - \dot{V}_i(t;p') \\
&= \lambda \int p_{ij}(t) \left(\left(\tilde{\Gamma}_{ij}(t) - O_i(t)\right) - \left(\tilde{V}_i(t;p) - O_i(t)\right)\right) \mathrm{d}F \\
&+ \left(\dot{\tilde{V}}_i(t;p) - \dot{O}_i(t)\right) - \left(\dot{\tilde{V}}_i(t;p') - \dot{O}_i(t)\right) \\
&= \tilde{V}_i(t;p) - \tilde{V}_i(t;p')\,.
\end{aligned}$$

□

Refer to the model with $O_i(t) = 0$ for all t and the related value function $\tilde{V}_i(t;p)$ and the payoffs $\tilde{\Gamma}_{ij}(t)$ as the normalized model. Part 1 shows that the normalized model also yields $\Gamma_{ij}(t) - V_i(t;p)$ as the difference in the value of acceping j relative to the value waiting if one expects assignments according to p. In particular, the result holds for $p_{ij}(t) = \pi_{ij}(t) 1\{\Gamma_{ij}(t) - V_i(t) > 0\}$. Therefore, the normalized model yields an identical choice rule and value function relative to no assignment.

Part 2 shows that the normalized model yields an identical difference in value functions between any two assignment rules as the original model. This is useful for evaluating both alternative mechanisms as well as for solving for equilibria. To see this, consider any action space $\mathcal{A}_t$ and strategy $\sigma_i(t;j) \to \mathcal{A}_t$. The action space need not be binary and may depend on time. For example, to consider a counterfactual with multiple wait-lists we can define the action set as the choice of list at birth and an accept/reject decision thereafter. As the notation indicates, each action can depend on the currently offered object, if any. As long as the analyst can then evaluate the assignment rule $p_{ij}(t;\sigma)$ as a function of the strategy profile $\sigma = (\sigma_i, \sigma_{-i})$, the result says that the normalized model can be used to determine the difference in values. To solve for equilibria, we would need to evaluate deviations (σ_i', σ_{-i}) and compare

$$V_i(t; p(\sigma_i', \sigma_{-i})) - V_i(t; p(\sigma_i, \sigma_{-i})) = \tilde{V}_i(t; p(\sigma_i', \sigma_{-i})) - \tilde{V}_i(t; p(\sigma_i, \sigma_{-i})).$$

To identify the value function relative to the current mechanism, we would need to compute

$$V_i(t; p(\sigma^*)) - V_i(t; \hat{p}) = \tilde{V}_i(t; p(\sigma^*)) - \tilde{V}_i(t; \hat{p}),$$

where $\hat{p}$ denotes the assignment probabilities under the factual mechanism and $p(\sigma^*)$ denotes the equilibrium assignment probabilities in an equilibrium of the counterfactual mechanism.

B.2 Details on the Estimator

Gibbs' Sampler

Define $y_{ijt} = V(x_i, t) - \Gamma(x_i, z_j, \eta_j, t) - \epsilon_{ijt} = \chi(x_i, z_j, \eta_j)\theta - \epsilon_{ijt}$ and $a_{ijt} = 1\{y_{ijt} < 0\}$. The sampler is initialized at any value of θ^0, σ_η^0 and guesses for η_j^0 and y_{ijt}^0 corresponding to observed decisions such that $y_{ijt}^0 \geq 0$ if and only if agent i rejected object j in period t. We then sample from the conditional posteriors and draws of y given the previous draws. The

sampler iterates through the following sequence

$$\begin{aligned} &y_{ijt}^{s+1}|\theta^s, \eta_j^s; a_{ijt} \\ &\eta_j^{s+1}|y_j^{s+1}, \theta^s \\ &\theta^{s+1}|y^{s+1}, \eta^{s+1} \\ &\sigma_\eta^{s+1}|\eta^{s+1}, \end{aligned} \tag{11}$$

where the conditioning on the priors and the observables is implicit, y^s and η^s are vectors with components y_{ijt}^s and η_j^s, and y_j^{s+1} is a vector that stacks y_{ijt}^{s+1} across all i,t. The first two steps involve data augmentation to simplify the sampling problem of the key parameters in the next step. Each of these steps involves draws from a closed-form distribution if the prior distribution on σ_η is specified as an inverse-Gamma distribution and the prior for $\theta \sim N\left(\bar{\theta}, \Sigma_\theta\right)$. With these priors, the first step involves sampling from a truncated normal, the second and third steps involve sampling from a normal distribution, and the final step involves sampling from an inverse-Gamma.

Computing the Value Function

Given t, for each patient i, the value of continuing is given by equation (7). Using equation (9), the sample analog of the value of continuing is given by

$$\hat{V}_i(t) = \lambda \int_t^{T_i} \exp\left(-\rho\left(\tau - t\right)\right) p\left(\tau|t; x_i\right) \hat{W}\left(x_i, \tau; \hat{\theta}\right) \mathrm{d}\tau.$$

We numerically approximate this integral. First, we re-write $\hat{V}_i(t)$ as follows:

$$\begin{aligned} \hat{V}_i(t) &= \lambda \int_t^{T_i} \exp\left(-\rho\left(\tau - t\right)\right) p\left(\tau|t; x_i\right) \frac{1}{J} \sum_{j=1}^{J} 1\left\{c_{ij} = 1\right\} 1\left\{s\left(\tau; x_i, z_j\right) > s_j^*\right\} \psi\left(\hat{P}_{ij\tau}\right) \mathrm{d}\tau \\ &= \lambda \frac{1}{J} \sum_{j=1}^{J} 1\left\{c_{ij} = 1\right\} \int_t^{T_i} \exp\left(-\rho\left(\tau - t\right)\right) p\left(\tau|t; x_i\right) 1\left\{s\left(\tau; x_i, z_j\right) > s_j^*\right\} \psi\left(\hat{P}_{ij\tau}\right) \mathrm{d}\tau \\ &= \lambda \frac{1}{J} \sum_{j=1}^{J} 1\left\{c_{ij} = 1\right\} \int_{\underline{\tau}_{ijt}}^{T_i} \exp\left(-\rho\left(\tau - t\right)\right) p\left(\tau|t; x_i\right) \psi\left(\hat{P}_{ij\tau}\right) \mathrm{d}\tau, \end{aligned}$$

where $\underline{\tau}_{ijt} = \inf\left\{\tau > t : s\left(\tau; x_i, z_j\right) > s_j^*\right\}$, with $\underline{\tau}_{ijt} = T_i$ if $s\left(\tau; x_i, z_j\right) < s_j^*$ for all $\tau \leq T_i$. For each i and j, we approximate the integral above using $B = 40$ equally spaced points $q^b = \dfrac{b}{B+1}$ for $b = 1, \ldots, B$ on the unit interval. Let $\tau_{ijt}^b = F^{-1}\left(q_b; \rho, \underline{\tau}_{ijt}, T_i\right)$ where $F\left(\cdot; \rho, \underline{\tau}_{ijt}, T_i\right)$ is the cumulative distribution function of an exponential random variable with parameter ρ that is truncated between $\underline{\tau}_{ijt}$ and T_i. We therefore compute the value

function as

$$\hat{V}_i(t) = \frac{\lambda}{\rho}\frac{1}{J}\sum_{j=1}^{J} 1\{c_{ij}=1\}\frac{1}{B}\sum_{b=1}^{B} p\left(\tau_{ijt}^b|t;x_i\right)\psi\left(\hat{P}_{ij\tau_{ijt}^b}\right).$$

This procedure ensures that there are B points of evaluation for each possible donor and patient-time pair. The numerical performance is superior to an alternative that approximates the integral in equation (7) as a sum over a fixed set of draws because some patient, donor, time combinations may have a very small window of availability, $\left[\underline{\tau}_{ijt}, T_i\right]$.

B.3 Auxiliary Models

Positive Crossmatch Probability

Not all accepted offers result in transplantation. Even after a provisional acceptance, additional testing may yield a positive crossmatch indicating that the patient is likely to develop an immune response to the donor's kidney. These transplants are not carried out, and if possible the organ is placed with another patient. To compute patient value functions and conduct counterfactual simulations, we must account for positive crossmatches. We therefore estimate a probit model to predict the probability that a patient has a positive crossmatch with an organ they have accepted. The specifications includes interactions between the patient's CPRA and the number of HLA mismatches with the donor, in addition to controls for patient age and number of years on dialysis.[41] We use a subset of the variables included in the CCP model to avoid overfitting. Coefficient estimates and standard errors are displayed in Table B.4. Higher CPRA is associated with a higher positive crossmatch probability, as are more tissue-type dissimilarities (as measured by DR or HLA mismatches). In addition, CPRA and tissue type matches interact: high CPRA patients have an additional benefit from fewer HLA mismatches. This is intuitive: patients with more sensitized immune systems may be more likely to test positive against foreign antibodies, even if they have not tested positive in the past. Patients who have been on dialysis longer at registration have lower positive crossmatch probabilities, but this pattern reverses above five years. This pattern may be driven by blood transfusions to treat anemia, which is common amongst patients with kidney failure. Similarly, positive crossmatch probability increases with age for young patients, but then declines with age for older patients.

Maximum Number of Offers and Discards

Our data contain cases in which at least one of a donor's organs is not offered to all compatible patients in NYRT. This usually occurs for two reasons. First, the organ may become unsuitable for transplantation if it remains outside donor's body for too long. Second, the organ

[41] We assume that test results are not manipulated. Therefore, crossmatch probabilities are identical in counterfactual mechanisms. Conversations with transplant surgeons support this assumption.

may be accepted by a patient in another OPO. We call these events "timeouts." Timeouts are driven by a combination of unobserved factors, including whether the organ remained in the donor's body during the offer process; the rate at which offers were made, which depends on patient/surgeon response times and the number of patients simultaneously contacted; the kidney's rate of physical deterioration once outside the body; and decisions of patients outside NYRT.

We model the maximum number of offers that can be made for a given organ using a censored exponential hazards model. Duration is the number of observed offers that met pre-specified screening criteria. Censoring occurs if the organ is placed, or if it is discarded after being offered to all compatible patients. The hazard function is given by

$$\lambda_o(z) = \lambda_o \exp(z\beta) \tag{12}$$

where z are characteristics of the donor, β is a vector of coefficients, and λ_0 is the constant baseline hazard rate. We allow the timeout hazard to depend on geography and indicators of donor quality. Specifically, we control for whether the donor is an expanded criteria donor (ECD); the donor's cause of death (DCD); and whether the donor was recovered in NYRT, as well as interactions among these variables. The estimated timeout hazards are inputs to the structural model.

In addition, we model the probability that a donor's unallocated kidneys are discarded after the maximum number of offers has been reached using a probit model. Specifically, this probability is given by $\Phi\left(z\tilde{\beta}\right)$. The model is estimated by tracking whether the kidneys were ultimately transplanted or not. With the remaining probability, the donor's kidneys are allocated to a patient not registered in NYRT. This probit model includes the identical set of covariates used to model the maximum number of offers that can be made. This part of the model does not influence allocation and incentives for patients in NYRT. It is used to properly account for changes in discards for kidneys not allocated to patients in NYRT.

B.4 Consistency of $\hat{W}\left(x_i, t; \hat{\theta}\right)$

We now show that $\hat{W}\left(x_i, t; \hat{\theta}\right)$ consistently estimates the quantity

$$\begin{aligned} W(x_i, t; \theta) &= \int \pi_{ij}(t)\, \psi(P_{ijt})\, \mathrm{d}F \\ &= \int H_{z_j,\eta_j}(s(t; x_i, Z))\, \mathbb{P}(c_{ij} = 1 | Z, x_i; \theta)\, \psi(x_i, Z, \eta, t; \theta)\, \mathrm{d}F_{Z,\eta}. \end{aligned}$$

To do this, we need to introduce some notation. Define

$$g_j(\theta) = p_c(z_j, x_i; \theta)\, \psi(x_i, z_j, \eta_j, t; \theta)\, 1\left\{s(t; x_i, z_j) > s_j^*\right\},$$

where $p_c(z_j, x_i; \theta) = \mathbb{P}(c_{ij} = 1 | z_j, x_i; \theta)$. For a vector $x = (x_1, \ldots, x_K)$, we write $|x| = (|x_1|, \ldots, |x_K|)$.

Finally, we index objects according to the order in which they arrive in our sample. Therefore, (z_j, η_j) denotes the observed and unobserved characteristics of the j-th donor that arrived. Therefore, the data on $\left(z_j, \eta_j, s_j^*\right)$ generates a sequence of object arrivals.

We make the following assumptions on $g_j(\theta)$:

Assumption 4. *(i) (z_j, η_j) is drawn i.i.d. with CDF F*

(ii) $g_j(\theta_0)$ is weakly stationary[42] *with $\sum_{k=-\infty}^{\infty} \gamma_k < \infty$, where $Cov(g_j(\theta_0), g_{j-k}(\theta_0)) = \gamma_k$.*

(iii) $\hat{\theta}_J$ is $\sqrt{J}$-consistent, i.e. $\left(\hat{\theta}_J - \theta_0\right) = O_p\left(J^{-1/2}\right)$

(iv) There exists a function $m(z)$, such that for each z_j $|g(z_j; \theta) - g(z_j; \theta')| \leq m(z_j) \cdot |\theta - \theta'|$, and $m(Z)$ has finite second moments.

Part (i), in our empirical context, assumes that the characteristics of the donor are drawn independently each time a donor arrives. Part (ii) assumes that, at θ_0, the offers and their values for any given patient type x_i, at any given time t, follows a weakly stationary process. That is, the covariance in these values across any two donors falls as they are further apart in the sequence. Given part (i), the only potential source of dependence between $g_j(\theta_0)$ and $g_k(\theta_0)$ is that the characteristics of donor j may affect the state of the waitlist for donor k because of patient decisions. However, we expect that this dependence to fall as these donors become further apart in their arrival sequence. Part (iii) assumes that $\hat{\theta}_J$ is consistently estimated at a rate that is at least as fast as the square-root of the number of donors. These parameters govern the conditional choice probabilities and the probability of a crossmatch failure at biological testing. Part (iv) is a regularity condition, assuming that $g(z_j; \theta)$ is Lipschitz continuous at each z, and imposes a bound on the second moment of the distribution of Lipschitz constants. Proposition 2 shows that this property is satisfied under more primitive conditions stated in Assumption 5.

We now show that for each x_i, t, $\hat{W} = \frac{1}{J} \sum_{j=1}^{J} g_j\left(\hat{\theta}\right)$ is a $\sqrt{J}$-consistent estimator of $W(x_i, t; \theta_0)$ under this assumption.

Theorem 1. *Fix x_i, t. If Assumption 4 is satisfied, then*

$$\left| W(x_i, t; \theta_0) - \frac{1}{J} \sum_{j=1}^{J} g_j\left(\hat{\theta}\right) \right| = O_p\left(J^{-1/2}\right).$$

[42] The process $\{g_j\}$ is weakly stationary if (i) $\mathbb{E}[g_j]$ does not depend on j, and (ii) $Cov(g_j, g_{j-k})$ exists, is finite and depends only on k, and not j.

Proof. For each x_i, t, Assumption 4(i) implies that

$$\begin{aligned}\mathbb{E}\left[g_j\left(\theta_0\right)\right] &= \mathbb{E}\left[p_c\left(z_j, x_i; \theta_0\right)\psi\left(x_i, z_j, \eta_j, t; \theta_0\right) 1\left\{s\left(t; x_i, z_j\right) > s_j^*\right\}\right] \\ &= \mathbb{E}\left[p_c\left(z_j, x_i; \theta_0\right)\psi\left(x_i, z_j, \eta_j, t; \theta_0\right)\mathbb{E}\left[1\left\{s\left(t; x_i, z_j\right) > s_j^*\right\}|z_j, \eta_j\right]\right] \\ &= \mathbb{E}\left[\mathbb{E}\left[p_c\left(z_j, x_i; \theta_0\right)\psi\left(x_i, z_j, \eta_j, t; \theta_0\right) H_{z_j,\eta_j}\left(s\left(t; x_i, z_j\right)\right)|z_j, \eta_j\right]\right] \\ &= W\left(x_i, t; \theta_0\right),\end{aligned}$$

where the equalities are a result of the law of iterated expectations, and the definitions of $H_{z_j,\eta_j}(s)$ and $W\left(x_i, t; \theta_0\right)$.

Because $W\left(x_i, t; \theta_0\right) = \mathbb{E}\left[g_j\left(\theta_0\right)\right]$, Chebychev's inequality implies that,

$$\mathbb{P}\left(J^{1/2}\left|W\left(x_i, t; \theta_0\right) - \frac{1}{J}\sum_{j=1}^{J} g_j\left(\theta_0\right)\right| > \varepsilon\right) \leq \frac{Var\left(\frac{1}{\sqrt{J}}\sum_{j=1}^{J} g_j\left(\theta_0\right)\right)}{\varepsilon^2}.$$

Assumption 4(i) and Proposition 6.8 in Hayashi (2001) imply that

$$\lim_{J\to\infty} Var\left(\frac{1}{\sqrt{J}}\sum_{j=1}^{J} g_j\left(\theta_0\right)\right) = K.$$

Therefore, we have that

$$W\left(x_i, t; \theta_0\right) - \frac{1}{J}\sum_{j=1}^{J} g_j\left(\theta_0\right) = O_p\left(J^{-1/2}\right). \tag{13}$$

Lemma 1 implies that

$$W\left(x_i, t; \theta_0\right) - \frac{1}{J}\sum_{j=1}^{J} g_j\left(\hat{\theta}\right) = O_p\left(J^{-1/2}\right),$$

as requirements (i) and (ii) of Lemma 1 are part of Assumption 4(iv), requirement (iii) is equivalent to Assumption 4(iii), and requirement (iv) is proved in equation (13). □

Lemma 1. *Fix x_i, t. Suppose that (i) $g\left(z_j; \theta\right)$ is Lipschitz continuous for each z_j with the Lipschitz constant $m\left(z_j\right) \in \mathbb{R}^K$ i.e. $\left|g\left(z_j; \theta\right) - g\left(z_j; \theta_0\right)\right| \leq m\left(z_j\right) \cdot \left|\theta - \theta_0\right|$, (ii) $m\left(z_j\right)$ has finite second moments, (iii) $\left|\hat{\theta}_J - \theta_0\right| = O_p\left(J^{-1/2}\right)$, and (iv) $\frac{1}{J}\sum_j g\left(z_j; \theta_0\right) - E\left[g\left(z_j; \theta_0\right)\right] = O_p\left(J^{-1/2}\right)$. Then*

$$\frac{1}{J}\sum_j g\left(z_j; \hat{\theta}_J\right) - E\left[g\left(z_j; \theta_0\right)\right] = O_p\left(J^{-1/2}\right).$$

Proof. Because $g(z_j;\theta)$ is Lipschitz continuous in θ, we have that for any $\theta \in \Theta$,

$$Var\left(\left|g(z_j;\theta) - g(z_j;\theta_0)\right|\right) \leq \left|\theta - \theta_0\right|^T \mathbb{E}\left(m(z_j)\, m^T(z_j)\right)\left|\theta - \theta_0\right|,$$

where x^T is the transpose of the vector x. Therefore, because $\left|\hat{\theta}_J - \theta_0\right| = O_p\left(J^{-1/2}\right)$, with probability approaching 1,

$$Var\left(g\left(z_j;\hat{\theta}_J\right) - g(z_j;\theta_0)\right) \leq V_M K J^{-1},$$

for some finite constant $K > 0$, where $V_M = \mathbb{E}\left(\sum_{k,k'} m_k(z_j)\, m_{k'}(z_j)\right)$ and $m_k(z_j)$ is the k-th component of $m(z_j)$. By the covariance inequality, with probability approaching 1,

$$Cov\left(g\left(z_j;\hat{\theta}_J\right) - g(z_j;\theta_0), g\left(z_k;\hat{\theta}_J\right) - g(z_k;\theta_0)\right) \leq V_M K J^{-1}.$$

Therefore, with probability approaching 1, for all $j,k \in \{1,\ldots,J\}$,

$$\begin{aligned} &Var\left(\frac{1}{\sqrt{J}}\sum_j g\left(z_j;\hat{\theta}_J\right) - \frac{1}{\sqrt{J}}\sum_j g(z_j;\theta_0)\right) \\ =&\frac{1}{J}\sum_{k=1}^{J}\sum_{j=1}^{J} Cov\left(g\left(z_j;\hat{\theta}_J\right) - g(z_j;\theta_0), g\left(z_k;\hat{\theta}_J\right) - g(z_k;\theta_0)\right) \leq V_M K. \end{aligned}$$

By Chebychev's inequality,

$$\mathbb{P}\left(\sqrt{J}\left|\frac{1}{J}\sum_j g\left(z_j;\hat{\theta}_J\right) - E\left[g\left(z_j;\hat{\theta}_J\right)\right] - \frac{1}{J}\sum_j g(z_j;\theta_0) + E\left[g(z_j;\theta_0)\right]\right| > \varepsilon\right) \leq \frac{V_M K}{\varepsilon^2}.$$

Therefore,

$$A_J = \frac{1}{J}\sum_j g\left(z_j;\hat{\theta}_J\right) - E\left[g\left(z_j;\hat{\theta}_J\right)\right] - \frac{1}{J}\sum_j g(z_j;\theta_0) + E\left[g(z_j;\theta_0)\right] = O_p\left(J^{-1/2}\right).$$

But, we know that $\frac{1}{J}\sum_j g(z_j;\theta_0) - E\left[g(z_j;\theta_0)\right] = O_p\left(J^{-1/2}\right)$. So, it must be that

$$\frac{1}{J}\sum_j g\left(z_j;\hat{\theta}_J\right) - E\left[g\left(z_j;\hat{\theta}_J\right)\right] = O_p\left(J^{-1/2}\right). \tag{14}$$

Lipschitz continuity of $g(z_j;\theta)$ and the Cauchy-Schwarz inequality imply that.

$$\begin{aligned} E\left[\left|g\left(z_j;\hat{\theta}_J\right) - g(z_j;\theta_0)\right|\right] &\leq E\left[m(z_j)\cdot\left|\hat{\theta}_J - \theta_0\right|\right] \\ &\leq \sqrt{V_M}\sqrt{E\left[\left|\hat{\theta}_J - \theta_0\right|\cdot\left|\hat{\theta}_J - \theta_0\right|\right]}. \end{aligned}$$

Because $\hat{\theta}_J$ belongs to the compact set Θ, and $\hat{\theta}_J - \theta_0 = O_p\left(J^{-1/2}\right)$, we have that $\sqrt{E\left[\left|\hat{\theta}_J - \theta_0\right| \cdot \left|\hat{\theta}_J - \theta_0\right|\right]} = O_p\left(J^{-1/2}\right)$. Together with the assumption that $V_M = \mathbb{E}\left(\sum_{k,k'} m_k(z_j) m_{k'}(z_j)\right)$ is finite, we have that

$$E\left[\left|g\left(z_j;\hat{\theta}_J\right) - g\left(z_j;\theta_0\right)\right|\right] = O_p\left(J^{-1/2}\right). \tag{15}$$

Finally, equation (14) and (15) together imply that

$$\begin{aligned}
&\frac{1}{J}\sum_j g\left(z_j;\hat{\theta}_J\right) - E\left[g\left(z_j;\hat{\theta}_J\right)\right] \\
=&\frac{1}{J}\sum_j g\left(z_j;\hat{\theta}_J\right) - E\left[g\left(z_j;\theta_0\right)\right] + E\left[g\left(z_j;\theta_0\right)\right] - E\left[g\left(z_j;\hat{\theta}_J\right)\right] \\
\leq&\frac{1}{J}\sum_j g\left(z_j;\hat{\theta}_J\right) - E\left[g\left(z_j;\theta_0\right)\right] + E\left[\left|g\left(z_j;\theta_0\right) - g\left(z_j;\hat{\theta}_J\right)\right|\right] \\
=&O_p\left(J^{-1/2}\right).
\end{aligned}$$

□

Lipschitz continuity of $g(z;\theta)$

We now show primitive regularity conditions under which Assumption 4(iv) is satisfied. Recall that $g_j(\theta) = \mathbb{P}(c_{ij} = 1|z_j, x_i;\theta)\,\psi(x_i, z_j, \eta_j, t;\theta)\,1\left\{s(t;x_i,z_j) > s_j^*\right\}$. Fix x_i, t and omit it from the notation for simplicity.

Assumption 5. *(i)* $\psi(z_j,\eta_j;\theta) = \mathbb{E}\left[\max\left\{0, \chi(z_j)\cdot\theta + \eta_j + \varepsilon\right\}\right]$ *where* ε *has cdf* F_ε

(ii) There exists a function $m(z)$*, such that* $m(Z)$ *has finite fourth moments and for all* θ, θ',

a. $\left|\mathbb{P}(c_{ij} = 1|z_j;\theta) - \mathbb{P}(c_{ij} = 1|z_j;\theta')\right| \leq m(z_j)\cdot|\theta - \theta'|$

b. $|\chi(z)| \leq m(z)$.

Part (i) follows from the definition of $\psi(z_j,\eta_j;\theta)$ and the parametrization of the conditional choice probabilities in our model. It is repeated simply to keep this exercise self-contained. Part (ii) is a regularity condition that assumes lipschitz continuity of primitives, with sufficiently small lipschitz constants.

Proposition 2. *If Assumption 5 is satisfied, then for all* $\theta, \theta' \in \Theta$, $|g_j(\theta) - g_j(\theta)| \leq \tilde{m}(z_j)\cdot|\theta - \theta'|$, *where* $\tilde{m}(z_j)$ *has finite second moments.*

Proof. First, we show that for all θ, $\theta' \in \Theta$ $|\psi(z_j,\eta_j;\theta) - \psi(z_j,\eta_j;\theta')| \leq m(z_j)\cdot|\theta - \theta'|$. Define $\gamma(x) = \mathbb{E}\left[\max\left\{0, x + \varepsilon\right\}\right] = \int_{-x}^{\infty}(x+\varepsilon)\,\mathrm{d}F_\varepsilon$. Libniz's rule implies that

$$\gamma'(x) = \int_{-x-\eta}^{\infty} 1\mathrm{d}F_\varepsilon = 1 - F(-x-\eta) \leq 1.$$

Therefore, $\gamma(x)$ is Lipschitz continuous with constant 1. Hence, Assumption 5(i) and (ii)b., and Lemma 3 imply that

$$\begin{aligned}|\psi(z_j,\eta_j;\theta)-\psi(z_j,\eta_j;\theta')| &= |\gamma(\chi(z_j)\theta+\eta_j)-\gamma(\chi(z_j)\theta'+\eta_j)| \\ &\leq |\chi(z_j)(\theta-\theta')| \\ &\leq |\chi(z_j)|\cdot|\theta-\theta'| \leq m(z_j)\cdot|\theta-\theta'|, \end{aligned} \tag{16}$$

where the first inequality is due to the fact that $\gamma(\cdot)$ is Lipschitz continuous with constant 1.

Equation (16), Assumption 5(ii)a and Lemma 2 imply that $|g_j(\theta)-g_j(\theta)| \leq 2(m(z)*m(z))\cdot|\theta-\theta'|$, where $*$ is the hadamard (or component-wise) product. Assumption 5(ii) implies that $\tilde{m}(z)=2(m(z)*m(z))$ has finite second moments. □

Lemma 2. *Suppose that there exists a function $m(z)$ such that (i) $\tilde{\chi}(z)\leq m(z)$ and $|\chi(z,\theta)-\chi(z,\theta')|\leq m(z)\cdot|\theta-\theta'|$, and (ii) $\sup_\theta|\tilde{\chi}(z,\theta)|\leq m(z)$ and $\sup_\theta|\chi(z,\theta)|\leq m(z)$. Then,*

$$|\tilde{\chi}(z,\theta)\chi(z,\theta)-\tilde{\chi}(z,\theta')\chi(z,\theta')| \leq 2(m(z)*m(z))\cdot|\theta-\theta'|,$$

where $*$ is the hadamard (or component-wise) product.

Proof. Suppose that $|\tilde{\chi}(z,\theta)-\tilde{\chi}(z,\theta')|\leq\tilde{m}(z)\cdot|\theta-\theta'|$ and $|\chi(z,\theta)-\chi(z,\theta')|\leq m(z)\cdot|\theta-\theta'|$. Consider

$$\begin{aligned}&|\tilde{\chi}(z,\theta)\chi(z,\theta)-\tilde{\chi}(z,\theta')\chi(z,\theta')| \\ =&|\tilde{\chi}(z,\theta)\chi(z,\theta)-\tilde{\chi}(z,\theta)\chi(z,\theta')+\tilde{\chi}(z,\theta)\chi(z,\theta')-\tilde{\chi}(z,\theta')\chi(z,\theta')| \\ \leq&|\tilde{\chi}(z,\theta)(\chi(z,\theta)-\chi(z,\theta'))|+|(\tilde{\chi}(z,\theta)-\tilde{\chi}(z,\theta'))\chi(z,\theta')| \\ \leq&|\tilde{\chi}(z,\theta)|\,m(z)\cdot|\theta-\theta'|+|\chi(z,\theta')|\,m(z)\cdot|\theta-\theta'| \\ \leq&2(m(z)*m(z))\cdot|\theta-\theta'|.\end{aligned}$$

□

Lemma 3. *Suppose that (i) $\psi:\mathbb{R}\to\mathbb{R}$ is Lipschitz continuous with constant $K<\infty$, and (ii) for each z, there exists $m(z)\in\mathbb{R}^{K_\theta}$ such that $|\tilde{\chi}(z,\theta)-\tilde{\chi}(z,\theta')|\leq m(z)\cdot|\theta-\theta'|$, then $|\psi(\tilde{\chi}(z,\theta))-\psi(\tilde{\chi}(z,\theta'))|\leq Km(z)\cdot|\theta-\theta'|$. In particular, if $\tilde{\chi}(z,\theta)=\chi(z)\cdot\theta$ where $\chi(z),\theta\in\mathbb{R}^{K_\theta}$, then $|\psi(\tilde{\chi}(z,\theta))-\psi(\tilde{\chi}(z,\theta'))|\leq K|\chi(z)|\cdot|\theta-\theta'|$.*

Proof. The first part follows definitionally because Lipschitz continuity of ψ implies that

$$|\psi(\tilde{\chi}(z,\theta))-\psi(\tilde{\chi}(z,\theta'))|\leq K|\tilde{\chi}(z,\theta)-\tilde{\chi}(z,\theta')|\leq Km(z)\cdot|\theta-\theta'|.$$

For the second part, note that

$$\chi(z) \cdot (\theta - \theta') \leq |\chi(z)| \cdot |\theta - \theta'|.$$

□

C Equilibria: Existence and Approximations

C.1 Approximations in Long Queues

C.1.1 Queue Length

In this section, we show that the stationary distribution of the length of the waitlist concentrates mass around the steady state value, N^*. This result suggests that using a deterministic queue length is a good approximation for large values of N^*.

Theorem 2. *Consider the continuous time Markov process N_τ, where τ denotes calendar time. For any given (π^*, m^*, σ^*), N_τ is an ergodic process with stationary distribution p_n. Moreover, for any $\varepsilon > 0$,*

$$\lim_{\tau \to \infty} \mathbb{P}\left(|N_\tau - N^*| > \varepsilon N^*\right) \leq 2 \exp\left(-\frac{N^* \varepsilon^2}{2(1+\varepsilon)}\right),$$

where

$$N^* = \frac{\int \gamma_x \mathrm{d}F_X}{\int \int m_x^*(t)\, \kappa_x(t)\, \mathrm{d}t \mathrm{d}F_X}.$$

Proof. Define $\kappa = \int \int m_x^*(t)\, \kappa_x(t)\, \mathrm{d}t \mathrm{d}F_X$ and $\gamma = \int \gamma_x \mathrm{d}F_X$. Observe that N_τ follows a birth-death process with birth-rate γ and death rate $N_\tau \kappa$. Therefore, N_τ is an ergodic Markov process. The stationary distribution, p_n, satisfies the detail balance conditions:

$$\begin{aligned} \gamma p_0 &= \kappa p_1 \\ (\gamma + n\kappa) p_n &= \gamma p_{n-1} + (n+1)\kappa p_{n+1} \text{ for } n \geq 1, \end{aligned}$$

where the left-hand side denotes the exit rate from state n and the right hand side is the entry rate. Solving the system recursively and using the fact that $\sum_n p_n = 1$ yields

$$\begin{aligned} p_0 &= \left[1 + \sum \frac{\gamma^n}{n! \kappa^n}\right]^{-1} \\ &= \exp\left(-\frac{\gamma}{\kappa}\right). \end{aligned}$$

and

$$p_n = \frac{\gamma^n}{n!\kappa^n} \exp\left(-\frac{\gamma}{\kappa}\right).$$

Note that p_n is the probability that a random variable N following a Poisson distribution with parameter $N^* = \frac{\gamma}{\kappa}$ takes on the value n. Theorem 1, part 3 in Canone (2017) implies the result. □

C.1.2 Offer Probabilities

This section derives a computationally tractable approximation to offer probabilities given a scoring rule s, a large waitlist N^* and an acceptance policy function.

In what follows, we fix a particular agent i with priority score s. Ties are broken randomly, and it is therefore without loss of generality to consider each agent's tiebreaker to be drawn from a uniform distribution on the unit interval. Let $1-\alpha$ be the tie-breaker for agent i.

There are two reasons why an offer for a kidney may be the last offer that can be made. The first reason is that the agent who received the offer accepts it. The second one is that the kidney expires after the offer is made. The first of these is governed by the acceptance behavior of agents and the priority rule. The second is governed by the probability that the agent's position on the list exceeds the maximum number of possible offers for the kidney. This model, specified in equation (12), is equivalent to an exponential hazards model with equal probability, $p_0 = \lambda_o(z)$ for an object of type z, of failure before the next offer is made. We fix z in what follows and drop if from the notation for simplicity.

An agent receives an offer if the total number of acceptances and expirations after offers to agents with a higher priority score than agent i is strictly less than the number of copies of the object available. We consider the probability of receiving an offer by considering waitlists that are composed of N agents drawn randomly drawn with distribution governed by m. That is, we draw N agents sequentially and track the number of kidney acceptances and failures. For each agent drawn from m, the probability that this agent is ordered above i and that the kidney is either accepted by the agent or expires is:

$$p(s,\alpha) = m_H(s)\, p_H(s) + m_E(s)\, \alpha p_E(s).$$

The first term represents the case when an agent with a higher priority (group H) is drawn. The probability of the kidney becoming unavailable conditional on an agent drawn from a higher priority group is:

$$p_H(s) = p_0 + (1-p_0)\frac{1}{m_H(s)} \sum_{t,x} m(t;x)\, 1\{s(t;x) > s\}\, \mathbb{P}(\Gamma(t;x) + \varepsilon > V_x(t)).$$

The second term represents the probability that an agent with priority score s is drawn. The

term $p_E(s)$ is defined analagously as $p_H(s)$.

The number of times that an kidney becomes unavailable after being offered to an agent ordered above i is a binomial random variable X with parameters N and $p(s,\alpha)$. In this notation, an object is available to agent i if $X < q$, where q is the total number of copies of the object. Hence, the probability that i receives an offer is given by

$$\int_0^1 \mathbb{P}(X < q|s,\alpha)\,\mathrm{d}\alpha, \tag{17}$$

where we have integrated over the tie-breaker α, and explicit conditioning on N is subsumed for simplicity.

For large N and small $p(s,\alpha)$, the distribution of X approaches the distribution of a Poisson random variable with parameter $Np(s,\alpha)$. Therefore, the expression in equation (17) yields the following expression for $\pi_x(t)$:

$$\pi_x(t) = \int_0^1 \sum_{q'<q} \frac{e^{-Np(s,\alpha)}\left(Np(s,\alpha)\right)^{q'}}{q'!}\mathrm{d}\alpha,$$

where we use the Poisson approximation to re-write $\mathbb{P}(X < q|s,\alpha)$. As a reminder, the object type z is dropped from the notation for simplicity as it is fixed, although the offer probabilities depend on it. This integral can be solved for in closed form. If $q \in \{1,2\}$,

$$\pi_x(t) = \frac{e^{-Np(s,0)} - e^{-Np(s,1)}}{N\left(p(s,1) - p(s,0)\right)} + 1\{q=2\}\,\frac{(1+Np(s,0))e^{-Np(s,0)} - (1+Np(s,1))e^{-Np(s,1)}}{N\left(p(s,1)-p(s,0)\right)}, \tag{18}$$

C.2 Existence of Steady-State Equilibria

In this section, we prove that a steady-state equilibrium exists for sequential offer mechanisms that use a scoring rule. Throughout, we assume that χ and ζ are finite sets, and that T is finite. This assumption greatly simplifies the technical argument. Moreover, they are also used when computing steady-state equilibria.

We make the following regularly assumptions on the primitive objects:

Assumption 6. *(i) The exogenous arrival and departure rates λ and γ_x are finite*

(ii) The exogenous departure rate $\delta(\tau;x)$ is bounded below by $\underline{\delta} > 0$ and bounded above, unifomly for $t \in [0,T)$ and all $x \in \chi$

(iii) The conditional probability density function $f_{\Gamma|t,x,z}$ exists, and is uniformly bounded

(iv) The conditional moment $\mathbb{E}[|\Gamma||\tau,x,z] = \int |\Gamma|\,\mathrm{d}F_{\Gamma|\tau,x,Z}$ is uniformly bounded in t, x, z

(v) The family of functions $g\left(t;x,z,\bar{\Gamma}\right)=F_{\Gamma|t,x,z}\left(\bar{\Gamma}\right)$ *indexed by* $\bar{\Gamma}$, x, z *is Lipschitz continuous in* t *with a common constant*

(vi) The object arrival rate λ *is strictly less than the total agent arrival rate* $\sum\gamma_x$

(vii) The set of scores $S=\{s\left(t;x,z\right):(t,x,z)\in[0,T]\times\chi\times\zeta\}$ *is finite.*

Most empirical models will satisfy the continuity and boundedness assumptions above. The two substantive assumptions that are worth discussing are parts (vi) and (vii). Part (vi) assumes that the objects that need to be assigned are scarce. This assumption ensures that the queue is unlikely to be empty. Part (vii) imposes a restriction on the mechanisms for which we prove existence. The assumption is used to ensure that the set of all functions $\pi_{xz}\left(t\right)$ is sufficiently small (more precisely, compact). Other assumptions that yield this conclusion would also suffice.

Our main result proves existence of a steady-state equilibrium.

Theorem 3. *Suppose Assumption 6 is satisfied. Then a steady-state equilibrium for a sequential offer mechanism with a scoring rule exists.*

Proof. The proof proceeds by applying the Brower-Schauder-Tychonoff Fixed Point Theorem (Corollary 17.56, Aliprantis and Border, 2006). The proof proceeds in three parts. First, we define a set Ω to which the equilibrium objects belong. Second, we define a map $A:\Omega\to\Omega$. Finally, we show that A has fixed points, and that the fixed points of A yield steady-state equilibria.

Part 1, Definition of Ω: The equilibrium objects are defined by five types of functions:

1. The conditional choice probability, given t and the agent and object characteristics x and z. We consider these choice probabilities as a function $p_\sigma:[0,T]\times\chi\times\zeta\to[0,1]$.
2. The value function $V:\chi\times[0,T]\to\mathbb{R}_+$. It is convenient to define this function, although it is somewhat redundant with the choice probabilities above.
3. The offer probabilities $\pi:[0,T]\times\chi\times\zeta\to[0,1]$ where $\pi\left(t;x,z\right)=H_z\left(s_{xz}\left(t\right)\right)\times\mathbb{P}\left(c_{ij}=1|x,z\right)$.
4. The distribution of agent types $m:\chi\times[0,T]\to\mathbb{R}_+$.
5. The queue length $N\in\mathbb{R}$.

We denote the tuple of these objects with $\omega=\left(p_\sigma,V,\pi,m,N\right)$. We endow each of the functions in the first four objects with the supremum norm over their respective domains. The norm for ω is denoted $\|\omega\|=\|p_\sigma\|+\|V\|+\|\pi\|+\|m\|+|N|$. Therefore, ω is an element of a Banach space.

We further restrict ω to belong to a subset Ω of this Banach space. Specifically, we restrict these components as follows:

1. The functions $V_x(t)$ are uniformly bounded by $\lambda T \sup_{\tau,X,z} \int |\Gamma| \, \mathrm{d}F_{\Gamma|\tau,x,Z}$, and are Lipschitz continuous with a common constant $\lambda \sup_{\tau,x,z} \int |\Gamma| \, \mathrm{d}F_{\Gamma|\tau,x,z}$.

2. The functions $p_\sigma(t;x,z)$ that are uniformly bounded by 1, and Lipschitz continuous with a common constant K, where

$$K = \lambda \sup_{\tau,x,z} \left(\int |\Gamma| \, \mathrm{d}F_{\Gamma|\tau,x,z} \sup_{\Gamma} f_{\Gamma|\tau,x,z}(\Gamma) \right) + \sup_{\bar{\Gamma},x,z,t,t'} \left| F_{\Gamma|t,x,z}\left(\bar{\Gamma}\right) - F_{\Gamma|t',x,z}\left(\bar{\Gamma}\right) \right| / |t - t'| .$$

   Note that Assumption 6 implies that K is finite.

3. The functions $\pi_{x,z}(t)$ such that $\pi_{x,z}(t) = \pi_{x,z}(t')$ if $s_{xz}(t) = s_{xz}(t')$ with range $[0,1]$.

4. The functions $m_x(t)$ are uniformly bounded by $T \sup_x \gamma_x$ and are Lipschitz continuous with a common constant $\sup_{x,\tau} \gamma_x \delta(\tau;x)$.

5. The term $N \in \left[\underline{N}, \bar{N}\right]$, where $\underline{N} = \left(\sum_x \gamma_x\right) \inf_x \int_0^T \exp\left(-\int_0^\tau \delta(\tau;x)\,\mathrm{d}\tau\right)/\lambda$ and $\bar{N} = \frac{T\sum_x \gamma_x}{\underline{\delta}}$. Note that $\bar{N} > 0$ because Assumption 6 requires that $\sum_x \gamma_x < \lambda$ and $\delta(\tau;x)$ is uniformly bounded above.

Part 2, definition of $A : \Omega \to \Omega$: Denote $A_V[\omega]$ as the V component of $A[\omega]$, where $\omega \in \Omega$. Likewise, define A_π, A_{p_σ}, A_m and A_N. This map is defined as follows:

$$\begin{aligned}
A_V[\omega](x,t) &= \int_t^T \exp\left(-\rho(\tau - t)\right) p(\tau|t;x) \left(\lambda \int \pi(\tau;x,Z) \int \max\left\{0, \Gamma - V(\tau;x)\right\} \mathrm{d}F_{\Gamma|\tau,x,Z} \mathrm{d}F_Z \right) \mathrm{d}\tau \\
A_{p_\sigma}[\omega](x,z,t) &= \int 1\left\{\Gamma \geq A_V[\omega](x,t)\right\} \mathrm{d}F_{\Gamma|x,z,t} \\
A_m[\omega](x,t) &= \gamma_x \exp\left(- \int_0^t \delta(\tau;x) + \lambda \int \pi(\tau;x,Z)\, p_\sigma(\tau;x,z)\, \mathrm{d}F_{\Gamma|\tau,x,Z} \mathrm{d}\tau \right) / N \\
A_N[\omega] &= \max\left\{ \underline{N}, \min\left\{ \frac{T\sum_x \gamma_x}{\sum_x \int_0^T m_x(t)\,\kappa_x(t)\,\mathrm{d}t}, \bar{N} \right\} \right\} \\
A_\pi[\omega](x,z,t) &= H_z\left(s_{xz}(t); A_{p_\sigma}[\omega], A_m[\omega], A_N[\omega]\right) \times \mathbb{P}(c_{ij} = 1|x,z)
\end{aligned}$$

where

$$p(\tau|t;x) = \exp\left(- \int_t^\tau \delta(\tau';x)\,\mathrm{d}\tau' \right)$$

is the probability that agent of type x departs the list prior to τ conditional on being on the list at t. It is clear that A is well defined. To ensure that the image is a subset of Ω, we need to show that $A[\omega] \in \Omega$ for all $\omega \in \Omega$. We do this for each of the components separately:

1. A_V: Since $\exp(-\rho(\tau-t))$, $p(\tau|t;x)$ and $\pi(\tau;x,Z)$ are in $[0,1]$, and

$$\int \max\{0,\Gamma - V(\tau;x)\}\,\mathrm{d}F_{\Gamma|\tau,x,Z} \leq \int |\Gamma|\,\mathrm{d}F_{\Gamma|\tau,x,Z},$$

we have that $A_V[\omega]$ is uniformly bounded by $\lambda T \sup_{\tau,x,z}\int |\Gamma|\,\mathrm{d}F_{\Gamma|\tau,x,z}$. Further, for any t, $t' \in [0,T]$, with $t<t'$, we have that

$$\begin{aligned}
&|A_V[\omega](t) - A_V[\omega](t')| \\
&= \left|\int_t^{t'} \exp(-\rho(\tau-t))\,p(\tau|t;x)\left(\lambda\int \pi(\tau;x,Z)\int \max\{0,\Gamma - V(\tau;x)\}\,\mathrm{d}F_{\Gamma|\tau,x,Z}\mathrm{d}F_Z\right)\mathrm{d}\tau\right| \\
&\leq \lambda|t'-t|\sup_{\tau,x,z}\int |\Gamma|\,\mathrm{d}F_{\Gamma|\tau,x,z}.
\end{aligned}$$

Therefore, $A_V[\omega]$ satisfies the necessary restrictions.

2. A_{p_σ} : Note that is $A_{p_\sigma}[\omega]$ uniformly bounded by 1. Moreover, for any x and z, and t, $t' \in [0,T]$, we have that

$$\begin{aligned}
&|A_{p_\sigma}[\omega](t,x,z) - A_{p_\sigma}[\omega](t',x,z)| \\
&= \left|\int 1\{\Gamma \geq A_V[\omega](x,t)\}\,\mathrm{d}F_{\Gamma|x,z,t} - \int 1\{\Gamma \geq A_V[\omega](x,t')\}\,\mathrm{d}F_{\Gamma|x,z,t'}\right| \\
&= \left|\int \left(1\{\Gamma \geq A_V[\omega](x,t)\} - 1\{\Gamma \geq A_V[\omega](x,t')\}\right)\mathrm{d}F_{\Gamma|x,z,t}\right| \\
&\quad + \left|\int 1\{\Gamma \geq A_V[\omega](x,t')\}\,\mathrm{d}\left(F_{\Gamma|x,z,t} - F_{\Gamma|x,z,t'}\right)\right| \\
&\leq \left|\int_{\min\{A_V[\omega](x,t),A_V[\omega](x,t')\}}^{\max\{A_V[\omega](x,t),A_V[\omega](x,t')\}} 1\mathrm{d}F_{\Gamma|x,z,t}\right| \\
&\quad + \left|F_{\Gamma|x,z,t'}(A_V[\omega](x,t')) - F_{\Gamma|x,z,t}(A_V[\omega](x,t'))\right| \\
&\leq \lambda|t'-t|\sup_{\tau,x,z}\left(\int |\Gamma|\,\mathrm{d}F_{\Gamma|\tau,x,z}\sup_{\Gamma} f_{\Gamma|\tau,x,z}(\Gamma)\right) + \sup_{\bar{\Gamma},x,z}\left(\left|F_{\Gamma|t,x,z}\left(\bar{\Gamma}\right) - F_{\Gamma|t',x,z}\left(\bar{\Gamma}\right)\right|/|t-t'|\right)|t-t'| \\
&\leq \left[\lambda\sup_{\tau,x,z}\left(\int |\Gamma|\,\mathrm{d}F_{\Gamma|\tau,x,z}\sup_{\Gamma} f_{\Gamma|\tau,x,z}(\Gamma)\right) + \sup_{\bar{\Gamma},x,z,t,t'}\left(\left|F_{\Gamma|t,x,z}\left(\bar{\Gamma}\right) - F_{\Gamma|t',x,z}\left(\bar{\Gamma}\right)\right|/|t-t'|\right)\right]|t-t'|
\end{aligned}$$

Therefore, $A_{p_\sigma}[\omega]$ satisfies the necessary restrictions.

3. A_π : Observe that $A_\pi[\omega](x,z,t) \in [0,1]$ and $A_\pi[\omega](x,z,t) = A_\pi[\omega](x,z,t')$ if $s_{xz}(t) = s_{xz}(t')$ by construction.

4. A_m : Since $\exp\left(-\int_0^t \delta(\tau;x) + \lambda\int \pi(\tau;x,Z)\,p_\sigma(\tau;x,z)\,\mathrm{d}F_{\Gamma|\tau,x,Z}\mathrm{d}\tau\right) \leq 1$ and $N \geq 1$, we have that $A_m[\omega]$ is uniformly bounded by $\sup_x \gamma_x$. Further, for any t, $t' \in [0,T]$, with

$t < t'$, we have that

$$\begin{aligned}
&|A_m[\omega](t) - A_m[\omega](t')| \\
\leq &\gamma_x \exp\left(-\int_t^{t'} \delta(\tau; x) + \lambda \int \pi(\tau; x, Z)\, p_\sigma(\tau; x, Z)\, \mathrm{d}F_Z \mathrm{d}\tau\right) \\
\leq &\gamma_x \exp\left(-\int_t^{t'} \delta(\tau; x)\, \mathrm{d}\tau\right) \\
\leq &|t' - t| \sup_{x,\tau} \gamma_x \delta(\tau; x).
\end{aligned}$$

Therefore, $A_m[\omega]$ satisfies the necessary restrictions.

5. A_N: By construction, $A_N[\omega]$ belongs to $\left[1, \frac{T\sum_x \gamma_x}{\underline{\delta}}\right]$, satisfying the necessary restrictions.

Part 3, existence of equilibria: It is straightforward to verify that Ω is convex. Lemma 4 imply that the components Ω_V, Ω_m and Ω_{p_σ} are compact sets. Lemma 5 shows that Ω_π is compact. Assumption 6 (i), (ii) and (vi) imply that $\underline{N} > 0$ and $\bar{N}$ is finite, implying that Ω_N is compact. Therefore, Ω is compact because it is the cartesian product of compact sets. Lemma 6 shows that A is a continous map. Therefore, by the Brower-Schauder-Tychonoff Theorem (Corollary 17.56, Aliprantis and Border, 2006) implies that there exists $\omega^* \in \Omega$ such that $A[\omega^*] = \omega^*$.

To complete the proof, we show that any fixed point $\omega^* = (p_\sigma^*, V^*, \pi^*, m^*, N^*)$ corresponds to a steady-state equilibrium. Observe that for each x,

$$V^*(t; x) = \int_t^T \exp(-\rho(\tau - t))\, p(\tau|t; x) \left(\lambda \int \pi^*(\tau; x, Z) \int \max\{0, \Gamma - V^*(\tau; x)\}\, \mathrm{d}F_{\Gamma|\tau,x,Z} \mathrm{d}F_Z\right) \mathrm{d}\tau.$$

Therefore, $V^*(t; x)$ is the value of declining an offer and following the optimal strategy given the offer rate π^*. Therefore,

$$p_\sigma^*(x, z, t) = A_{p_\sigma}[\omega^*](x, z, t) = \int 1\{\Gamma \geq V^*(t; x)\}\, \mathrm{d}F_{\Gamma|x,z,t}.$$

For each x, z, t, the quantity $F^{-1}_{\Gamma|x,z,t}(p_\sigma^*(x, z, t)) = V^*(t; x)$. Therefore,

$$\sigma^*(\Gamma, t) = 1\left\{\Gamma \geq F^{-1}_{\Gamma|x,z,t}(p_\sigma^*(x, z, t))\right\}$$

is an optimal strategy, satisfying requirement 1 in Definition 1.

By construction, $\pi^*(x, z, t) = A_\pi[\omega^*](x, z, t) = H_z(s_{xz}(t); p_\sigma^*, m^*, N^*) \times \mathbb{P}(c_{ij} = 1|x, z)$ satisfies requirement 2 of Definition 1 because p_σ^* equals the acceptance probability of a type z object by an agent of type x at time t.

Finally, $m^* = A_m[\omega^*]$ and $N^* = A_N[\omega^*]$ together satisfy requirement 3 in Definition 1. The restriction of $A_N[\omega^*]$ to $\left[\underline{N}, \bar{N}\right]$ cannot strictly bind because $\underline{N}$ and $\bar{N}$ denote the smallest and largest possible queue lengths given the exogenous arrival and departure rates.

□

C.3 Lemmata

Lemma 4. *Suppose $X \subset L_\infty([a,b])$ is the set of all functions on the bounded interval $[a,b]$ that are uniformly bounded by K_1 and have a common Lipschitz constant K_2. Then X is compact.*

Proof. Note that the set of functions X is uniformly equicontinuous. By the Arzela-Ascoli theorem, any sequence of functions $x_n \in X$ has a uniformly convergent subsequence x_{n_k}. Let the limit of this sequence by x^*, i.e. for each t, $x^*(t) = \lim_{k\to\infty} x_{n_k}(t)$. Therefore, $\sup_t |x^*(t)| \leq \lim_{k\to\infty} \sup_t |x_{n_k}(t)| \leq K_1$. Similarly, $|x^*(t) - x^*(t')| = \lim_{k\to\infty} |x_{n_k}(t) - x_{n_k}(t')| \leq K_2 |t - t'|$. Hence, $x^* \in X$. Consquently, we have that X is sequentially compact, which is equivalent to X being compact. □

Lemma 5. *Assumption 6(vii) implies that the set Ω_π consisting of functions $\pi : [0,T] \times \chi \times \zeta \to [0,1]$ endowed with the supremum norm such that $\pi_{xz}(t) = \pi_{xz}(t')$ if $s_{xz}(t) = s_{xz}(t')$ is compact.*

Proof. Assumption 6(vii) and finiteness of χ and ζ imply that Ω_π is finite dimensional. Further, Ω_π is closed and bounded by definition. By the Heine-Borel theorem, Ω_π is compact. □

Lemma 6. *Suppose Assumption 6 is satisfied. Then the map $A : \Omega \to \Omega$ is continuous.*

Proof. We do this for each component of A separately.

A_V: Let Ω_0 be an arbitrary subset of Ω. Consider $\omega \in \bar{\Omega}_0$, where $\bar{\Omega}_0$ is the closure of Ω_0. Since $\omega \in \bar{\Omega}_0$, there exists a sequence $\omega_n \in \Omega_0$ such that $\|\omega_n - \omega\| = \varepsilon_n \to 0$. Denote

$\tilde{V}_n = A_V[\omega_n]$ and drop x from the notation as it belongs to a finite set. Now, consider

$$\begin{aligned}
&\left|\tilde{V}_n(t) - \tilde{V}(t)\right| \\
=&\left|\int_t^T \exp(-\rho(\tau - t))\, p(\tau|t)\, \lambda \left(\int \pi_n(\tau; Z) \int \max\{0, \Gamma - V_n(\tau)\}\, \mathrm{d}F_{\Gamma|\tau,Z} \mathrm{d}F_Z\right) \mathrm{d}\tau\right. \\
&\left. - \int_t^T \exp(-\rho(\tau - t))\, p(\tau|t)\, \lambda \left(\int \pi(\tau; Z) \int \max\{0, \Gamma - V(\tau)\}\, \mathrm{d}F_{\Gamma|\tau,Z} \mathrm{d}F_Z\right) \mathrm{d}\tau\right| \\
\leq& T\lambda \sup_{t,z} \left|\pi_n(t; z) \int \max\{0, \Gamma - V_n(t)\}\, \mathrm{d}F_{\Gamma|t,z} - \pi(t; z) \int \max\{0, \Gamma - V(t)\}\, \mathrm{d}F_{\Gamma|t,z}\right| \\
\leq& T\lambda \sup_{t,z} \left|\pi_n(t; z) \int |\max\{0, \Gamma - V_n(t)\} - \max\{0, \Gamma - V(t)\}|\, \mathrm{d}F_{\Gamma|t,z}\right| \\
&+ T\lambda \sup_{t,z} \left||\pi_n(t; z) - \pi(\tau; z)| \int \max\{0, \Gamma - V(t)\}\, \mathrm{d}F_{\Gamma|t,z}\right| \\
\leq& T\lambda \sup_{t,z} |V_n(t) - V(t)| + T\lambda \sup_{t,z} \int |\Gamma|\, \mathrm{d}F_{\Gamma|t,z} \sup_{t,z} |\pi_n(t; z) - \pi(\tau; z)| \\
\leq& T\lambda \left(1 + \sup_{t,z} \int |\Gamma|\, \mathrm{d}F_{\Gamma|t,z}\right) \varepsilon_n.
\end{aligned}$$

Since $\varepsilon_n \to 0$, Assumption 6(i) and (iv) imply that the right hand side converges to zero. Therefore, $A_V\left[\bar{\Omega}_0\right] \subset \overline{A_V[\Omega_0]}$, implying that A_V is continuous (Theorem 2.27, Aliprantis and Border, 2006).

A_{p_σ}: Continuity follows by noting that A_V is continuous in the sup-norm, and $F_{\Gamma|t,x,z}$ is absolutely continuous with respect to Lebesgue measure for each t, x, z (Assumption 6(iii)).

A_m : It is sufficient to fix x because χ is a finite set. Lemma 7 imply that the map defined by $A_\kappa[\omega](t) = \delta(t; x) + \lambda \int \pi(t; x, Z)\, p_\sigma(t; x)\, \mathrm{d}F_Z$ is continuous. Moreover, $\sup_t A_\kappa[\omega](t)$ is bounded above (Assumption 6(i)). Therefore, $A_{\kappa^*}[\omega](t) = -\int_0^t \delta(\tau; x) + \lambda \int \pi(\tau; x, Z)\, \sigma_x(\Gamma, t)\, \mathrm{d}F_Z \mathrm{d}\tau$ defines a continuous map from Ω to $C([0, T])$. Because a composition of continuous functions is continuous, and $g(a) = \gamma_x \exp(a)/N$ is continuous for all $N > 0$, we have that A_m is continuous.

A_N: First we show that $A_N[\omega_n]$ is continuous. Lemma 7 implies that the map $A_\kappa[\omega](t) = \delta(t; x) + \lambda \int \pi(t; x, Z)\, p_{\sigma_n}(t; x, Z)\, \mathrm{d}F_Z$ is continuous for each x. A similar argument implies that $A_{\bar{\kappa}}[\omega] = \sum_x \int_0^T m_x(t)\, \kappa_x(t)\, \mathrm{d}t$ is continuous because $m_x(t)$ is bounded by γ_x. Further, $A_{\bar{\kappa}}[\omega] \in [\underline{\delta}, \infty]$ since $\delta(t; x)$ is uniformly bounded below by $\underline{\delta}$ (Assumption 6(ii)). Since the composition of real-valued continuous functions is continuous, and the reciprocal function is continuous for all arguments other than 0, we have that A_N is a continuous map.

A_π: Denote $\tilde{A}[\omega] = (A_{p_\sigma}[\omega], A_m[\omega], A_N[\omega])$. We have shown that $\tilde{A}$ is continuous and compact. Note that for any sequence ω_n,

$$\sup_{x,z,t} |A_\pi[\omega_n](x, z, t)| \leq \sup_{x,z,t} \left|H_z\left(s_{xz}(t); \tilde{A}[\omega_n]\right)\right| \leq \sup_{z,s} \left|H_z\left(s; \tilde{A}[\omega_n]\right)\right|,$$

where the first inequality follows from the fact that $\mathbb{P}(c_{ij}=1|x,z)\in[0,1]$ and the second inequality follows from set inclusion. Therefore, Lemma 8 and continuity of $\tilde{A}$ implies that for each z, $\sup_s\left|H_z\left(s;\tilde{A}[\omega_n]\right)-H_z\left(s;\tilde{A}[\omega]\right)\right|\to 0$ if ω_n converges to ω. Since z belongs to a finite set, we therefore have that $\sup_{x,z,t}|A_\pi[\omega_n](x,z,t)-A_\pi[\omega](x,z,t)|\to 0$. Hence, A_π is a continuous map. Finally, Lemma 8 and the fact that $\tilde{A}[\Omega]$ is compact imply that the image of A_π is compact. □

Lemma 7. *Fix x. The map $A_\kappa:\Omega\to L_\infty([0,T])$, where*

$$A_\kappa[\omega](t)=\delta(t;x)+\lambda\int\pi(t;x,Z)\,p_\sigma(\tau;x,Z)\,\mathrm{d}F_Z$$

is continuous if λ is finite, and π and p_σ are uniformly bounded by 1.

Proof. Let Ω_0 be an arbitrary subset of Ω. Consider $\omega\in\bar{\Omega}_0$. Since $\omega\in\bar{\Omega}_0$, there exists a sequence $\omega_n\in\Omega_0$ such that $\|\omega_n-\omega\|=\varepsilon_n\to 0$. Now, consider $A_\kappa[\omega_n](t)=\lambda\int\pi_n(t;x,Z)\,p_{\sigma_n}(\tau;x,Z)\,\mathrm{d}F_{\Gamma|\tau,x,Z}$, where we endow the range with the supremum norm.

$$\begin{aligned}
\|A_\kappa[\omega_n]-A_\kappa[\omega]\| &= \lambda\left\|\int\pi_n(t;x,Z)\,p_{\sigma_n}(t;x,Z)\,\mathrm{d}F_Z-\int\pi(t;x,Z)\,p_\sigma(t;x,Z)\,\mathrm{d}F_Z\right\| \\
&\leq \lambda\sup_{z,t}|\pi_n(t;x,z)\,p_{\sigma_n}(t;x,z)-\pi(t;x,z)\,p_\sigma(t;x,z)| \\
&\leq \lambda\sup_{z,t}|\pi_n(t;x,z)\,(p_{\sigma_n}(t;x,z)-p_\sigma(t;x,z))| \\
&+\lambda\sup_{z,t}|(\pi_n(t;x,z)-\pi(t;x,z))\,p_\sigma(t;x,z)| \\
&\leq \lambda\sup_{z,t}|p_{\sigma_n}(t;x,z)-p_\sigma(t;x,z)|+\lambda\sup_{z,t}|\pi_n(t;x,z)-\pi(t;x,z)| \\
&\leq 2\lambda\varepsilon_n.
\end{aligned}$$

Therefore, $A_\kappa\left[\bar{\Omega}_0\right]\subset\overline{A_\kappa[\Omega_0]}$, implying that A_κ is continuous (Theorem 2.27, Aliprantis and Border, 2006). □

Lemma 8. *Fix z. The map $A_H:\Omega\to L_\infty(\mathbb{R})$ defined by $A_H[\omega](s)=H_z(s;p_\sigma,m,N)$ is continuous.*

Proof. We omit z from the notation for simplicity as it is fixed. Equation (18) derives the following expression for A_H:

$$A_H[\omega](t,x,z)=\int_0^1\sum_{q'<q}\frac{e^{-Np(s,\alpha)}\left(Np(s,\alpha)\right)^{q'}}{q'!}\mathrm{d}\alpha,$$

where

$$p(s,\alpha)=m_H(s)\,p_H(s)+m_E(s)\,\alpha p_E(s),$$

$$p_H(s) = p_0 + (1-p_0)\frac{1}{m_H(s)}\sum_{t,x} m(t;x)\,1\{s(t;x) > s\}\,p_\sigma(t;x),$$

$p_E(s)$ is defined analagously as $p_H(s)$, and p_0 is the probability of a failure ocurring. Here, we have $\mathbb{P}(\Gamma(t;x,z) + \varepsilon > V_x(t))$ with the acceptance probabilities $p_\sigma(t;x,z)$. Recall that

$$m_H(s) = \sum_{t,x} m(t;x)\,1\{s(t;x) > s\},$$
$$m_E(s) = \sum_{t,x} m(t;x)\,1\{s(t;x) = s\}.$$

We are now ready to prove continuity of A_H. We do this by first proving continuity of the components m_H, m_E, p_H and p_E.

Continuity of m_H and m_E: Consider a sequence m_n that converges in sup norm on x, t to m we have that

$$\begin{aligned}|m_{n,H}(s) - m_H(s)| &= \sum_x \int_0^T |m_n(t;x) - m(t;x)|\,1\{s(t;x) > s\}\,\mathrm{d}t \\ &\leq |\chi|\,T \sup_{x,t} |m_n(t;x) - m(t;x)|.\end{aligned}$$

Because this bound is independent of s, we have that $\sup_s |m_{n,H}(s) - m_H(s)|$ converges to zero. Therefore, $A_{m_H} : \Omega \to L_\infty(\mathbb{R})$ defined by $A_{m_H}[\omega](s) = m_H(s)$ is a continuous map because $A_{m_H}\left(\bar{\Omega}_0\right) = \overline{A_{m_H}(\Omega_0)}$ for any $\Omega_0 \subseteq \Omega$ (Theorem 2.27, Aliprantis and Border, 2006). An identical argument yields that $A_{m_E} : \Omega \to L_\infty(\mathbb{R})$ defined by $A_{m_E}[\omega](s) = m_E(s)$ is a continuous map. We do this by first proving continuity of the various components.

Continuity of p_H and p_E: We show the argument only for p_H because the argument for p_E is identical. Consider a sequence of ω_n that converges to ω, and the map $A_{p_H} : \Omega \to L_\infty(\mathbb{R})$ defined by $A_{p_H}[\omega](s) = p_0 + (1-p_0)\frac{1}{m_H(s)}\sum_{t,x} m(t;x)\,1\{s(t;x) > s\}\,p_\sigma(t;x)$. Since p_0 is fixed, we only need to show continuity of the map from ω to $\frac{1}{m_H(s)}\sum_{t,x} m(t;x)\,1\{s(t;x) > s\}\,p_\sigma(t;x)$.

For each s, we have that

$$
\begin{aligned}
&\left|\frac{1}{m_{n,H}(s)}\sum_{t,x} m_n(t;x)\,1\{s(t;x)>s\}\,p_{n,\sigma}(t;x,z)\right.\\
&\left.-\frac{1}{m_H(s)}\sum_{t,x} m(t;x)\,1\{s(t;x)>s\}\,p_\sigma(t;x)\right|\\
\leq&\left|\frac{1}{m_{n,H}(s)}\sum_{t,x} m_n(t;x)\,1\{s(t;x)>s\}\,p_{n,\sigma}(t;x)\right.\\
&\left.-\frac{1}{m_H(s)}\sum_{t,x} m(t;x)\,1\{s(t;x)>s\}\,p_{n,\sigma}(t;x)\right|\\
&+\left|\frac{1}{m_H(s)}\sum_{t,x} m(t;x)\,1\{s(t;x)>s\}\,p_{n,\sigma}(t;x)\right.\\
&\left.-\frac{1}{m_H(s)}\sum_{t,x} m(t;x)\,1\{s(t;x)>s\}\,p_\sigma(t;x)\right|\\
\leq&\left|\frac{1}{m_{n,H}(s)}\sum_{t,x} m_n(t;x)\,1\{s(t;x)>s\}-\frac{1}{m_H(s)}\sum_{t,x} m(t;x)\,1\{s(t;x)>s\}\right|\left|p_{n,\sigma}(t;x)\right|\\
&+\left|\frac{1}{m_H(s)}\sum_{t,x} m(t;x)\,1\{s(t;x)>s\}\right|\left|p_{n,\sigma}(t;x)-p_\sigma(t;x)\right|\\
\leq&\left|\frac{1}{m_{n,H}(s)}\sum_{t,x} m_n(t;x)\,1\{s(t;x)>s\}-\frac{1}{m_H(s)}\sum_{t,x} m(t;x)\,1\{s(t;x)>s\}\right|\\
&+\left|p_{n,\sigma}(t;x)-p_\sigma(t;x)\right|\\
=&\left|p_{n,\sigma}(t;x)-p_\sigma(t;x)\right|
\end{aligned}
$$

The first inequality follows fromt he triangle inequality. The third inequality follows from the fact that $|p_{n,\sigma}(t;x)-p_\sigma(t;x)|$ is bounded by 1 and $m_H(s)=\sum_{t,x} m(t;x)\,1\{s(t;x)>s\}$ by definition. The final inequality follows from the definition that $m_{n,H}(s)=\sum_{t,x} m_n(t;x)\,1\{s(t;x)>s\}$ and $m_H(s)=\sum_{t,x} m(t;x)\,1\{s(t;x)>s\}$ for all s. If ω_n converges to ω, we have that $\sup_{t,x}|p_{n,\sigma}(t;x)-p_\sigma(t;x)|$ conveges to zero. Therefore, we have that $\sup_s |A_{p_H}[\omega_n](s)-A_{p_H}[\omega](s)|$ also converges to zero. Hence, A_{p_H} is continuous because $A_{p_H}\left(\bar{\Omega}_0\right)=\overline{A_{p_H}(\Omega_0)}$ for any $\Omega_0\subseteq\Omega$ (Theorem 2.27, Aliprantis and Border, 2006).

Continuity of $p(s,\alpha)$: The map $A_{p^H}:\Omega\to L_\infty(\mathbb{R}\times[0,1])$ defined by $A_p[\omega](s,\alpha)=m_H(s)\,p_H(s)+m_E(s)\,\alpha p_E(s)$ is continuous because α is bounded by 1, the maps from ω to $m_H(s)$, $p_H(s)$, $m_E(s)$, $p_E(s)$ are continuous, and multiplication and addition are continuous.

Continuity of A_π: The map from Ω to $\sum_{q'<q}\frac{e^{-Np(s,\alpha)}(Np(s,\alpha))^{q'}}{q'!}$ is continuous beause the components are continuous, and the composition and multiplication operators are continuous.

This term is bounded by 1. Therefore, the integral

$$\int_0^1 \sum_{q'<q} \frac{e^{-Np(s,\alpha)} \left(Np\left(s,\alpha\right)\right)^{q'}}{q'!} \mathrm{d}\alpha$$

defines a continous map from Ω to the $L_\infty\left([0,T]\right)$ for each x. □

D Computational Details

D.1 Counterfactual Scoring Mechanisms

We compute steady-state equilibria for counterfactual scoring mechanisms using the algorithm described in the pseudo-code below. It is based on three key steps:

Value Function Computation (Backwards Induction):

For a small h, the value function derived in equation (4) can be approximated as

$$\left(\rho + \delta_x\left(t\right)\right) V_x\left(t\right) \approx \lambda \int \pi_x\left(t;z\right) \mathbb{E} \max\left\{0, \Gamma\left(t;x,z\right) + \varepsilon - V_x\left(t\right)\right\} \mathrm{d}F + \frac{V_x\left(t+h\right) - V_x\left(t\right)}{h}$$

Because the right-hand side is monotonically decreasing in $V_x\left(t\right)$, there is a unique value of $V_x\left(t\right)$ that satisfies the equation. We will use this expression to obtain the value function by backwards induction. At iteration k, given $V_x^k\left(t_{l+1}\right)$we use the bisection method to calculate the value of v that solves:

$$\left(\rho + \delta_x\left(t_l\right)\right) v = \lambda \int \pi_x^k\left(t_l;z\right) \mathbb{E} \max\left\{0, \Gamma\left(t_l;x,z\right) + \varepsilon - v\right\} \mathrm{d}F + \frac{V_x^k\left(t_{l+1}\right) - v}{t_{l+1} - t_l} \tag{19}$$

Because this problem can be written as finding $v = f\left(v\right)$ where $f\left(\cdot\right)$ is strictly decreasing, we can take any initial guess $v_0$and set the lower bound to $\min\left(v_0, f\left(v_0\right)\right)$and the upper bound to $\max\left(v_0, f\left(v_0\right)\right)$. We use the initial guess $v_0 = V_x^k\left(t_{l+1}\right)$.

Offer Probabilities, $\pi_{x,z}\left(t\right)$:

The expression in equation (18) can be simplified and solved for analytically. We use that solution in our algorithm.

Waitlist Size/Composition (Forward Simulation), m, N:

We use $\kappa_x\left(t\right)$ and γ_x to update the queue composition. Solving the ODE in Definition 1, part 3(a), we get that for any $h > 0$,

$$m_x\left(t+h\right) = m_x\left(t\right) \exp\left(-\int_0^h k_x\left(t+\tau\right) \mathrm{d}\tau\right),$$

Algorithm 1 Steady State Equilibrium

Inputs: Patient and donor characteristics, scoring rule s, parameters Γ, δ, ρ, and patient age grid $\{t_0, \ldots, t_L = T\}$. Let $t_{l_x^0}$ be the arrival time for patient of type x.
Outputs: V^*, π^*, m^*, N^*
Initialize $k = 0$ and beliefs $\pi_x^k(t)$ for all x and $t \in \{t_0, \ldots, t_L\}$
repeat
    $V^k \leftarrow$ Backwards Induction(π^k)
    $\kappa_x^k(t_l) \leftarrow \delta_x(t_l) + \lambda \sum_z \pi_{x,z}^k(t_l) \mathbb{P}(\Gamma(t_l; x, z) + \varepsilon > V_x^k(t_l))$
    $m^k, N^k \leftarrow$ Forward Simulation(κ^k) ▷ Waitlist Composition
    $\pi^k \leftarrow$ Compute Offer Probabilites(V^k, m^k, N^k) ▷ Offer Probabilities
    $k \leftarrow k + 1$
until $k > 1$, $\|V^k - V^{k-1}\|_\infty < \epsilon$, $\|m^k - m^{k-1}\|_\infty < \epsilon$, and $N^k = N^{k-1}$ ▷ Convergence
$V^* \leftarrow V^k, m^* \leftarrow m^k, N^* \leftarrow N^k, \pi^* \leftarrow \pi^k$
function Backwards Induction(π)
    for all x **do**
        Set $V_x(T) = 0$
        for all x and $t_l = t_{L-1}$ to $t_{l_x^0}$ **do**
            Compute $V_x(t_l)$ by solving for v in equation (19)
        end for
    end for
    return $V_x(t_l)$ for all x and $t_l \in \{t_{l_x^0}, \ldots, T\}$
end function
function Forward Simulation(κ)
    for all x **do**
        $m_x(t_{l_x^0}) \leftarrow \lambda_x$
        for all $t_l = t_{l_x^0+1}$ to T **do**
            $m_x(t_{l+1}) \leftarrow m_x(t_l) \exp(-\kappa_x(t_l)(t_{l+1} - t_l))$
        end for
    end for
    $N^k \leftarrow \sum_{x,t_l} m_x^k(t_l) \kappa_x^k(t_l)$ ▷ Waitlist Size: Definition 1, part 3(b)
    $m_x(t_l) \leftarrow m_x(t_l)/N^k$ for all x and t_l
    return $m_x(t_l)$ for $t_l \in \{t_{l_x^0}, \ldots, T\}$ and N^k
end function
function Compute Offer Probabilities(m, V, N)
    $p^a(t_l; x, z) \leftarrow \mathbb{P}(\Gamma(t_l; x, z) + \varepsilon > V_x(t_l))$ for all x, t_l
    for all $s = \max s(t_l; x, z)$ to $\min s(t_l; x, z)$ **do**
        Compute π using equation (18)
    end for
    return π^k
end function

where $m_x(0) = \lambda_x$. Appoximating $\kappa_x(t+\tau) = \kappa_x(t+h)$ for all $\tau \in (0,h)$, we have that

$$m_x(t_{l+1}) = m_x(t_l) \exp\left(-\kappa_x(t_{l+1})(t_{l+1} - t_l)\right). \tag{20}$$

Finally, we scale the output so that $m_x(t_l)$ is a probability measure.

The size of the waitlist, N, is determined by part 3(b) of Definition 1.

D.2 Optimal Assignments and Optimal Offer Rates

The objective functions for these two problems are identical. It is given by:

$$\sum \frac{1}{\bar{V}_x^{\mathcal{M}_0}(\lambda_0)} \left[\frac{\gamma_x}{\rho} V_x(0) + \sum_l N m_x(t_l)(t_{l+1} - t_l) V_x(t_l) \right],$$

where $\bar{V}_x^{\mathcal{M}_0}(\lambda_0)$ is defined in equation (10), $\tilde{m} \equiv Nm$ and V are choice variables with interpretations as in the rest of the paper. The variable $\tilde{m}$ differs from m in only that it integrates across $\chi \times [0, T]$ to the total queue length, instead of being a probability density function that integrates to 1. The constraints on the two problems differ and each has a separate, third choice variable. For the optimal assignment mechanism, we choose assignment policies parametrized by μ. For the optimal offer mechanism, we choose offer rates parametrized by π. We describe these variables and constraints below. The nonlinear problem is solved using KNITRO optimizer interfaced with MATLAB. We supply analytic Jacobians and Hessians to the solver.

D.2.1 Optimal Assignments

The allocation maximizes the objective function above by assigning an object of type z to agents currently on the list. The social planner has full information about the payoffs Γ_{xzt} as well as the idiosyncratic shocks ε. She knows the steady-state distribution of agents waiting for an assignment but not the future arrivals of objects or agents. The choice variable in this problem is the probability μ_{zxt} with which an object of type z is allocated to an agent of type x who has waited for t periods upon arrival. Given μ, the assignment is made to compatible agents of type x that have waited for t periods and have the highest draws of ε. Choosing μ is equivalent to choosing a cutoff $\underline{\varepsilon}_{xzt}$ such that $\mu_{xzt} = \mathbb{P}(a(\varepsilon; x, z, t) = 1) = \mathbb{P}(\varepsilon > \underline{\varepsilon}_{xzt})$.

There are three constraints:

1. Value Function: Finally, we chosen value to equal the agent's net present value from the expected stream of assignments under the policy μ_{zxt} :

$$\left(1 + \left(\rho + \delta_x(t_l) + \sum_z \lambda_z \mu_{xzt_l}\right)(t_{l+1} - t_l)\right) V_x(t_l) = \lambda(t_{l+1} - t_l) w_x(t_l) + V_x(t_{l+1}),$$

where

$$w_x(t) = \frac{1}{\sum_z \lambda_z \mu_{xzt}} \sum_z \lambda_z \mu_{xzt} c_{xz} \left[\mathbb{E}\left[\Gamma_{xzt} + \varepsilon | \varepsilon > \underline{\varepsilon}_{xzt}\right] \mathbb{P}(\varepsilon > \underline{\varepsilon}_{xzt}) + (\Gamma_{xzt} + \underline{\varepsilon}_{xzt}) \mathbb{P}(\varepsilon > \underline{\varepsilon}_{xzt})\right].$$

This expression of V and w is obtained from solving the value function from following the policy of accepting offers with ε above $\underline{\varepsilon}_{xzt}$, with offers made whenever an object

arrives. The term $w_x(t)$ denotes the expected value to an agent of type x for each object arrival. It is the sum of the values of assignment of each object type conditional on the payoff shock exceeding ε_{xzt}, weighted by the probability of assignment.

2. Feasibility: The total mass of type z objects that are assigned upon arrival must not exceed the mass of objects that arrive. Specifically, for each z, we impose the constraint:

$$\sum_{x,l} \tilde{m}_x(t_l)(t_{l+1} - t_l) c_{xz} \mu_{zxt_l} \leq q_z,$$

where c_{xz} is the known (estimated) compatibility probability. The left hand side is the cumulative product of the (discretized) masses of each type of agent on the waitlist, $\tilde{m}_x(t_l)(t_{l+1} - t_l)$, multiplied by the assignment probabilities $c_{xz}\mu_{xzt_l}$ for each agent. This quantity cannot exceed the right hand side, q_z, which is the mass of objects that arrive.

3. Steady-State Composition: The measure of agents of type x that have waited for t periods is in steady state. This constraint is analogous to equation (20) above. Specifically, for each x and $l > 0$, we have that

$$\tilde{m}_x(t_{l+1}) = \tilde{m}_x(t_l) \exp\left(-\left(\delta_x(t_l) + \sum_z \lambda_z c_{xz} \mu_{xzt_l}\right)(t_{l+1} - t_l)\right)$$
$$\tilde{m}_x(t_0) = \gamma_x.$$

The term $\sum_z \lambda_z c_{xz} \mu_{xzt_l}$ is the cumulative assignment rate across object for an agent of type x at time t_l. This, when added to $\delta_x(t_{l+1})$, yields the total departure rate.

In addition, we impose that each μ_{xzt} belongs to unit interval.

D.2.2 Optimal Offer Rates

The problem maximizes the objective function above by choosing a probability of offering an object of type z to agents currently on the list. The social planner has full information about the payoffs Γ_{xzt}, but does not know the idiosyncratic shocks ε. She knows the steady-state distribution of agents waiting for an assignment but not the future arrivals of objects or agents. The choice variable in this problem is the probability π_{zxt} with which an object of type z is offered to an agent of type x who has waited for t periods upon arrival. Agents make optimal choices, given π, on which offers to accept.

As before, there are three constraints:

1. Value Function: Finally, we chosen value to equal the agent's net present value from

the expected stream of assignments under the policy μ_{zxt} :

$$\left(1+\left(\rho+\delta_x\left(t_l\right)\right)\left(t_{l+1}-t_l\right)\right)V_x\left(t_l\right)=\lambda\left(t_{l+1}-t_l\right)w_x\left(t_l\right)+V_x\left(t_{l+1}\right),$$

where

$$w_x\left(t\right)=\frac{1}{\sum_z\lambda_z\mu_{xzt}}\sum_z\lambda_z\mu_{xzt}\mathbb{E}\left[\max\left\{0,\Gamma_{xzt}+\varepsilon-V_x\left(t\right)\right\}\right]$$

and

$$\mu_{xzt}=\pi_{xzt}c_{xz}\mathbb{P}\left(\Gamma_{xzt}+\varepsilon>V_x\left(t\right)\right).$$

As for the optimal assignment problem, $w_x\left(t\right)$ is the expected value to an agent of type x for each object arrival. However, in this problem, the agent makes optimal decisions and offers do not depend on the payoff shocks. Therefore, an assignment occurs only if the agent is offered the object and the agent accepts. Acceptance occurs if the payoff shock exceeds $V_x\left(t\right)-\Gamma_{xzt}$.

2. Feasibility: The total mass of type z objects that are assigned upon arrival must not exceed the mass of objects that arrive. Specifically, for each z, we impose the constraint:

$$\sum_{x,l}\tilde{m}_x\left(t_l\right)\left(t_{l+1}-t_l\right)\pi_{zxt_l}\left[c_{xz}\mathbb{P}\left(\Gamma_{xzt_l}+\varepsilon>V_x\left(t_l\right)\right)+p_{0,z}\right]\leq q_z.$$

This constraint is also analogous to the feasibility constraint in the optimal assignment problem. The difference is that the assignment rate $c_{xz}\mu_{xzt}$ is replaced by the term

$$\pi_{zxt_l}\left[c_{xz}\mathbb{P}\left(\Gamma_{xzt_l}+\varepsilon>V_x\left(t_l\right)\right)+p_{0,z}\right].$$

The term π_{zxt_l} denotes the probability that an agent of type x receives an offer for an object of type z after she has waited for t_l periods. The term in brackets is the probability that any such offer is the last offer for the object that can be made. It is the sum of the probability that object is compatible and transplanted

$$c_{xz}\mathbb{P}\left(\Gamma_{xzt_l}+\varepsilon>V_x\left(t_l\right)\right)$$

and the probability that no more offers can be made after this one. This term arises from the technological constraint on the number of offers that can be made for an object. The model used to determine $p_{0,z}$ is described in Appendix B.3.

It is worth noting that this constraint only places a restriction on the expected number of assignments. Therefore, the offer rates π_{xzt} may not be implementable for specific donor arrivals.

3. Steady-State Composition: The measure of agents of type x that have waited for t peri-

ods is in steady state. This constraint is analogous to equation (20) above. Specifically, for each x and $l > 0$, we have that

$$\tilde{m}_x(t_{l+1}) = \tilde{m}_x(t_l) \exp\left(-\left(\delta_x(t_{l+1}) + \sum_z \lambda_z \mu_{xzt_l}\right)(t_{l+1} - t_l)\right)$$
$$\tilde{m}_x(t_l) = \gamma_x,$$

where

$$\mu_{xzt} = \pi_{zxt} c_{xz} \mathbb{P}\left(\Gamma_{xzt} + \varepsilon > V_x(t)\right).$$

The constraint is identical to the one used in the optimal assignment problem. However, in this problem, the assignment probability μ_{xzt} depends on the agents acceptance decision.

In addition, we impose that each π_{xzt} belongs to unit interval.

E Robustness

Finally, we assess sensitivity of the counterfactual results to three limitations of our analysis. We show that steady state comparisons of the queueing systems considered in Section 7 are robust to persistent patient-level unobserved heterogeneity, alternative values of the discount factor ρ, and a large sample of patients and donors.

E.1 Patient Unobserved Heterogeneity

Our baseline results abstracted away from patient unobserved heterogeneity to simplify estimation. This restriction could bias our results if patients differ in ways not captured by the rich patient covariates in our data. For example, if some patients are systematically more selective than others and many patients are rarely willing to accept a kidney, we could overstate the amount that changes to the priority system affect queue lengths and compositions.

To assess sensitivity to allowing for patient unobserved heterogeneity, we re-estimated the model allowing for two unobserved patient types. Specifically, we introduced patient unobserved types α_i and re-parametrized equation (8) as follows:

$$V(\alpha_i, x_i, t) - \Gamma(\alpha_i, x_i, z_j, \eta_j, t) = \alpha_i + \chi(x_i, z_j, t)\theta + \eta_j,$$

where we allow $\alpha_i \in \{\alpha_1, \alpha_2\}$ with the parameters α_1 and α_2 to be estimated. In addition, we estimate the share $\pi_1 \in (0, 1)$ for unobserved type α_1. The share of the other type is $1 - \pi_1$. This parameterization allows patients to have systematically higher or lower

values of all transplants relative to their outside options.[43] We assume that the exogenous departure rates do not depend on this unobserved preference type, and abstract away from the initial conditions problem, setting the proportion of each patient type in our sample to the population average. This latter assumption is appropriate for patients that registered on the waiting list during our sample period, but it abstracts away from selection that should arise for patients that registered prior to the sample of offers we consider.

We estimate this model by adding a data augmentation step to the Gibbs' sampler. This step draws α_i for each agent i given their observed decisions and the parameters α_1, α_2, and π_1. Conditional on $(\alpha_1, \alpha_2, \pi_1)$, the posterior probability that $\alpha_i = \alpha_1$ is proportional to the likelihood of observing the decisions made by agent i multiplied by π_1. This likelihood is simple to calculate as it is the product of the cumulative density functions of normal distributions. With this data augmentation step, α_1, α_2, and π_1 can be updated in the Gibbs' sampler using conjugate priors. We specify diffuse normal priors for α_1 and α_2 and a Dirichlet prior for π_1 (see Section 3.4, Gelman et al., 2014). As recommended in Gelman et al. (2014), we check for re-ordering and impose the restriction that $\alpha_1 > \alpha_2$.

Table B.5 presents the results for the steady-states of scoring mechanisms considered in the main text. The results are both qualitatively and quantitatively similar to those from our main specification. In particular, pre- and post-2014 priorities, first come first served, and greedy priorities have similar queue lengths (about 5,000) and total patient welfare. Last come first served causes both queue lengths and patient welfare to fall dramatically. Table B.6 shows that the distributional consequences are also similar to those from our main specification, though there are some small differences. Given that these differences are few and small in magnitude, the results suggest that omitting patient-level unobserved heterogeneity does not substantially affect our conclusions about the welfare or distributional impacts of alternative assignment mechanisms.

E.2 Discount Factor

As discussed in Section 3, the discount faction ρ is not identified. The baseline results set this parameter to 5 percent per year. Here, we evaluate sensitivity of our results to using an annual discount rate of 10 percent. This change holds the estimated conditional choice probabilities fixed, but changes the calculation of $\hat{V}(t; x_i)$ based on equation (7). Only Step 4 in Section 4.1 must be revised to obtain estimates with an alternative discount rate.

Table B.7 presents the main counterfactuals and Table B.8 presents subgroup analysis. Equilibrium queue lengths and welfare comparisons are very close to those predicted by the base-

[43] A further relaxation would allow time-varying patient-level unobserved heterogeneity. This modification would raise additional identification challenges Connault (2016). It would also increase the computational burden of our estimation procedure and counterfactuals; patients would have to form beliefs about the evolution of unobserved state variables governing their types, in addition to the distribution of future offers.

line specification; apart from last come first served, all queue length predictions are within 100 of the baseline predictions, and welfare comparisons within a 1 percent change in equivalent donor supply. And as in the baseline specification, a 10 percent discount factor predicts small subgroup effects, with somewhat larger effects for patients who are above 50 years old and not on dialysis at registration.

One reason why the discount factor affects results minimally is that a large portion of discounting comes from patient departure rates, which are 16 percent annually for the average patient.

E.3 Larger Samples

Due to the computational burden of solving the optimal assignment and optimal offer mechanisms, baseline estimates in the main text limit the number of types used in counterfactual calculations to 300 patient types and 500 donor types. To assess whether the results are sensitive to the specific sample and number of types, we re-calculated the counterfactuals by drawing 1,000 patient types and 1,500 donor types. We recalculate equilibrium allocations and welfare under the scoring mechanisms considered in the main text using the same estimates of $\hat{\Gamma}_{ij}(t)$ as in the baseline specification.

Table B.9 presents the overall results and Table B.10 presents the sub-group analyses. Once again, equilibrium allocations and changes in patient welfare are very similar to those from the smaller sample of patients and donors. The characteristics of transplanted donors are slightly different in the larger sample: transplanted donors are on average older, more likely to be DCD, and less likely to be hypertensive. This difference is due in part to the composition of donors in the larger sample. Distributional effects are also very similar in this larger sample.

Table A.1: Patient Sample Restrictions

	Number of Patients Registered
Kidney Candidates Registered in NYRT Between 2010 and 201	14499
Excluding Candidates Who Were Not Interested in a Transplant	13950
Excluding Inactive Candidates	9985
Excluding Candidates Receiving Non-Standard Allocations	9917

Notes: candidates who were not interested in a transplant include patients who departed the waitlist because they refused transplantation, received a transplant in another country, could not be contacted, or had an improved condition. Inactive candidates are patients who registered on the waitlist but never changed their status to "active," and therefore never received kidney offers, during the sample period. Candidates receiving non-standard allocations include placements from military or directed donations, expedited placement attempts, and medical emergencies.

Table A.2: Offer Sample Restrictions

	Number of Offers
Offers in U.S. sample made on or before September 31st, 2015	61038882
Offers made to NYRT Patients	4516460
Offers made on or before December 31st, 2013	2883287
Excluding non-genuine refusals	1880672
Excluding offers after the donor's cutoff	1318961
Excluding patients and donors receiving non-standard allocations	1281024

Notes: non-genuine refusals include offers in the Potential Transplant Recipient (PTR) dataset which did not meet the patient's pre-set screening criteria; for which the patient or transplant surgeon was unavailable; or where the transplant could not occur for medical reasons. Non-standard allocations include placements from military or directed donations, expedited placement attempts, and medical emergencies. All offers were made on or after January 1st, 2010.

Table A.3: Fit of Mechanism Code: Predicted Offers

		In PTR Data		
		No	Yes	Total
Predicted by Simulation	No	14,907,971	88,366	14,996,337
	Yes	502,239	1,192,658	1,694,897
	Total	15,410,210	1,281,024	16,691,234

Table B.1: Evidence of Response to Dynamic Incentives

	Dependent Variable: Offer Accepted				
	(1)	(2)	(3)	(4)	(5)
Calculated Panel Reactive Antibodies (CPRA)	0.0155	0.00879	0.00838	0.00776	0.00786
	(0.000769)	(0.000893)	(0.000884)	(0.000839)	(0.000841)
Variables Affecting Priority		X	X	X	X
Patient Characteristics			X	X	X
Donor and Match Characteristics				X	X
Interaction between CPRA and # HLA Mismatches					X
Mean Acceptance Rate	0.150%	0.150%	0.150%	0.150%	0.150%
Observations	2840937	2840937	2840937	2840937	2840937
R-squared	0.003	0.006	0.009	0.099	0.099

Notes: Estimates from a linear probability model of offer acceptance on patient Calculated Panel Reactive Antibodies (CPRA). The sample is offers made to NYRT patients between 2010 and 2013, including offers that did not meet pre-set screening criteria. CPRA is measured on a [0,1] scale at the time of the offer. Column 1 controls for a CPRA=0 indicator. Column 2 adds controls affecting patient priority: indicators for CPRA>=0.2, CPRA>=0.8, and age<18, as well as waiting time indicators and linear controls for 1-3, 3-5, and >5 years. Column 3 adds other patient characteristics. Column 4 adds controls for donor and match characteristics. Column 5 adds interactions between CPRA indicators and # HLA mismatches. Patient characteristics are indicators for age 18-35, 35-50, and 50-65; indicators for diabetes, blood type, and the patient's transplant center; linear controls and indicators for dialysis time 1-3, 3-5, 5-10, and >10 years; and an indicator for health status at listing. Donor controls are linear age; linear creatinine with indicators for 0.6-1.8 and >1.8; the donor's mean acceptance rate; and indicators for diabetes, donation after cardiac death (DCD), and expanded criteria donor (ECD). Match characteristics are linear # HLA mismatches; indicators for zero HLA mismatch, 0 and 1 DR mismatch, identical blood type, offer year, and local donor; linear controls for (+) and (-) age difference; and interactions between local and zero-HLA mismatch, and local and donor age, donor over 40 and pediatric patient, donor over 55 and patient age 18-35, and donor over 60 and patient age 35-50 and over 50. Standard errors, clustered by donor, are in parentheses.

Table B.2: Cutoff Rank Autocorrelation Tests

Donor Type	N	Autocorrelation Statistic	p-value
Panel A: Donor Category			
Standard Criteria, Age < 35	1065	2.01	0.55
Standard Criteria, Age >= 35	1598	1.99	0.46
Cardiac Death, Age < 35	178	2.02	0.56
Cardiac Death, Age >= 35	404	2.01	0.51
Expanded Criteria	2462	1.95	0.10
Expanded Criteria or Cardiac Death	156	2.12	0.78
Panel B: Donor Category and Origin			
Standard Criteria, Age < 35; NYRT	234	2.09	0.74
Standard Criteria, Age < 35; non-NYRT	831	1.91	0.08
Standard Criteria, Age >= 35; NYRT	252	1.99	0.49
Standard Criteria, Age >= 35; non-NYRT	1346	2.01	0.60
Cardiac Death, Age < 35; NYRT	15	1.91	0.43
Cardiac Death, Age < 35; non-NYRT	163	2.25	0.95
Cardiac Death, Age >= 35; NYRT	50	2.51	0.97
Cardiac Death, Age >= 35; non-NYRT	354	2.08	0.77
Expanded Criteria; NYRT	227	2.16	0.88
Expanded Criteria; non-NYRT	2235	1.99	0.41
Expanded Criteria or Cardiac Death; NYRT	6	2.63	0.83
Expanded Criteria or Cardiac Death; non-NYRT	150	2.16	0.83
Panel C: Standard Criteria NYRT Donors, by Age and Blood Type			
Standard Criteria, Age < 35; Blood Type O	117	1.98	0.45
Standard Criteria, Age < 35; Blood Type B	37	1.70	0.20
Standard Criteria, Age < 35; Blood Type AB	5	1.50	0.25
Standard Criteria, Age < 35; Blood Type A	75	1.74	0.11
Standard Criteria, Age >= 35; Blood Type O	131	1.87	0.24
Standard Criteria, Age >= 35; Blood Type B	32	2.00	0.49
Standard Criteria, Age >= 35; Blood Type AB	7	1.86	0.45
Standard Criteria, Age >= 35; Blood Type A	82	1.98	0.46

Notes: results from tests for autocorrelation of donor cutoffs in the NYRT sample based on the rank version of von Neumann's ratio statistic (Bartels, 1982). Each donor's cutoff is the priority score above which a patient would have received an offer from that donor, which is determined by the last patient in the donor's offer sequence. The rank of each donor's cutoff is its order statistic among the cutoffs of donors of the same type, with ties broken by a random number. The autocorrelation statistic for each donor type is computed for the observed sequence of donor cutoff ranks. Each p-value is the fraction of 1,000 randomly sampled permutations of donor arrival sequences for which the rank autocorrelation statistic is below that observed in sample.

Table B.3: Conditional Choice Probability of Acceptance (Detailed)

	Base Specification		Unobserved Heterog.		Waiting Time + UH	
	(1)		(2)		(3)	
Constant	-3.69	(0.02)	-4.44	(0.04)	-4.46	(0.05)
Patient Diabetic	-0.06	(0.01)	-0.05	(0.02)	-0.03	(0.02)
Calculated Panel Reactive Antibody (CPRA)	0.60	(0.05)	0.67	(0.06)	0.54	(0.08)
CPRA >= 0.8	0.27	(0.04)	0.13	(0.06)	0.17	(0.08)
CPRA = 0	-0.09	(0.02)	-0.03	(0.03)	-0.04	(0.03)
CPRA - 0.8 if CPRA >= 0.8	-0.41	(0.35)	-0.39	(0.45)	-0.58	(0.46)
Patient had Prior Transplant	0.38	(0.02)	0.36	(0.02)	0.16	(0.03)
Donor Age < 18	0.30	(0.10)	-0.10	(0.18)	-0.07	(0.19)
Donor Age 18-35	0.60	(0.12)	0.09	(0.18)	0.14	(0.18)
Donor Age 50+	-0.83	(0.15)	-0.81	(0.20)	-0.85	(0.21)
Donor Cause of Death Anoxia	-0.03	(0.02)	-0.09	(0.06)	-0.09	(0.07)
Donor Cause of Death Stroke	0.01	(0.02)	0.02	(0.06)	0.04	(0.07)
Donor Cause of Death CNS	0.17	(0.08)	-0.20	(0.29)	-0.18	(0.29)
Donor Creatinine 0.5-1.0	-0.06	(0.03)	-0.01	(0.10)	-0.01	(0.10)
Donor Creatinine 1.0-1.5	0.02	(0.03)	-0.02	(0.11)	-0.01	(0.11)
Donor Creatinine >= 1.5	-0.13	(0.03)	-0.23	(0.11)	-0.22	(0.10)
Donor Pancreas Offered	0.35	(0.02)	0.52	(0.08)	0.51	(0.08)
Patient awaits Pancreas	-2.49	(0.94)	-8.62	(1.36)	-14.56	(2.62)
Expanded Criteria Donor (ECD)	-0.15	(0.02)	-0.51	(0.08)	-0.54	(0.08)
Donation from Cardiac Death (DCD)	-0.11	(0.02)	-0.49	(0.08)	-0.49	(0.07)
Donor Male	0.00	(0.01)	0.07	(0.05)	0.05	(0.05)
Donor History of Hypertension	0.01	(0.01)	-0.02	(0.05)	-0.03	(0.05)
Perfect Tissue Type Match	2.28	(0.31)	2.79	(0.42)	2.75	(0.43)
2 A Mismatches	-0.08	(0.01)	-0.01	(0.02)	-0.01	(0.02)
2 B Mismatches	0.06	(0.02)	0.03	(0.02)	0.02	(0.02)
2 DR Mismatches	-0.07	(0.02)	-0.06	(0.02)	-0.06	(0.02)
ABO Compatible	-0.36	(0.05)	-0.43	(0.08)	-0.46	(0.09)
Regional Offer	-1.34	(0.05)	-2.69	(0.17)	-2.75	(0.17)
National Offer	-1.50	(0.04)	-2.92	(0.11)	-2.95	(0.12)
Non-NYRT Donor, NYRT Match Run	1.21	(0.02)	1.97	(0.05)	2.01	(0.06)
Patient Blood Type A	-0.17	(0.02)	-0.29	(0.06)	-0.29	(0.07)
Patient Blood Type O	-0.31	(0.02)	-0.40	(0.06)	-0.39	(0.06)
Patient on Dialysis at Registration	-0.04	(0.01)	-0.12	(0.02)	-0.11	(0.02)
Patient Age at Registration	0.03	(0.01)	0.09	(0.01)	0.09	(0.01)
Patient Age - 18 if Age >= 18	-0.04	(0.01)	-0.10	(0.01)	-0.10	(0.01)
Patient Age - 35 if Age >= 35	0.01	(0.00)	0.01	(0.01)	0.01	(0.01)
Patient Age - 50 if Age >= 50	0.00	(0.00)	0.00	(0.00)	0.00	(0.00)
Patient Age - 65 if Age >= 65	-0.01	(0.00)	-0.01	(0.01)	-0.01	(0.01)
Log Waiting Time (years)					-0.01	(0.05)
Log Waiting Time * Over 1 Year					-0.10	(0.06)
Log Waiting Time * Over 2 Years					-0.17	(0.12)
Log Waiting Time * Over 3 Years					0.42	(0.11)
Patient BMI at Departure	-0.04	(0.02)	-0.08	(0.03)	-0.07	(0.03)
Patient BMI - 18.5 if BMI >= 18.5	0.03	(0.02)	0.07	(0.03)	0.06	(0.03)
Patient BMI - 25 if BMI >= 25	0.02	(0.01)	0.02	(0.01)	0.02	(0.01)
Patient BMI - 30 if BMI >= 30	-0.01	(0.01)	-0.02	(0.01)	-0.02	(0.01)
Patient Serum Albumin	-0.04	(0.03)	-0.03	(0.03)	-0.03	(0.03)
Serum Albumin - 3.7 if >= 3.7	-0.02	(0.05)	-0.05	(0.05)	-0.03	(0.06)
Serum Albumin - 4.4 if >= 4.4	0.11	(0.04)	0.16	(0.06)	0.15	(0.06)
Log Dialysis Time at Registration (Years)	0.05	(0.00)	0.05	(0.00)	0.05	(0.01)
Log Dialysis Time at Registration * Over 5 years	0.48	(0.03)	0.42	(0.03)	0.41	(0.04)
Perfect Tissue Type Match * Prior Transplant	-0.43	(0.19)	-0.37	(0.26)	-0.28	(0.26)
Perfect Tissue Type Match * Diabetic Patient	0.02	(0.16)	0.04	(0.22)	0.04	(0.22)
Perfect Tissue Type Match * Patient Age	-0.01	(0.01)	-0.02	(0.01)	-0.02	(0.01)
Perfect Tissue Type Match * CPRA	0.87	(0.34)	1.38	(0.47)	1.61	(0.47)
Perfect Tissue Type Match * CPRA above 80%	-0.56	(0.30)	-0.43	(0.40)	-0.55	(0.41)
Perfect Tissue Type Match * ECD Donor	-0.60	(0.16)	-0.71	(0.23)	-0.69	(0.23)
Perfect Tissue Type Match * DCD Donor	-0.46	(0.33)	-1.06	(0.46)	-1.04	(0.46)
Perfect Tissue Type Match * NYRT Donor	0.50	(0.18)	0.10	(0.26)	0.12	(0.26)
Perfect Tissue Type Match * ABO Compatible	0.04	(0.17)	0.12	(0.23)	0.14	(0.23)
Donor Pancreas Offered * Patient awaits Pancrea	2.34	(1.07)	8.65	(1.46)	14.59	(2.68)
NYRT Donor * 2 A Mismatches	0.15	(0.02)	0.07	(0.04)	0.07	(0.04)
NYRT Donor * 2 B Mismatches	-0.02	(0.03)	-0.06	(0.04)	-0.05	(0.04)
NYRT Donor * 2 DR Mismatches	-0.02	(0.02)	0.01	(0.03)	0.01	(0.03)

NYRT Donor * Donor Age < 18	-0.05	(0.06)	0.22	(0.20)	0.23	(0.22)
NYRT Donor * Donor Age 18-35	0.10	(0.04)	0.11	(0.13)	0.14	(0.14)
NYRT Donor * Donor Age 50+	-0.42	(0.03)	-0.62	(0.11)	-0.62	(0.13)
Patient Age * Donor Age < 18	-0.01	(0.00)	0.00	(0.00)	0.00	(0.00)
Patient Age * Donor Age 18-35	-0.02	(0.00)	0.00	(0.01)	0.00	(0.01)
Patient Age * Donor Age 50+	0.02	(0.00)	0.02	(0.01)	0.02	(0.01)
Patient Age - 35 if Age >= 35 * Donor Age 18-35					0.00	(0.01)
Patient Age - 35 if Age >= 35 * Donor Age 50+					0.00	(0.01)
Log Waiting Time * Prior Transplant					0.22	(0.02)
Log Waiting Time * Patient Diabetic					-0.03	(0.02)
Log Waiting Time * Patient Age					0.00	(0.00)
Log Waiting Time * CPRA					0.10	(0.05)
Log Waiting Time * CPRA >= 80					-0.01	(0.05)
Log Waiting Time * Patient Serum Albumin					0.00	(0.01)
Log Waiting Time * Patient BMI at Departure					0.00	(0.00)
Log Waiting Time * Patient Blood Type A					0.01	(0.03)
Log Waiting Time * Patient Blood Type O					0.01	(0.02)
Patient BMI Missing	-0.81	(0.41)	-1.47	(0.56)	-1.27	(0.56)
Patient Serum Albumin Missing	-0.01	(0.09)	-0.02	(0.11)	-0.10	(0.12)
Donor Unobservable Std. Dev.			0.98	(0.21)	1.00	(0.23)
Idiosyncratic Shock Std. Dev.	1.00		1.00		1.00	
Acceptance Rate	0.150%		0.150%		0.150%	
Number of Offers	2850572		2850572		2850572	
Number of Donors	5863		5863		5863	
Number of Patients	9788		9788		9788	

Table B.3: Value of Transplant Estimates

	Base Specification	Unobserved Heterog.	Waiting Time + UH
	(1)	(2)	(3)
Constant	-3.14 (0.00)	-0.33 (0.00)	-0.21 (0.00)
Patient Diabetic	-0.16 (0.00)	-0.89 (0.00)	-0.98 (0.00)
Calculated Panel Reactive Antibody (CPRA)	1.98 (0.01)	2.09 (0.01)	1.11 (0.01)
CPRA >= 0.8	2.36 (0.01)	0.49 (0.02)	3.02 (0.02)
CPRA = 0	-0.69 (0.00)	-4.04 (0.00)	-3.87 (0.00)
CPRA - 0.8 if CPRA >= 0.8	-23.21 (0.08)	-55.63 (0.15)	-74.35 (0.15)
Patient had Prior Transplant	1.59 (0.00)	4.31 (0.00)	6.49 (0.00)
Donor Age < 18	0.34 (0.01)	0.31 (0.02)	0.32 (0.02)
Donor Age 18-35	0.69 (0.02)	0.39 (0.03)	0.82 (0.03)
Donor Age 50+	-0.87 (0.01)	-0.90 (0.02)	-1.17 (0.02)
Donor Cause of Death Anoxia	-0.03 (0.00)	-0.09 (0.00)	-0.09 (0.00)
Donor Cause of Death Stroke	0.01 (0.00)	0.01 (0.00)	0.04 (0.00)
Donor Cause of Death CNS	0.19 (0.01)	-0.12 (0.02)	-0.16 (0.02)
Donor Creatinine 0.5-1.0	-0.06 (0.00)	-0.03 (0.01)	-0.01 (0.01)
Donor Creatinine 1.0-1.5	0.01 (0.00)	-0.06 (0.01)	-0.03 (0.01)
Donor Creatinine >= 1.5	-0.14 (0.00)	-0.26 (0.01)	-0.23 (0.01)
Donor Pancreas Offered	0.38 (0.00)	0.75 (0.01)	0.52 (0.01)
Patient awaits Pancreas	-2.88 (0.01)	-10.85 (0.02)	-16.94 (0.02)
Expanded Criteria Donor (ECD)	-0.15 (0.00)	-0.50 (0.00)	-0.53 (0.00)
Donation from Cardiac Death (DCD)	-0.12 (0.00)	-0.50 (0.00)	-0.50 (0.00)
Donor Male	0.00 (0.00)	0.08 (0.00)	0.06 (0.00)
Donor History of Hypertension	0.01 (0.00)	-0.03 (0.00)	-0.03 (0.00)
Perfect Tissue Type Match	2.46 (0.11)	2.58 (0.23)	3.13 (0.23)
2 A Mismatches	-0.08 (0.00)	0.06 (0.00)	0.04 (0.00)
2 B Mismatches	0.07 (0.00)	0.08 (0.00)	0.05 (0.00)
2 DR Mismatches	-0.06 (0.00)	-0.03 (0.00)	-0.06 (0.00)
ABO Compatible	-0.29 (0.00)	1.51 (0.01)	2.00 (0.01)
Regional Offer	-1.36 (0.01)	-2.99 (0.01)	-2.75 (0.01)
National Offer	-1.52 (0.01)	-3.23 (0.01)	-2.96 (0.01)
Non-NYRT Donor, NYRT Match Run	1.27 (0.00)	2.63 (0.00)	2.03 (0.00)
Patient Blood Type A	-0.04 (0.00)	0.56 (0.00)	1.07 (0.00)
Patient Blood Type O	-0.20 (0.00)	0.97 (0.00)	0.91 (0.00)
Patient on Dialysis at Registration	0.06 (0.00)	1.20 (0.00)	1.19 (0.00)
Patient Age at Registration	0.07 (0.00)	0.30 (0.00)	0.33 (0.00)
Patient Age - 18 if Age >= 18	-0.11 (0.00)	-0.32 (0.00)	-0.41 (0.00)
Patient Age - 35 if Age >= 35	0.03 (0.00)	0.06 (0.00)	0.14 (0.00)
Patient Age - 50 if Age >= 50	0.00 (0.00)	-0.11 (0.00)	-0.15 (0.00)
Patient Age - 65 if Age >= 65	-0.03 (0.00)	-0.09 (0.00)	-0.07 (0.00)
Log Waiting Time (years)			-1.00 (0.01)
Log Waiting Time * Over 1 Year			0.77 (0.01)
Log Waiting Time * Over 2 Years			0.30 (0.01)
Log Waiting Time * Over 3 Years			5.05 (0.01)
Patient BMI at Departure	-0.09 (0.00)	-0.26 (0.00)	-0.37 (0.00)
Patient BMI - 18.5 if BMI >= 18.5	0.07 (0.00)	0.28 (0.00)	0.44 (0.00)
Patient BMI - 25 if BMI >= 25	0.04 (0.00)	0.13 (0.00)	0.09 (0.00)
Patient BMI - 30 if BMI >= 30	-0.02 (0.00)	-0.12 (0.00)	-0.13 (0.00)
Patient Serum Albumin	0.02 (0.00)	1.07 (0.00)	0.96 (0.00)
Serum Albumin - 3.7 if >= 3.7	-0.09 (0.00)	-1.19 (0.01)	-0.96 (0.01)
Serum Albumin - 4.4 if >= 4.4	0.36 (0.00)	2.60 (0.01)	2.40 (0.01)
Log Dialysis Time at Registration (Years)	0.09 (0.00)	0.28 (0.00)	0.28 (0.00)
Log Dialysis Time at Registration * Over 5 years	3.46 (0.00)	7.94 (0.01)	8.39 (0.01)
Perfect Tissue Type Match * Prior Transplant	-0.34 (0.07)	-0.97 (0.14)	-1.83 (0.14)
Perfect Tissue Type Match * Diabetic Patient	-0.11 (0.05)	0.08 (0.11)	-0.06 (0.11)
Perfect Tissue Type Match * Patient Age	-0.01 (0.00)	-0.02 (0.00)	-0.02 (0.00)
Perfect Tissue Type Match * CPRA	0.53 (0.13)	-0.39 (0.27)	1.19 (0.27)
Perfect Tissue Type Match * CPRA above 80%	-0.75 (0.13)	1.39 (0.26)	0.12 (0.27)
Perfect Tissue Type Match * ECD Donor	-0.57 (0.05)	-0.59 (0.10)	-0.66 (0.10)

Perfect Tissue Type Match * DCD Donor	-0.54	(0.10)	-1.25	(0.19)	-1.33	(0.19)
Perfect Tissue Type Match * NYRT Donor	0.53	(0.09)	0.12	(0.17)	0.16	(0.18)
Perfect Tissue Type Match * ABO Compatible	-0.05	(0.05)	-1.55	(0.11)	-2.01	(0.11)
Donor Pancreas Offered * Patient awaits Pancre	2.28	(0.06)	8.24	(0.12)	14.39	(0.12)
NYRT Donor * 2 A Mismatches	0.15	(0.00)	0.10	(0.01)	0.07	(0.01)
NYRT Donor * 2 B Mismatches	-0.02	(0.00)	-0.07	(0.01)	-0.04	(0.01)
NYRT Donor * 2 DR Mismatches	-0.02	(0.00)	0.00	(0.01)	0.01	(0.01)
NYRT Donor * Donor Age < 18	-0.07	(0.01)	0.07	(0.02)	0.22	(0.02)
NYRT Donor * Donor Age 18-35	0.11	(0.01)	0.13	(0.01)	0.19	(0.01)
NYRT Donor * Donor Age 50+	-0.43	(0.00)	-0.77	(0.01)	-0.62	(0.01)
Patient Age * Donor Age < 18	-0.01	(0.00)	-0.01	(0.00)	-0.01	(0.00)
Patient Age * Donor Age 18-35	-0.02	(0.00)	-0.01	(0.00)	-0.02	(0.00)
Patient Age * Donor Age 50+	0.02	(0.00)	0.02	(0.00)	0.03	(0.00)
Patient Age - 35 if Age >= 35 * Donor Age 18-35	0.02	(0.00)	0.01	(0.00)	0.02	(0.00)
Patient Age - 35 if Age >= 35 * Donor Age 50+	-0.01	(0.00)	-0.01	(0.00)	-0.02	(0.00)
Log Waiting Time * Prior Transplant					2.05	(0.00)
Log Waiting Time * Patient Diabetic					-0.29	(0.00)
Log Waiting Time * Patient Age					0.00	(0.00)
Log Waiting Time * CPRA					2.33	(0.01)
Log Waiting Time * CPRA >= 80					-3.20	(0.01)
Log Waiting Time * Patient Serum Albumin					0.06	(0.00)
Log Waiting Time * Patient BMI at Departure					0.02	(0.00)
Log Waiting Time * Patient Blood Type A					0.33	(0.00)
Log Waiting Time * Patient Blood Type O					0.29	(0.00)
Patient BMI Missing	-1.79	(0.04)	-5.95	(0.08)	-8.64	(0.08)
Patient Serum Albumin Missing	0.39	(0.01)	4.31	(0.02)	3.41	(0.02)
Donor Unobservable Std. Dev.			0.98	(0.21)	1.00	(0.23)
Idiosyncratic Shock Std. Dev.	1.00		1.00		1.00	

Table B.3: Net Present Value Estimates

	Base Specification	Unobserved Heterog.	Waiting Time + UH
	(1)	(2)	(3)
Constant	0.54 [0.00]	4.11 [0.00]	4.25 [0.00]
Patient Diabetic	-0.11 [0.00]	-0.84 [0.00]	-0.95 [0.00]
Calculated Panel Reactive Antibody (CPRA)	1.38 [0.01]	1.40 [0.01]	0.54 [0.01]
CPRA >= 0.8	2.08 [0.01]	0.39 [0.02]	2.83 [0.02]
CPRA = 0	-0.59 [0.00]	-4.03 [0.00]	-3.86 [0.00]
CPRA - 0.8 if CPRA >= 0.8	-22.83 [0.08]	-55.36 [0.15]	-73.63 [0.15]
Patient had Prior Transplant	1.21 [0.00]	3.97 [0.00]	6.36 [0.00]
Patient awaits Pancreas	-0.39 [0.01]	-2.23 [0.01]	-2.40 [0.02]
Patient Blood Type A	0.11 [0.00]	0.30 [0.00]	0.56 [0.00]
Patient Blood Type O	0.09 [0.00]	0.82 [0.00]	0.50 [0.00]
Patient on Dialysis at Registration	0.10 [0.00]	1.33 [0.00]	1.30 [0.00]
Patient Age at Registration	0.04 [0.00]	0.21 [0.00]	0.24 [0.00]
Patient Age - 18 if Age >= 18	-0.07 [0.00]	-0.22 [0.00]	-0.30 [0.00]
Patient Age - 35 if Age >= 35	0.02 [0.00]	0.05 [0.00]	0.12 [0.00]
Patient Age - 50 if Age >= 50	0.00 [0.00]	-0.12 [0.00]	-0.15 [0.00]
Patient Age - 65 if Age >= 65	-0.01 [0.00]	-0.08 [0.00]	-0.06 [0.00]
Log Waiting Time (years)			-1.24 [0.01]
Log Waiting Time * Over 1 Year			0.84 [0.01]
Log Waiting Time * Over 2 Years			0.41 [0.01]
Log Waiting Time * Over 3 Years			4.67 [0.01]
Patient BMI at Departure	-0.04 [0.00]	-0.19 [0.00]	-0.31 [0.00]
Patient BMI - 18.5 if BMI >= 18.5	0.04 [0.00]	0.21 [0.00]	0.38 [0.00]
Patient BMI - 25 if BMI >= 25	0.02 [0.00]	0.12 [0.00]	0.07 [0.00]
Patient BMI - 30 if BMI >= 30	-0.01 [0.00]	-0.10 [0.00]	-0.12 [0.00]
Patient Serum Albumin	0.06 [0.00]	1.10 [0.00]	1.00 [0.00]
Serum Albumin - 3.7 if >= 3.7	-0.07 [0.00]	-1.17 [0.01]	-0.96 [0.01]
Serum Albumin - 4.4 if >= 4.4	0.25 [0.00]	2.47 [0.01]	2.27 [0.01]
Log Dialysis Time at Registration (Years)	0.04 [0.00]	0.23 [0.00]	0.23 [0.00]
Log Dialysis Time at Registration * Over 5 years	2.98 [0.00]	7.50 [0.01]	7.94 [0.01]
Log Waiting Time * Prior Transplant			1.84 [0.00]
Log Waiting Time * Patient Diabetic			-0.26 [0.00]
Log Waiting Time * Patient Age			0.00 [0.00]
Log Waiting Time * CPRA			2.25 [0.01]
Log Waiting Time * CPRA >= 80			-3.18 [0.01]
Log Waiting Time * Patient Serum Albumin			0.07 [0.00]
Log Waiting Time * Patient BMI at Departure			0.01 [0.00]
Log Waiting Time * Patient Blood Type A			0.59 [0.00]
Log Waiting Time * Patient Blood Type O			0.57 [0.00]
Patient BMI Missing	-0.99 [0.04]	-4.55 [0.08]	-7.55 [0.08]
Patient Serum Albumin Missing	0.40 [0.01]	4.35 [0.02]	3.50 [0.02]

Table B.4: Positive Crossmatch Model

Dependent Variable: Positive Crossmatch	
CPRA	1.039
	(0.145)
0 or 1 HLA Mismatches	-1.433
	(0.477)
2 or 3 HLA Mismatches	0.181
	(0.0820)
0 DR Mismatches	-0.455
	(0.0895)
CPRA * (0 or 1 HLA Mismatches)	-0.337
	(0.662)
CPRA * (2 or 3 HLA Mismatches)	-0.449
	(0.162)
CPRA 0	-0.592
	(0.0787)
CPRA - 0.8 if CPRA > 0.8	-3.426
	(0.785)
Log Dialysis Time at Registration (Years)	-0.0300
	(0.00797)
Log Dialysis Time at Registration * Over 5 Years	0.983
	(0.0760)
Patient Age at Registration (Years)	0.0115
	(0.00462)
Age at Registration - 35 if Age > 35	-0.0290
	(0.00592)
Constant	-0.239
	(0.161)
Observations	4283

Notes: coefficient estimates from a probit regression of positive crossmatch on patient CPRA, the number of tissue type mismatches, patient age, and years on dialysis at registration. The sample is all offers accepted by NYRT patients between 2010 and 2013. Positive crossmatches are identified by the appropriate refusal code in the PTR data. CPRA is measured on a [0,1] scale.

Table B.5: Robustness: Outcomes in Various Mechanisms, allowing for Patient Unobserved Heterogeneity

	Waitlist			Characteristics of Transplanted Donors				Fraction of Patients Better Off		Change in Equivalent Donor Supply (Mean)	
	Queue Length	Reduction in Discard Rate	Years on Waitlist	Age	Died of Head Trauma	Cardiac Death (DCD)	Hyper-tensive	At Listing $V_x(0)$	Steady State $\bar{V}_x$	At Listing $V_x(0)$	Steady State $\bar{V}_x$
Panel A: Steady State Equilibrium, All Patients											
Pre-2014 Priorities	5083.5	--	2.59	44.0	25.6%	11.2%	38.6%	--	--	--	--
Post-2014 Priorities	5034.5	0.2%	2.58	44.0	25.6%	11.3%	38.5%	33.3%	18.7%	-0.6%	-1.0%
First Come First Served	5195.2	-1.5%	2.63	44.0	25.7%	11.1%	38.6%	83.7%	87.3%	1.0%	1.7%
Last Come First Served	3053.3	22.7%	2.73	46.2	23.9%	10.1%	45.9%	13.7%	0.0%	-26.7%	-37.7%
Greedy Priorities	5036.3	0.1%	2.66	43.7	25.9%	11.1%	37.7%	56.3%	53.0%	0.2%	-0.7%
Panel B: Estimated Choice Probabilities from Pre-2014 Mechanism, All Patients											
Pre-2014 Priorities	5617.3	--	3.05	43.1	26.3%	11.6%	35.2%	--	--	--	--
Post-2014 Priorities	5587.2	0.0%	3.05	43.1	26.3%	11.6%	35.1%	--	--	--	--
First Come First Served	5662.8	-0.1%	3.00	43.2	26.3%	11.5%	35.3%	--	--	--	--
Last Come First Served	5546.7	3.8%	5.46	43.4	25.8%	11.5%	36.4%	--	--	--	--
Greedy Priorities	5361.9	2.4%	3.22	43.4	26.1%	11.3%	36.0%	--	--	--	--

Table B.6: Robustness: Outcomes in Various Mechanisms, by Patient Group, allowing for Patient Unobserved Heterogeneity

	Waitlist	Characteristics of Transplanted Donors				Fraction of Patients Better Off		Change in Equivalent Donor Supply (Mean)	
	Years on Waitlist	Age	Died of Head Trauma	Cardiac Death (DCD)	Hyper-tensive	At Listing $V_x(0)$	Steady State $\bar{V}_x$	At Listing $V_x(0)$	Steady State $\bar{V}_x$
					Panel A: Age < 50, Not on Dialysis at Registration				
Pre-2014 Priorities	2.49	38.6	35.9%	13.9%	27.2%	--	--	--	--
Post-2014 Priorities	2.48	39.2	37.5%	14.0%	29.1%	44.7%	34.2%	0.0%	-0.5%
First Come First Served	2.52	41.1	30.0%	12.6%	37.2%	63.2%	68.4%	-6.5%	-5.6%
Last Come First Served	2.56	42.6	26.7%	11.1%	41.8%	2.6%	0.0%	-38.7%	-45.5%
Greedy Priorities	2.56	38.5	33.0%	12.1%	31.1%	57.9%	60.5%	-3.8%	-3.8%
					Panel B: Age 50+, Not on Dialysis at Registration				
Pre-2014 Priorities	2.59	47.1	22.2%	11.1%	44.0%	--	--	--	--
Post-2014 Priorities	2.58	46.6	22.5%	10.9%	43.0%	23.9%	14.1%	-1.0%	-1.3%
First Come First Served	2.61	45.6	25.1%	11.2%	39.8%	95.8%	98.6%	5.1%	5.6%
Last Come First Served	2.91	48.6	21.9%	10.4%	50.1%	12.7%	0.0%	-37.8%	-48.1%
Greedy Priorities	2.72	44.8	26.3%	10.3%	38.0%	53.5%	54.9%	2.2%	1.7%
					Panel C: Age < 50, on Dialysis at Registration				
Pre-2014 Priorities	2.60	40.4	27.3%	11.7%	35.0%	--	--	--	--
Post-2014 Priorities	2.57	40.4	26.9%	11.9%	34.0%	42.3%	22.5%	-0.5%	-0.9%
First Come First Served	2.65	41.5	27.1%	10.6%	37.0%	80.3%	88.7%	-0.9%	0.0%
Last Come First Served	2.81	43.2	26.6%	9.4%	42.6%	11.3%	0.0%	-24.9%	-35.0%
Greedy Priorities	2.61	40.5	27.1%	11.0%	35.0%	66.2%	60.6%	-2.5%	-3.3%
					Panel D: Age 50+, on Dialysis at Registration				
Pre-2014 Priorities	2.62	46.5	22.9%	10.1%	41.8%	--	--	--	--
Post-2014 Priorities	2.61	46.5	22.5%	10.2%	42.0%	30.0%	14.2%	-0.7%	-1.1%
First Come First Served	2.66	45.6	23.9%	10.9%	39.4%	85.0%	85.8%	2.0%	2.6%
Last Come First Served	2.60	47.6	22.5%	10.2%	46.9%	19.2%	0.0%	-17.4%	-30.7%
Greedy Priorities	2.68	46.6	22.9%	11.3%	41.2%	51.7%	45.0%	1.8%	0.4%

Table B.7: Robustness: Outcomes in Various Mechanisms, Annual Discount Factor 0.9

	Waitlist			Characteristics of Transplanted Donors				Fraction Better Off		Change in Equivalent Donor Supply (Mean)	
	Queue Length	Reduction in Discard Rate	Years on Waitlist	Age	Died of Head Trauma	Cardiac Death (DCD)	Hyper-tensive	At Listing $V_x(0)$	Steady State $\bar{V}_x$	At Listing $V_x(0)$	Steady State $\bar{V}_x$
Panel A: Steady State Equilibrium, All Patients											
Pre-2014 Priorities	5016.8	--	2.54	43.7	25.6%	11.6%	38.0%	--	--	--	--
Post-2014 Priorities	4944.0	0.4%	2.51	43.8	25.5%	11.6%	38.0%	36.3%	14.0%	-0.3%	-1.5%
First Come First Served	5114.2	-1.3%	2.56	43.7	25.5%	11.6%	37.8%	86.3%	91.3%	1.0%	2.1%
Last Come First Served	2954.2	23.2%	2.61	45.8	24.3%	11.7%	44.1%	7.7%	0.0%	-19.1%	-41.9%
Greedy Priorities	4957.4	0.1%	2.57	43.6	25.7%	11.4%	37.8%	59.3%	50.3%	1.1%	0.5%
Panel B: Estimated Choice Probabilities from Pre-2014 Mechanism, All Patients											
Pre-2014 Priorities	5387.6	--	2.86	43.3	25.8%	11.5%	36.5%	--	--	--	--
Post-2014 Priorities	5337.8	0.0%	2.86	43.3	25.8%	11.5%	36.5%	--	--	--	--
First Come First Served	5460.6	-0.1%	2.84	43.3	25.8%	11.5%	36.5%	--	--	--	--
Last Come First Served	5175.0	3.6%	5.39	43.6	25.5%	11.3%	37.7%	--	--	--	--
Greedy Priorities	5248.7	0.9%	2.88	43.4	25.7%	11.4%	36.8%	--	--	--	--

Table B.8: Robustness: Outcomes in Various Mechanisms, by Patient Group, Annual Discount Factor 0.9

	Waitlist	Characteristics of Transplanted Donors				Fraction Better Off		Change in Equivalent Donor Supply (Mean)	
	Years on Waitlist	Age	Died of Head Trauma	Cardiac Death (DCD)	Hyper-tensive	At Listing $V_x(0)$	Steady State $\bar{V}_x$	At Listing $V_x(0)$	Steady State $\bar{V}_x$
					Panel A: Not on Dialysis at Registration, Age 0-49				
Pre-2014 Priorities	2.42	38.2	32.3%	13.3%	27.3%	--	--	--	--
Post-2014 Priorities	2.39	39.3	33.9%	13.4%	28.3%	57.9%	26.3%	1.2%	-0.1%
First Come First Served	2.45	40.9	29.4%	12.7%	34.9%	68.4%	71.1%	-5.7%	-4.1%
Last Come First Served	2.46	42.4	26.7%	12.9%	40.4%	2.6%	0.0%	-31.9%	-46.8%
Greedy Priorities	2.47	38.0	33.6%	11.3%	29.4%	68.4%	63.2%	1.0%	2.0%
					Panel B: Not on Dialysis at Registration, Age 50+				
Pre-2014 Priorities	2.52	47.0	21.6%	12.0%	44.5%	--	--	--	--
Post-2014 Priorities	2.49	46.6	21.9%	11.8%	44.0%	25.4%	8.5%	-0.7%	-1.8%
First Come First Served	2.52	45.6	23.4%	12.0%	40.8%	95.8%	98.6%	4.5%	5.1%
Last Come First Served	2.71	48.3	22.1%	12.3%	48.2%	2.8%	0.0%	-25.6%	-48.6%
Greedy Priorities	2.62	44.7	23.7%	11.8%	38.1%	54.9%	62.0%	3.0%	4.8%
					Panel C: On Dialysis at Registration, Age 0-49				
Pre-2014 Priorities	2.55	40.2	27.4%	11.5%	33.9%	--	--	--	--
Post-2014 Priorities	2.51	40.2	27.2%	11.5%	33.5%	45.1%	18.3%	0.1%	-1.1%
First Come First Served	2.58	40.9	27.0%	11.0%	35.7%	84.5%	91.5%	-0.8%	0.6%
Last Come First Served	2.66	42.6	26.9%	11.3%	40.8%	4.2%	0.0%	-21.1%	-40.7%
Greedy Priorities	2.52	40.5	27.3%	10.7%	35.3%	70.4%	52.1%	-0.5%	-2.5%
					Panel D: On Dialysis at Registration, Age 50+				
Pre-2014 Priorities	2.58	46.0	24.3%	10.9%	40.7%	--	--	--	--
Post-2014 Priorities	2.56	46.0	23.6%	10.9%	41.0%	30.8%	10.8%	-0.7%	-2.0%
First Come First Served	2.60	45.2	24.4%	11.4%	38.5%	87.5%	93.3%	2.1%	3.2%
Last Come First Served	2.57	47.2	23.3%	11.4%	45.0%	14.2%	0.0%	-10.1%	-37.2%
Greedy Priorities	2.59	46.6	23.2%	11.6%	41.8%	52.5%	38.3%	0.9%	-0.8%

Table B.9: Robustness: Outcomes in Various Mechanisms, Large Sample

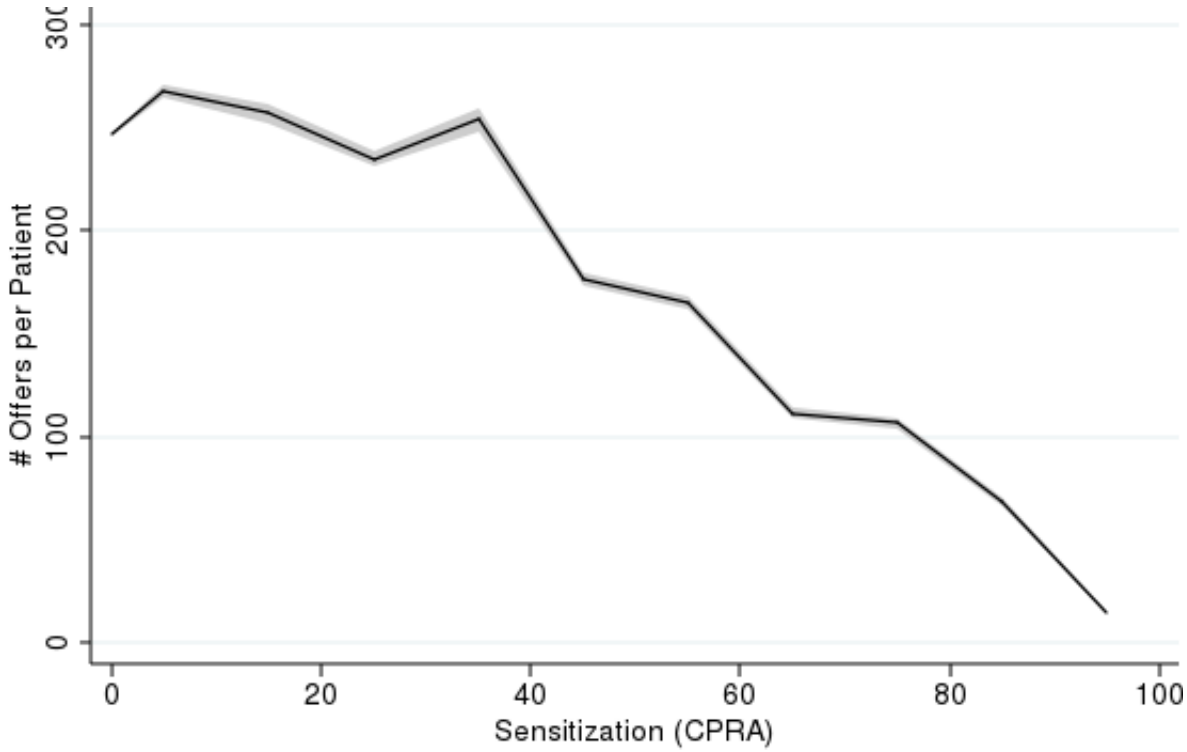
	Waitlist			Characteristics of Transplanted Donors				Fraction Better Off		Change in Equivalent Donor Supply (Mean)	
	Queue Length	Reduction in Discard Rate	Years on Waitlist	Age	Died of Head Trauma	Cardiac Death (DCD)	Hyper-tensive	At Listing $V_x(0)$	Steady State $\bar{V}_x$	At Listing $V_x(0)$	Steady State $\bar{V}_x$
Panel A: Steady State Equilibrium, All Patients											
Pre-2014 Priorities	5049.5	--	2.71	45.4	26.7%	8.3%	45.1%	--	--	--	--
Post-2014 Priorities	4964.9	0.6%	2.68	45.4	26.6%	8.3%	45.1%	32.3%	14.8%	0.5%	-0.3%
First Come First Served	5170.0	-1.5%	2.75	45.3	26.9%	8.3%	45.2%	90.7%	90.7%	0.7%	1.5%
Last Come First Served	2884.3	25.6%	2.98	46.9	22.8%	9.6%	49.5%	3.7%	0.3%	-21.2%	-33.0%
Greedy Priorities	4964.7	0.6%	2.79	45.2	26.7%	8.3%	45.0%	60.0%	53.7%	4.6%	3.3%
Panel B: Estimated Choice Probabilities from Pre-2014 Mechanism, All Patients											
Pre-2014 Priorities	5645.1	--	3.18	44.9	28.1%	7.7%	43.8%	--	--	--	--
Post-2014 Priorities	5593.7	0.0%	3.16	44.9	28.1%	7.7%	43.8%	--	--	--	--
First Come First Served	5721.8	-0.1%	3.17	44.9	28.2%	7.7%	43.8%	--	--	--	--
Last Come First Served	5505.7	3.9%	5.88	45.3	27.1%	7.9%	44.4%	--	--	--	--
Greedy Priorities	5566.5	1.1%	3.44	44.9	27.9%	7.7%	43.9%	--	--	--	--

Table B.10: Robustness: Outcomes in Various Mechanisms, by Patient Group, Large Sample

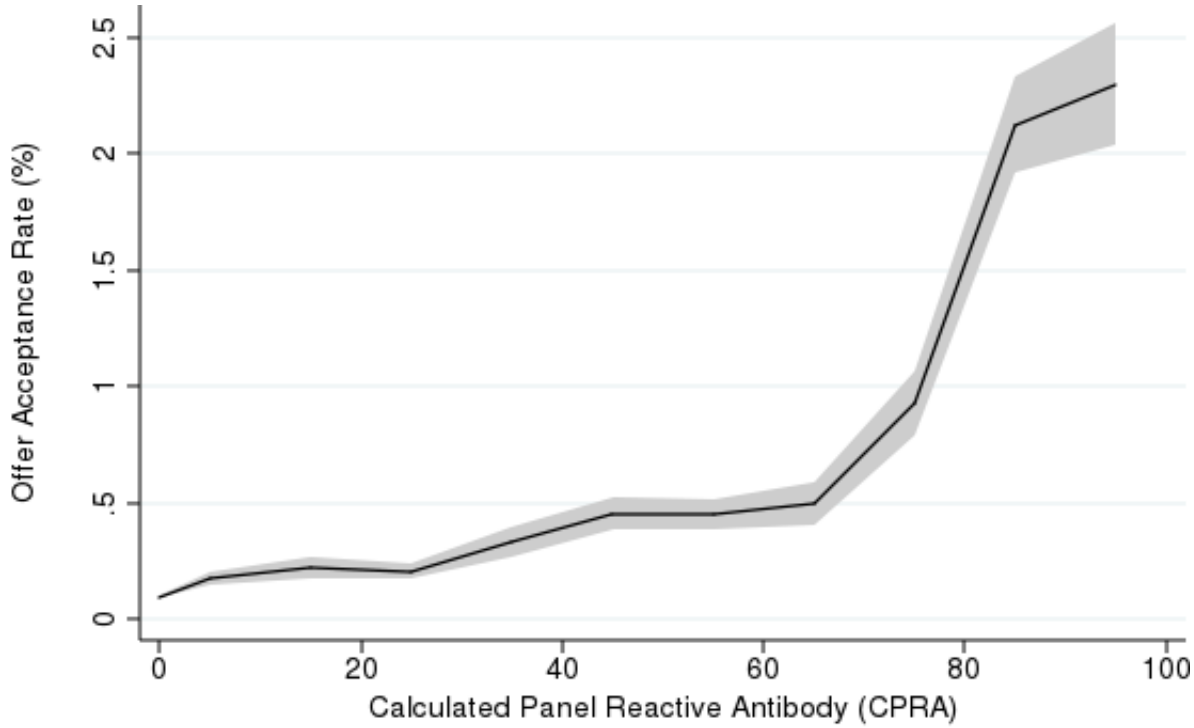
	Waitlist	Characteristics of Transplanted Donors				Fraction Better Off		Change in Equivalent Donor Supply (Mean)	
	Years on Waitlist	Age	Died of Head Trauma	Cardiac Death (DCD)	Hyper-tensive	At Listing $V_x(0)$	Steady State $\bar{V}_x$	At Listing $V_x(0)$	Steady State $\bar{V}_x$
					Panel A: Not on Dialysis at Registration, Age 0-49				
Pre-2014 Priorities	2.47	40.7	32.8%	7.7%	36.3%	--	--	--	--
Post-2014 Priorities	2.44	40.7	32.5%	7.7%	36.5%	29.9%	18.7%	-0.3%	-0.8%
First Come First Served	2.50	42.6	28.7%	9.0%	41.7%	86.6%	85.8%	-4.1%	-3.3%
Last Come First Served	2.41	43.9	24.2%	10.4%	45.8%	0.7%	0.0%	-31.2%	-39.5%
Greedy Priorities	2.48	41.1	31.4%	8.2%	37.0%	65.7%	64.9%	0.4%	0.3%
					Panel B: Not on Dialysis at Registration, Age 50+				
Pre-2014 Priorities	2.51	48.1	24.7%	8.2%	49.9%	--	--	--	--
Post-2014 Priorities	2.49	47.8	24.7%	7.9%	49.3%	26.4%	13.7%	-0.2%	-0.9%
First Come First Served	2.54	47.2	26.5%	7.7%	48.4%	95.6%	96.0%	3.9%	4.5%
Last Come First Served	2.58	49.2	21.7%	9.2%	53.0%	1.3%	0.4%	-27.3%	-38.9%
Greedy Priorities	2.57	46.2	30.5%	7.5%	45.3%	59.0%	60.8%	15.4%	13.5%
					Panel C: On Dialysis at Registration, Age 0-49				
Pre-2014 Priorities	2.99	41.8	29.9%	8.8%	39.5%	--	--	--	--
Post-2014 Priorities	2.93	42.0	30.1%	8.9%	39.4%	41.6%	16.8%	1.6%	0.5%
First Come First Served	3.04	42.0	29.1%	9.0%	40.0%	86.0%	86.4%	-0.9%	0.1%
Last Come First Served	3.91	43.5	24.8%	10.4%	44.8%	1.2%	0.0%	-21.0%	-32.0%
Greedy Priorities	3.23	41.9	27.4%	9.3%	40.5%	61.2%	49.6%	-0.7%	-2.2%
					Panel D: On Dialysis at Registration, Age 50+				
Pre-2014 Priorities	2.72	48.3	23.2%	8.1%	49.8%	--	--	--	--
Post-2014 Priorities	2.68	48.3	23.0%	8.2%	50.1%	30.6%	12.9%	0.6%	-0.3%
First Come First Served	2.76	47.5	25.0%	7.8%	48.2%	92.3%	92.0%	1.4%	2.3%
Last Come First Served	2.76	48.8	21.8%	9.1%	51.7%	7.7%	0.5%	-14.3%	-28.0%
Greedy Priorities	2.72	48.4	23.0%	7.9%	50.5%	57.8%	48.3%	3.0%	1.9%

Figure B.1: Offer and Acceptance Rate by cPRA

(a) Offer Rate



(b) Acceptance Rate



Note: Sample includes all offers made to NYRT patients between 2010 and 2013, including offers that did not meet pre-set donor screening criteria. Positive crossmatches are counted as acceptances. In each figure, the black line plots the mean among offers to patients in each CPRA bin, and the shaded region represents pointwise 95 percent confidence intervals.

Figure B.2: Comparing Hazard Rates for Gompertz and Cox Proportional Hazards Models