Abstract

A transplant can improve a patient’s life while saving several hundred thousands of dollars of healthcare expenditures. Organs from deceased donors, like many other common pool resources (e.g. public housing, child-care slots, publicly funded long-term care), are rationed via a waitlist. The efficiency and equity properties of design choices such as penalties for refusing offers or object-type specific lists are not well understood and depend on agent preferences. This paper establishes an empirical framework for analyzing the trade-offs involved in waitlist design and applies it to study the allocation of deceased donor kidneys. We model the decision to accept an offer from a waiting list as an optimal stopping problem and use it to estimate the value of accepting various kidneys. Our estimated values for various kidneys is highly correlated with predicted patient outcomes as measured by life-years from transplantation (LYFT). While some types of donors are preferable for all patients (e.g. young donors), there is substantial heterogeneity in willingness to wait for good donors and also substantial match-specific heterogeneity in values (due to biological similarity). We find that the high willingness to wait for good donors without considering the effects of these decisions on other results in agents being too selective relative to socially optimal. This suggests that mild penalties for refusal (e.g. loss in priority) may improve efficiency. Similarly, the heterogeneity in willingness to wait for young, healthy donors suggests that separate queues by donor quality may increase efficiency by inducing sorting without significantly hurting assignments based on match-specific payoffs.
Introduction

As of January 12, 2017, there were 119,121 patients on the national organ waiting list, but only 33,594 transplants were performed in 2016. Roughly 22 people die each day while waiting for a transplant. Ethical concerns and the current legal framework require allocation systems that do not use money, making traditional price-based market-clearing mechanisms infeasible. This project builds a new empirical framework for studying deceased donor organ allocations and uses it to study alternative systems for allocating deceased donor kidneys. In the long run, I plan to adapt this model to study the allocation of other deceased donor organs.

Although End-Stage Renal Disease (ESRD) can be managed through dialysis, kidney transplantation is the treatment of choice. It not only improves life expectancy and quality of life, but it is also cost-effective through savings in dialysis costs. Patients who are transplanted with deceased donor kidneys survive 10 years longer than patients who remain on dialysis (Wolfe et.al. 1999). Compared with the cost of dialysis, transplanting one patient saves Medicare more than $250,000 over five years (USRDS 2014).

Roughly two-thirds of transplantation currently occurs through deceased donors, with the remaining occurring through live-donor transplants. These organs are allocated through a steadily growing waiting list. Over 100,000 patients are on the national kidney waiting list, but under 12,000 patients are transplanted with a deceased donor kidney in a typical year.

The allocation system used to match deceased donor kidneys with patients relies a coarse point system based on donor and patient characteristics and the patient’s waiting time. While the organ offer system can control who is prioritized for a kidney, the ultimate decision of whether or not to accept that offer remains with the patient and the surgeon. This decision is likely to be influenced by whether waiting for a more suitable donor is preferable to accepting the current offer and the patient’s health and tolerance for dialysis treatment. This aspect of patient-surgeon choice and its dependence on the organ offer system has been ignored when designing the allocation system.

Investigating the determinants of this choice can suggest improvements in several ways. First, offering kidneys to patients who are likely to accept the offer can reduce the lag time between organ procurement and transplantation (also called cold ischemic time), which can directly increase the life-years supported by an organ. Second, any offer system will have patients who are commonly prioritized and others who have low priority. While sometimes justified on specific grounds (e.g. pediatric patients, hard-to-match patients, or patients with long waiting times), such differences can cause unintended harms. For example, patients who rarely receive offers are likely to accept organs that would provide greater benefit to another patient. Finally, and most importantly, studying patient-surgeon choice can suggest how to reduce the discard rate of marginal organs by offering them to patients who are likely to accept them before the the 24-48 hour transplantation window expires.

This paper establishes an empirical framework for analyzing the trade-offs involved in

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1The National Organ Transplantation Act (NOTA) outlaws contracts written on human organs.
3While the design of scoring rules has been an active area of research in the Medical and Operations Research communities (see e.g. Su and Zenios (2006); Zenios et al. (2000); Kong et al. (2010); Bertsimas et al. (2012)), this previous research and the KPSAM acceptance module used by the Scientific Registry of Transplant Recipients (SRTR) to simulate the effects of various allocation systems do not model the incentives for accepting or rejecting an organ offer.
waitlist design and applies it to study the allocation of deceased donor kidneys. We model the decision to accept an offer from a waiting list as an optimal stopping problem and use it to estimate the value of accepting various kidneys. Our methodology promises to provide a new framework for simulating future changes to the offer system for all organs, not just kidneys. The study therefore advances the approaches used in the market-design literature in economics by directly using data-driven methods to improve an allocation system.

Data
The primary data source for this study is the Pre-transplant (PTR) and the Standard Transplant Analysis and Research (STAR) data collected by the Organ Procurement and Transplantation Network (OPTN) and UNOS. The PTR data include all deceased donor kidney offers made since 2000 in the United States, with details on the waiting-list position for each offer, acceptance/refusal decisions, and refusal reasons. Importantly, the dataset also includes patient and donor encrypted identifiers that allow merging with datasets in the STAR and other secondary files on patient and donor characteristics. For the patient, these include demographics, age, weight, blood-type, histo-compatibility, coarse health status indicators (diabetes, heart disease), measures of sensitivity to foreign organs (PRA and cPRA), unacceptable antigens listed by the surgeon, and the listing center with the date of listing. For the deceased donors, the data include antigens, age/weight, cause of death, Organ Procurement Organization (OPO), and other major variables that are reported when then the kidney offer is made to the transplant center for the patient. These data are therefore sufficient to assess measures of kidney graft failure such as the KDPI, the patients’ expected post-transplant survival, match-specific quality, and the decisions made by patients. In all, the data has records on about 40,000 deceased donors and 250,000 wait-listed patients.

Descriptive statistics from the data are consistent with the framework, and suggests that patients are likely waiting for a more preferable offer. The average number of accepted organ offers is only about 2%. This low acceptance rate results in about 18% of organs that are suitable for transplantation being discarded. This is despite the fact that the patient could not have been known to be biologically incompatible, and that patients known to be perfectly compatible are given the highest priority. The most commonly recorded refusal reason is that the donor’s age/quality is not considered acceptable. Similar considerations where organs are rejected in the hope that a better organ is offered in the future have been documented previously (Zhang, 2010).

A Dynamic Choice Framework
The decision to accept or reject an organ can be viewed in (a continuous time version of) the framework of a dynamic choice (Rust, 1987; Hotz and Miller, 1993). When offered an organ, the agent considers the benefits of transplantation with the offered organ and weighs them against the costs of waiting for the next offer before making another choice. When considering the option to wait and see, the agent does not know when another offer will be made or what type of organ will be offered. Typically, agents make judgments based on prior experience. In this market, we see the role of surgeons as advising patients about whether accepting an organ or waiting for another offer is in their best medical interest, and surgeons should be able to draw on their experience to advise patients
appropriately.\footnote{Computational models similar in spirit have been used by scientists in operations research to discuss deceased donor kidney allocations, but to our knowledge, a detailed micro-level model of decision-making has not been estimated with data on real choices (see Alagoz, Schaefer, and Roberts (2009) and Zenios (2004) for surveys). Estimating the parameters of the model using data from observed decisions allows for a quantitative analysis with a stronger empirical basis.}

For simplicity of exposition, we exposit a framework in which, at time $t$, agent $i$ is choosing between receiving the organ from donor $j$ and remaining on dialysis. This abstracts away from the possibility of receiving a live-donor transplant and of departures from the organ donor donor list. Although this proposal explains the simpler version, we plan to extend the framework to one in which patients may receive a live-donor transplant or depart due to exogenous reasons (e.g. death). These extensions add notational burden, without significant changes in the insights or basic mechanics.

At time $t$, let $d_i(t)$ be the flow (dis-)utility of dialysis for patient $i$, and let $\gamma_{ij}(t)$ be the flow payoff of having a functioning organ transplant from donor $j$. We assume that $d_i(t) = d(x_i, \beta_i, t)$ and $\gamma_{ij}(t) = \gamma(x_i, \beta_i, z_j, \eta_j, t)$, where $x_i$ are patient observed characteristics, $\beta_i$ are taste shifters, $z_j$ are donor observed characteristics, and $\eta_j$ is donor-level unobserved heterogeneity. We will choose these observables based on the medical literature. Elements involved in this trade-off are likely to depend on the individual surgeon and the patient’s biological characteristics. For example, the effects of dialysis or the life-expectancy for the organ will depend on the health status of the patient. In addition we will account for match-specific quality in terms of tissue-type matching as well as donor quality. As we discuss below, this heterogeneity will be important in determining the optimal design of the mechanism.

With a discount rate of $\rho$, the net present value of receiving a transplant from donor $j$ is:

$$\Gamma(x_i, z_j, \beta_i, \eta_j, t, \varepsilon) = \int_0^\infty \exp(-\rho \tau) \gamma_i(t + \tau) d\tau + \varepsilon_{ij},$$

where $\varepsilon_{ij}$ an patient-donor specific idiosyncratic value due to the variable health of the patient, and the specifics of the match. When making a decision on whether to accept an organ offer, the patient-surgeon pair consider the value of remaining on the list with this payoff. We assume that this agent is aware of her own characteristics and the time she has waited, $t$, but not the precise state of the list.\footnote{This is consistent with the information surgeons appear to have in this setting, particularly because HIPAA rules limit the information surgeons may have about other patients.} In this notation, the value of remaining on the list at time $t$ satisfies

$$\rho V_i(t) = d_i(t) + \dot{V}_i(t) + \lambda \int \pi_{ij}(t) \mathbb{E}_i \left[ \max \{0, \Gamma_{ij} - V_i(t)\} \right] dF(z, \eta),$$

\hfill (1)

, where $\lambda$ is the rate at which organs arrive, $F$ is the distribution of organ characteristics, and $\pi_{ij}(t)$ is the probability that $i$ receives an offer for organ $j$ at time $t$. $\pi_{ij}(t)$ depends on the decision rules used by patients who were offered the kidney before patient $i$. To capture a realistic notion of agent decisions in this context, we assume that the patients only condition their decision on their own state variables and an understanding of types of offers they receive.\footnote{This is akin to the concept of Oblivious Equilibrium proposed by Weintraub, Benkard and Van Roy (2008).} Therefore, this formulation captures the trade-off between accepting an offer and waiting for a future offer in terms of the frequency, waiting times, and the quality of the next offer.
Through $\pi_{ij}(t)$, this framework captures the dependence between the benefits and the organ offer system itself. An alternative allocation system affects this quantity by influencing the offer sequence for any donor and the decisions of the various agents on this list. As discussed below, we will solve for an equilibrium for particular mechanisms to predict the effects of a change on the transplantations that occur. The model can therefore be used to not only predict who would be allocated an organ, but to also predict a wide range of health outcomes that may be of particular importance to patients.

**Empirical Implementation**

Assuming that the flow utility dialysis is not affected by the organ offer system, normalizing $d_i(t)$ to zero is without loss of generality and does not affect the evaluation of any alternative mechanism. Intuitively, with this normalization, $\Gamma$ represents the discounted value of the transplant relative to remaining on dialysis.

Given this normalization, the first step in estimating the parameters of the model is based on analyzing the acceptance decisions. Specifically, the agent therefore chooses to accept an organ if $V_i(t) < \Gamma_{ij}(t)$. The first step is to flexibly estimate the probability that an organ offer is accepted, or the conditional-choice probability (CCP):

$$\Pr(V_i(t) < \Gamma_{ij}(t) | x_i, z_j, t).$$

Specifically, we have set up a Gibbs’ sampling method for estimating this probability using the form

$$V_i(t) - \Gamma_{ij}(t) = \chi(x_i, z_j, t)\beta_i + \eta_j + \varepsilon_{ij},$$

where $\chi$ is a flexibly chosen set of basis functions, $\eta_j \sim N(0, \sigma_\eta)$, $\beta_i \sim N(\bar{\beta}, \Sigma_\beta)$ and $\varepsilon_{ij} \sim N(0, 1)$. This formulation allows for significant patient- and donor-level heterogeneity.

The distribution of donor and patient unobserved heterogeneity is identified because we observe multiple decisions for each donor and each patient. Using this parametrization, the parameters $\bar{\beta}$, $\sigma_\eta$ and $\Sigma_\beta$ can be estimated.

We have also formulated a tractable simulation technique for recovering the primitive of interest, $\Gamma$, from these parameters. Solving the ODE in equation (1) (recall that $d_i = 0$), we have that

$$V_i(t) = \lambda \int_t^\infty \exp(-\rho(t - t)) \int \pi_{ij}(t) \mathbb{E}_x \left[ \max \{0, \Gamma_{ij} - V_i(t)\} \right] dF(z, \eta) + c$$

where $\psi(p) = \phi(\Phi^{-1}(p)) + \Phi^{-1}(p)p$, and $\phi$ and $\Phi$ are the PDF and CDF of the standard normal respectively. The second equality follows from Hotz-Miller inversion. The expression in equation (2) yields an expression for $\Gamma$ in terms of $V_i(t)$ as derived above and the estimated parameters.

The remaining challenge of approximating the integral above is solved by (i) simulating $\pi_{ij}(t)$ using the empirical sequence of donor arrivals ($\lambda$ and $F$) and (ii) using quadrature rules to approximate integration with respect to $\exp(-\rho(t - \tau))$. For alternative mechanisms that are not observed, this object needs to be solved for.\(^7\)

\(^7\)The notation abstracts away from the fact that the counterfactual involves solving for an equilibrium of an induced game. This is discussed further below.
There are two additional issues to account for in the model. First, a potential complication in choice environment is the possibility of obtaining a live donor. To accommodate this, estimates of the probability of receiving a live donor can be allowed to depend on patient characteristics and time on the waiting list. This approach is appropriate if the probability of receiving a live donor does not change with the allocation system. For example, the model captures a situation in which live donors are strictly preferable, but it may take time for a family member or friend to offer this option to the patient.

Second, it is possible that patients and surgeons are not perfectly rational. For instance, they may have biased beliefs about the probability of kidney offers. This may occur if surgeons are not attuned to the fine distinctions in the organ offer system and instead rely on the average offer rates for patients across broad categories, including age, blood-type, and sensitivity groups. It is straightforward to adapt the model above by altering $\pi$ to allow for such coarse beliefs. Another possibility is to allow for adaptive expectations based on prior year information, which is also straightforward.

**Comparison of Alternative Dynamic Allocation Systems**

A particularly interesting comparison is between a first-come-first-served system with a single queue and a multiple-queue system with choice over which queue a patient would like to join. The pre-2014 system is akin to a first-come-first-served queue. In the New York Donor Service Area, for example, the typical first offer was made to a patient that has waited for 4.5 years while the typical 100th offer is made to a patient that has waited for only 3.5 years. On the other hand, many public housing allocation systems use multiple queue mechanisms in which each queue restricts the set of possible housing options and offers are made based on priorities determined by arrival date.

An advantage of the first-come-first-served system is that it is intuitive and procedurally fair. However, agents in this system may have to wait a significant amount of time before they receive offers for desirable objects because the best objects are accepted by those on top of the list. Once patients have waited sufficiently long, they have reasons to become selective because they are likely to receive good offers. This selectivity can be a feature because agents at the top of the queue are willing to wait for offers for which they have an idiosyncratically high match-specific value. It therefore encourages efficiency in allocation.

A problem with this system in the organ allocation context is that marginal kidneys may have to be offered to many patients before someone ultimately accepts them. This adds to the lag time between organ extraction and transplantation, further deteriorating the quality of the kidney. Many of these kidneys are unlikely to be transplanted even though they were medically suitable when first extracted. Indeed, our data shows that almost one-fifth of kidneys extracted for transplantation are ultimately discarded.

A multiple queue system in which kidneys are partitioned based on quality, for example, can address the problems with the first-come-first-served system. In this system, agents choose which queue to sign-up for when they arrive. By doing so, they forgo offers in other queues. If the queue with the lowest quality kidneys is under-subscribed, a patient can be fairly certain that she can receive a transplant quickly. This may be valuable for many patients for whom waiting imposes serious health costs.

This advantage of the multiple queue system comes at the cost of reducing allocations based on idiosyncratic match quality. To see this, consider a system with a very fine partition of kidneys based on donor quality. Patients, even at the top of each queue, have
a low organ arrival rate and are therefore not particularly selective. This makes them willing to accept organs even if they have low idiosyncratic match values for them.

The empirical approach developed in this paper will help us determine whether and which partitions of kidneys into multiple queues are likely to be beneficial. We will approach this based on a data-driven as well as a practical perspective. Input from practitioners and results from the model will be combined to think about reasonable divisions of organ types.

It is important to note that conducting counterfactual exercises of this type is feasible and conceptually straightforward. This is because the nature of strategic interactions in a first-come-first-served system allows for an inductive approach for solving for the unique equilibrium. The agent with first position on the list receives an exogenous flow of kidneys that does not depend on the decision rules by the other agents. The next agent takes this as given to solve for her decision rule. Therefore, the equilibrium can be computed inductively. For the multiple queue version, one can solve the queue choice problem, taking the length and composition of each of the queues as given.

### Comparison of Existing and Prior Organ Allocation Systems

The trade-off between a first-come-first-served system and specific queues based on donor type is similar to the 2014 change in the kidney offer system (but with added queue choice). Prior to this change, patients were prioritized based on waiting-time within coarsely defined categories that depended on the donor. In the new system, the healthiest patients are prioritized for the best donors.

In contrast to a first-come-first-served system, a match-value-based offer system prioritizes patients based on the quality of the match. In principle, not only does this system provide the healthiest patients with the best offers, but it also presents those offers earlier than a first-come-first-served system would. This has the benefit of transplanting patients before they become sick. However, this comes at a large potential cost to relatively unhealthy patients.

A system that prioritizes clinically critical patients appears to save lives, but it is less clear whether the total number of life-years obtained is higher. It may have been preferable to transplant a patient that is very likely to be critical earlier rather than keeping him/her waiting. The liver allocation system prioritizes the most critical patients.

The available data allows us to compare these systems based on the pre-post change without having to simulate an equilibrium of the mechanism. As the data from future years become available, we will also be able to directly track patients from the time they are registered on the organ donor list to assess their acceptance behavior and to evaluate their progression through ESRD and ultimately to transplantation. We will also be able to track death and post-transplant graft survival outcomes. This will allow a quantitative evaluation of the equity and efficiency effects of the change in 2014. In particular, it will be possible to evaluate the extent to which acceptance behavior responds to the offer system.

### Transplant Center Incentives and the National Sharing of Organs

One important issue in transplantation is that surgeons and centers may be making decisions on behalf of patients, particularly because patients are likely to have relatively little knowledge. Historically, the kidney allocation system offered organs to patients in
the local area (usually defined by state lines) where they were extracted before offering them more widely, first to the region and then to the national waiting list. This structure changed in 2014 with the national sharing of organs.

This geographic stratification of organ offers presents a unique opportunity to assess the extent to which transplant center incentives play a role and the extent to which transplant center incentives may be different from a patient’s incentives. Some transplant centers are the sole kidney transplant center in their local geographic area (Donor Service Area, or DSAs), while others have as many as 16 transplant centers in their local area. A center with no other transplant centers in their local area can refuse organs for many of their patients while being fairly certain that the offer will trickle down to their patients who are lower on the list. Centers in DSAs with many others cannot reliably engage in this behavior. Anecdotal evidence suggests that this is an important difference.

On the one hand, skipping patients on the top of the list allows sole center DSAs the flexibility to allocate the organs to the patients who will benefit from them the most at that time. On the other hand, these centers may not be acting in the best interest of their patients. At the same time, too much competition can also be counter-productive: centers may be more willing to take risks because future offers may be relatively scarce.

It is possible to evaluate whether these incentives and a difference between patient incentives and transplant center incentives are at play by combining the dispersion in the relative concentration of transplant centers in DSAs and the wider sharing of organs following the change in 2014. Addressing this question is interesting from the perspective of incentives in health-care and for evaluating the effects of nationwide organ sharing.

Implications for Allocation of Other Resources

While the model and the exercises above were presented with the application to deceased donor kidney allocation in mind, the approach can be applied to study the allocation of other organs such as livers and lungs, as well as public housing, nursing homes, and wait lists of various types. The two most general contributions of the proposed project are (i) an empirical approach for analyzing decisions in a dynamic allocation mechanism, and (ii) a study of the empirical importance of heterogeneity vs vertical preferences in the design of dynamic mechanisms. The framework may have to be adapted for specific applications, but does provide a base that future research can appropriately extend.