What drives the geographical differences in deceased donor organ procurement in the United States?

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Abstract

The deceased-donor kidney allocation system suffers from a severe shortage of available organs. At the same time, there is significant variation in the deceased-donor kidney procurement rates across different geographies in the United States. A deceased-donor organ is procured if there is intent of transplanting it. The empirical analysis of the kidney procurement, donor and recipient data reveals that the intent increases significantly with organ quality, the median waiting time for a transplant, and the competition among transplant centers. A counterfactual study, motivated by a proposed policy change to the kidney allocation system, shows that broader sharing of the bottom 15% quality kidneys leads to stronger intent for and an increase in the procurement rates of those organs, thus increasing the supply. In particular, the regional sharing of those organs leads to 56 additional procured kidneys per year whereas the national sharing results in 124 additional deceased-donor kidneys per year.

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1 Introduction

There are currently over 94,000 End-Stage Renal Disease (ESRD) patients waiting for a transplant in the United States (US); and the list is growing steadily.[1] The first order issue in the (deceased-donor) organ transplant system is the supply shortage. This turns the allocation policy (where an available organ is given to the most appropriate recipient) essentially into a rationing rule and leads to a large number of deaths every year.[2] In other words, the organ allocation problem is really a *supply problem*. Consequently, any increase in the supply of organs will lead to a direct improvement in the well-being of ESRD patients.

Most of the existing work in the operations research literature has focused on the demand side of the deceased-donor allocation problem. Several researchers have made important contributions to the analysis and improvement of the organ allocation policy; see Alagoz et al. (2009) for an overview and the references therein. However, virtually the entire operations research literature takes the supply of deceased-donor organs as given and focus on improving their allocation to the patients.[3] In contrast, we focus on the supply side of the problem, which complements the existing literature.

Unfortunately, not every medically acceptable (deceased-donor) organ is procured and offered for transplant. This is rather surprising given the severe organ shortage. Understanding the subtleties of the organ allocation system sheds some light on the reasons for this. The United Network of Organ Sharing (UNOS) has managed the allocation of organs in the US since 1984. UNOS divided the country into 11 regions, which are further divided into 58 Donor Service Areas (DSA). Associated with each DSA is an Organ Procurement Organization (OPO), which administers the procurement of deceased-donor organs in its DSA. An OPO is a non-profit entity regulated by the government. Its responsibilities include arranging for recovery, testing, tissue typing of organs, and packaging and transporting them to transplant hospitals.

An OPO procures a deceased-donor organ in its DSA when there is intent. According to Department of Health and Human Services' Final Rule[4], there is intent unless one of the following occurs:

[1] See `http://optn.transplant.hrsa.gov/data`.
[2] During 2006-2011, more than 4500 patients died while waiting for a kidney each year.
[3] The medical literature focusing on increasing the supply of deceased-donor organs will be reviewed in Section 2.
[4] Department of Health and Human Services (ruling no: CMS-1543-R, December 21, 2006).

- The donor does not meet criteria for eligible donor.
- The organ has been ruled out by basic donor information or by laboratory data prior to the donor entering the operating room for excision of organs.
- The family does not agree to donate the organ.
- The search for a recipient for that organ has ended unsuccessfully prior to the donor's entrance into the operating room.

Therefore, restricting attention to those organs which are medically acceptable for transplant (and consented by the family), the intent is determined by the search prior to the donor's entrance in the operating room. In essence, an organ is procured if and only if there is intent. As will be discussed in Section 4, our dataset includes the information of whether or not an organ is procured. Thus, we observe in the data if there was intent for each medically eligible organ.

Our primary research objective is to understand what drives the geographical differences in organ procurement rates. This requires understanding how the intent changes across different DSAs. Although modeling the intent directly does not seem possible, modeling the process by which deceased-donor kidneys are allocated helps that effort. The current UNOS allocation policy has a geographically tiered structure. It offers an available organ first within the DSA. If no potential recipient accepts it, then it is offered to the patients in the region. If no patient within the region accepts it, then it is offered nationally. Therefore, given the limited time until the donor's entrance in the operating room, the intent is strongly correlated with the acceptance of the organ (by a recipient in the local DSA). In particular, both increase although the intent is a weaker requirement, as the organ quality improves. In what follows, we use the probability of acceptance of an organ as a proxy for intent and advance a simple model of a DSA to study the patients' accept/reject decisions for deceased-donor organ offers. This model helps glean insights on what drives the acceptance probability of an organ, and hence, the intent, and helps develop testable hypotheses.

The (deceased-donor) organs vary in their quality as captured by the Kidney Donor Profile Index (KDPI). This index converts a set of donor characteristics into a single number that captures the risk of graft failure after kidney transplant. The calculated score for each donor comes from "mathematical models based on a retrospective analysis of data collected by the Scientific Registry

of Transplant Recipients on donor and recipient characteristics over the past several years" (Hippen et al. 2011, p. 1285). The main purpose of KDPI is to help transplant professionals better evaluate the quality and appropriateness of deceased donor kidneys and also to assist potential candidates in making more informed decisions. There are 10 factors considered in calculating the KDPI. These factors are donor age, height, weight, ethnicity, history of hypertension, diabetes status, serum creatinine level, cause of death, Hepatitis C Virus status, and DCD (donation after circulatory death) status. In order to obtain the KDPI, one should first calculate the Kidney Donor Risk Index (KDRI) for a deceased donor. KDRI is an estimate of the relative risk of a graft failure after transplant of a particular donor compared to the median donor. This index and its mathematical model was first developed by Rao et al. (2009); see Con (2011) and Gui (2012) for further details. The KDPI metric is also intended to be used in the proposed new deceased-donor allocation policy; see http://optn.transplant.hrsa.gov/PublicComment/pubcommentPropSub_311.pdf.

It is also documented in the literature that there are significant differences in access to and waiting times for transplant across different DSAs (see, for example, Davis (2011), Ata et al. (2012), and Yeh et al. (2011)). Such disparity among different DSAs emerges because of UNOS' geographically-tiered allocation policy and differences in the supply/demand characteristics of different DSAs. To understand how the acceptance probability of a deceased-donor organ (and hence, the intent) changes with the organ quality and the congestion in a DSA (eg. the waiting time for a transplant), we develop a simple model of a DSA in Section 3. In our model, organs are of varying quality, and patients decide between accepting an organ offer or waiting for a better quality organ. This model of patient behavior leads to several useful results which help us formulate our hypothesis which are tested in Section 5.

To test our hypotheses, we model the decision to procure an organ from a donor using a binary decision model. The dependent variable is 1 if an organ is procured and is 0 otherwise. The conditional expectation of the dependent variable is written as a linear combination of regressors related to the donor and DSA characteristics. Using the maximum likelihood estimation, we compute the coefficient estimates and test our hypothesis based on these results.

We find that the organ quality and the waiting time in a DSA are the most important factors determining intent. Namely, the intent (and the procurement rate) increases as the quality improves. Moreover, the harvesting rate in a DSA also increases as the waiting time in that DSA increases.

We also observe that the competition among transplant centers can increase the procurement rates, in particular, of O, A and B blood-type kidneys.

Lastly, we undertake a counterfactual study that looks at the impact of sharing the lowest quality kidneys (bottom 15%) more broadly, e.g., regionally or nationally. This policy change is suggested as part of the proposal to substantially revise the kidney allocation policy.[5] The analysis of Section 6 shows that 56 additional organs will be procured per year under regional sharing of the bottom 15% of the organs. Similarly 124 additional organs will be procured per year under national sharing of the bottom 15% of the organs, increasing the supply of organs significantly.

The rest of the paper is structured as follows. Section 2 provides a literature review. Section 3 develops a simple model of a DSA, which helps formulate testable hypotheses. Section 4 describes the data. Section 5 introduces the empirical model and the estimation results. The counterfactual study is undertaken in Section 6. Section 7 concludes. Proofs and additional estimation results are provided in the appendix.

2 Background and Literature Review

U.S. Congress passed the National Organ Transplant Act (NOTA) in 1984 to address the deceased-donor organ shortage. Since this legislation, United Network of Organ Sharing (UNOS) has managed the allocation of deceased donor organs in the U.S. The current kidney allocation policy of UNOS is a point system that prioritizes the potential transplant candidates based on medical criteria and the waiting time; see OPTN (2011) for details. Su and Zenios (2004) notes that "The continued shortage of organs and the associated explosion in waiting times has contributed to a convergence of this point system to a system that resembles first-come-first-served (FCFS)."

As mentioned earlier, this point system is crucially embedded in the geographically-tiered structure: A deceased-donor kidney is first offered to the patients based in the same DSA. If no patient within the DSA accepts the offer, then it is offered to the patients in the same region. Finally, if no patient in the region accepts the offer, then the kidney is offered nationally. This geographically tiered structure of the policy makes it difficult for organs to be shared across different DSAs. Under the current policy, the vast majority (more than 70%, see Davis (2011)) of deceased donor kidneys are transplanted locally. Therefore, the differences in supply and demand characteristics of different

[5] See `http://communication.unos.org/wp-content/uploads/2012/09/KTC_Allocation_System_Part_2.mp4`.

DSAs lead to a significant disparity in waiting times and access to transplant across different DSAs. Davis (2011) notes that "The overall median waiting time to receive kidney transplantation during 2000-2009 varies from 0.93 years to 4.14 years depending on a patient's local area of listing." This discrepancy is even more pronounced for patients with blood types B and O.

The demand side (i.e., the allocation of deceased organs) of the organ transplantation has received significant attention in the operations research literature. To design optimal allocation policies, researchers seek to match patients and organs to maximize social welfare, see Righter (1989), David (1995), David and Yechiali (1990), and David and Yechiali (1995). Zenios et al. (2000) explores the efficiency-equity trade-off and proposes a dynamic index policy for deceased-donor kidney allocation. Akan et al. (2012) explores the trade-off between medical urgency and efficiency in the liver allocation system.

Su and Zenios (2004, 2005, 2006) study the impact of patient choice on the kidney allocation system. Bertsimas et al. (2011) designs a scalable, data-driven allocation policy which incorporates fairness constraints. CONSAD (1995), Pritsker et al. (1995), Zenios et al. (1999), Taranto et al. (2000), Kreke et al. (2002), Roberts et al. (2002), and Shechter et al. (2005) use simulation models to study the impact of possible changes to the organ allocation policy.

Davis (2011) proposes probabilistic sharing of available kidneys in neighboring DSAs to address the geographic inequities. Ata et al. (2012) proposes an operational solution using jets to multiple-list patients to ameliorate the geographic inequity. Their proposal is an incremental solution within the existing system and does not require a policy change.

Several researchers consider an individual patient's problem of accepting/rejecting an organ offer while waiting for a transplant; see for example, David and Yechiali (1990), Ahn and Hornberger (1996), Hornberger and Ahn (1997), Alagoz et al. (2004, 2007a,b), Sandikci et al. (2008), and Sandikci et al. (2011).

Virtually the entire operations research literature takes the supply of organs as given and focuses on the allocation problem. An exception to this is the work on paired kidney exchange, see for example Roth et al. (2005, 2007) and Zenios (2002); also see Ashlagi and Roth (2011). This stream of literature aims at maximizing the use of living donors by resolving various matching difficulties between recipient-donor pairs, which may lead to an increase in the supply of living donors. In contrast, we focus on understanding ways of increasing the supply of deceased-donor organs.

Recent strategies to increase the supply of organs in practice include the use of expanded criteria donor (ECD) kidneys[6] and donation after cardiac death (DCD) kidneys; see for example Metzger et al. (2003) and O'Connor and Delmonico (2005). Medical research shows that short-term (Stratta et al. (2004)) and the intermediate-term (Stratta et al. (2006)) outcomes of transplants using ECD organs are comparable to those using standard criteria organs. Our work complements these efforts and helps understand what drives the procurement rate of organs. Thus, it can help increase the supply of deceased-donor organs further.

3 A Simple Model of Organ Acceptance

This section develops an overloaded fluid model of a DSA and considers patients' accept/reject decisions for deceased-donor organ offers. The model helps glean insights on what drives the acceptance probability of an organ, and hence, the OPO's intent. We formalize the findings of the model as hypotheses and test them in Section 5. As mentioned earlier, when a kidney becomes available, it is procured if the OPO expresses intent. This signal of intent is not a guarantee that the organ will ultimately be transplanted if procured. Although the OPO's intent is not captured directly in our model, the intent is the result of the OPO's belief that at least one patient in the DSA may accept the organ. The model derives the equilibrium quality threshold of patients accepting organ offers in a DSA which can serve as a proxy for the OPO's intent.

To be specific, we consider a DSA in isolation and develop a stylized game theoretic model which incorporates: *i*) the organs offered by the OPO are of varying quality, and thus, correspond to different post-transplant life years; and *ii*) patients can turn down organ offers with no penalty.

We assume that time-to-death has an exponential distribution with rate γ so that $1/\gamma$ is the life expectancy on dialysis. The expected post-transplant life years associated with an organ takes a value in the range $[\underline{L}, \bar{L}]$, where $\underline{L} > 1/\gamma$ which means patients prefer receiving a transplant to staying on dialysis. The post-transplant life expectancy L associated with an organ can be thought of as the organ's quality as there is a strong correlation between the two. Let λ and $G(y)$ denote the patient arrival rate and the quantity (measure) of organs whose life expectancy is less than or equal to y years, respectively. We assume that G is continuously differentiable on $[\underline{L}, \bar{L})$ but has a

[6]These kidneys are from donors older than sixty, or between the ages of 50-59 with at least two of the following comorbidities: hypertension history, serum creatinine > 1.5 mg/dl or cause of death from cerebrovascular accident.

jump at $\bar{L}$, i.e.

$$\Delta G(\bar{L}) = G(\bar{L}) - G(\bar{L}-) > 0, \tag{1}$$

which corresponds to assuming that the number of highest quality organs is not zero. In our model, these organs are always transplanted, as will be seen below. Morever, the high-quality organs are (almost) always transplanted in practice. Therefore, $\Delta G(\bar{L})$ can be viewed as the arrival rate of organs with sufficiently high KDPI so that they are always transplanted.

We assume that G, λ, and γ are common knowledge among patients. Each patient chooses a threshold life-expectancy for organs acceptable to him as a function of how long he has been waiting. That is, the patient is willing to accept any organ whose life expectancy is above a threshold, but not otherwise. We assume a stationary (overloaded) fluid model of the system, i.e. the model parameters are not time varying; and we are interested in the steady-state equilibrium behavior of the system. Namely, the transplant waiting list will be stationary in steady-state. Let τ denote the longest waiting time in that stationary system which is determined endogenously. Then the strategy of a patient is denoted by a function $l : [0, \tau] \to [\underline{L}, \bar{L}]$, where $l(t)$ denotes the life-years threshold associated with the lowest quality organ a patient, who has waited for t time units, is willing to accept. We restrict attention to (pure strategy) symmetric equilibria, where each patient chooses the same $l(\cdot)$. Also, without loss of generality[7] we restrict attention to nondecreasing $l(\cdot)$ functions. That is, patients become more selective as they wait longer because they are closer to the top of the queue. Moreover, it is straightforward to argue that[8] $l(\tau) = \bar{L}$.

Let $\{Q(t) : t \in [0, \tau]\}$ denote the stationary queue length profile. That is, $Q(t)$ denotes the intensity of patients who waited for t time units in the system. The following flow-balance equations

[7]Given a general function $f(\cdot)$ as a patient's strategy, it can be replaced by the largest nondecreasing function $\hat{f}$ such that $\hat{f} \leq f$ without changing the outcomes because organs are allocated on a FCFS basis and the system is overloaded. Recall that patients are assumed homogeneous, and they are differentiated only through their waiting time.

[8]If $l(\tau) < \bar{L}$, then a patient who waited for τ time units can deviate and wait for $\epsilon > 0$ time units more (resulting in a total wait of $\tau + \epsilon$) and can receive an organ which offers $\bar{L}$ life years. This results in a strict improvement in the patient's utility provided $\epsilon > 0$ is sufficiently small, but contradicts that τ is the longest wait in the system. Therefore, $l(\tau) = \bar{L}$.

characterize the stationary queue length profile:

$$Q(0) = \lambda, \tag{2}$$

$$Q'(t) = -\gamma Q(t) - G'(l(t))\, l'(t), \quad 0 < t < \tau, \tag{3}$$

$$Q(\tau) = \Delta G(\bar{L}), \tag{4}$$

where the last equation follows since $l(\tau) = \bar{L}$ and that, the intensity of patients who have waited for τ time units, i.e. $Q(\tau)$, must equal the intensity of organs of $\bar{L}$ life years, i.e. $\Delta G(\bar{L})$.

The following proposition characterizes the (pure strategy) symmetric Nash equilibrium for patients' accept/reject decisions and the resulting queue length profile.

Proposition 1 *The patients' equilibrium decisions are characterized by the threshold function* $l(\cdot)$ *given by*

$$l(t) = \max\left\{\underline{L}, \frac{1}{\gamma} + (\bar{L} - \frac{1}{\gamma})e^{-\gamma(\tau - t)}\right\},\ t \in [0, \tau], \tag{5}$$

where τ *is the unique solution of the following equation:*

$$e^{\gamma\tau} \int_{l(0)}^{\bar{L}} (u - \frac{1}{\gamma}) dG(u) = \lambda(\bar{L} - \frac{1}{\gamma}). \tag{6}$$

Moreover, the stationary queue-length profile is characterized by

$$Q(t) = e^{-\gamma t}\left[\lambda - e^{\gamma\tau} \int_{l(0)}^{l(t)} \frac{u - 1/\gamma}{\bar{L} - 1/\gamma}\, dG(u)\right] \quad \textit{for } t < \tau. \tag{7}$$

The $l(t)$ curve is the equilibrium solution of all the patients in the OPO, defining their willingness to accept an organ of a specific quality at a particular time since they listed as a transplant patient. The interpretation of $l(t)$ is that it reflects the OPO's intent. The OPO knows the population and profile of patients who are listed at transplant centers in the DSA and thus, the patient's acceptance threshold acts as a surrogate for the OPO's statement of intent, as discussed earlier.

The following corollary is immediate from equations (5)-(6) of Proposition 1.

Corollary 1 *As* λ *increases,* τ *increases strictly, i.e. patients wait longer. Moreover, as* λ *increases* $l(t)$ *decreases strictly (unless it equals* $\underline{L}$*) for all* $t < \tau$*. That is, the patients waiting for a transplant are willing to accept lower quality organs as the DSA gets more congested.*

Therefore, as the DSA gets more congested, i.e. as λ increases, the waiting time increases, and the patients become less selective in the sense that they are willing to accept lower quality organs. This, in turn, increases the acceptance probability of organs, and hence, the intent. We also see from Proposition 1 that organs with life expectancy $l(0)$ or higher are accepted (and transplanted), whereas those with life expectancy lower than $l(0)$ are rejected. Therefore, we arrive at the intuitive conclusion that the intent is stronger for higher quality organs. We formalize these insights into testable hypotheses.

Hypothesis 1 *As the organ quality increases, the OPO's intent increases.*

This hypothesis is motivated by the non-decreasing nature of the threshold function $l(t)$. As the organ quality improves, more patients within the DSA will be willing to accept the organ.

Hypothesis 2 *As the waiting time in a DSA increases, the OPO's intent increases.*

This hypothesis suggests that as the waiting time across all patients in the DSA increases, the willingness of patients to accept an organ also increases. This hypothesis follows from Corollary 1 and reflects the patients' increased willingness to accept a potentially lower quality organ as the waiting time in the DSA increases.

Hypothesis 3 *As the competition within a DSA increases, the OPO's intent increases.*

This hypothesis is inspired by Paarsch et al. (2011) who examine the number of transplants conducted at a transplant center relative to the number of transplant centers in the DSA. Although Paarsch et al. (2011) specifically examines the transplant center market share, the degree of competition between transplant centers may induce a higher intent by the OPO.

Next we describe our data sources, the variables, the models, and test these hypotheses.

4 Data Description

4.1 Data Sources

The data used for this study comes from UNOS' Standard Transplant Analysis and Research (STAR) Files. Our data set contains information regarding i) all deceased kidney donors (i.e., donor

data) and *ii*) waiting list and transplants performed (i.e., recipient data) in the U.S. Our period of study is from January 1, 2000 through June 30, 2010. Overall, we have detailed information of 76,866 deceased donors and 111,579 actual or potential recipients. Table 1 shows some descriptive statistics of the relevant variables we used in our analysis. In Table 1, Y_i is the indicator variable showing if organ i is procured (i.e., dependent variable), $KDRI_i$ is the quality of organ i, $W_{j,t}$ is the median waiting time in DSA j in quarter t, $W_{j,k,t}$ is the median waiting time in DSA j for blood-type k in quarter t, $\lambda_{j,t}$ is the patient arrival rate in DSA j in quarter t, $\mu_{j,t}$ is the organ arrival rate in DSA j in quarter t, and N_j is the number of transplant centers in DSA j. The term $\frac{\lambda_{j,t}}{\mu_{j,t}} N_j^2$ captures the competition between transplant centers in a DSA and will be discussed further in Section 5. The donor data set contains detailed information regarding each deceased

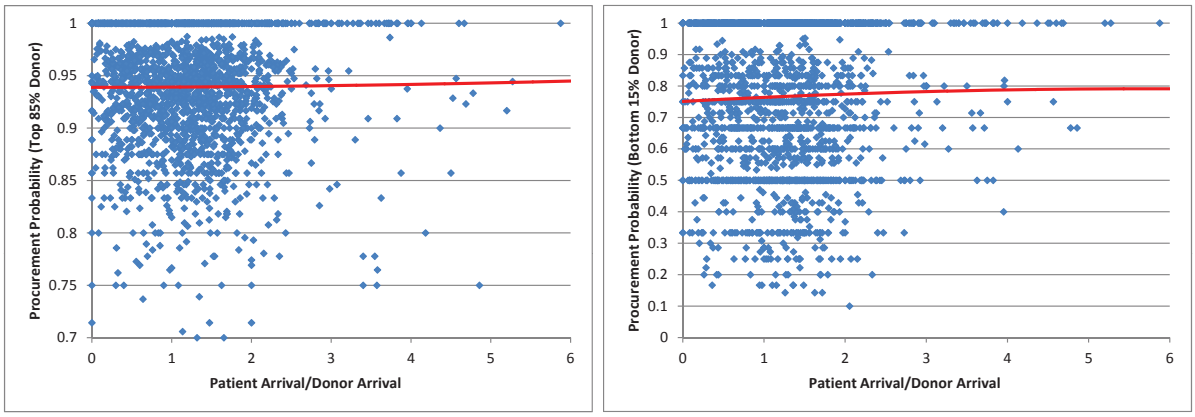
Variable	**N**	**Mean**	**Std. Dev.**	**Median**
Y_i	76,866	0.90	0.30	1.00
$KDRI_i$	76,399	1.33	0.51	1.21
$W_{j,t}$	75,152	1.67	0.73	1.55
$\frac{\lambda_{j,t}}{\mu_{j,t}} N_j^2$	76,326	74.45	98.45	32.00
$W_{j,A,t}$	28,760	1.39	0.62	1.26
$W_{j,O,t}$	36,146	1.87	0.71	1.74
$W_{j,AB,t}$	1,569	1.22	0.79	1.05
$W_{j,B,t}$	8,677	1.94	0.78	1.84

Table 1: Descriptive Statistics of dependent and independent variables.

kidney donor such as a disposition code, the date of recovery, demographic information of the donor, and several health indicators. The disposition code variable is especially important for our purposes. It helps identify the intent. There are 6 disposition codes for each kidney: 1) organ consent not requested, 2) organ consent requested but not obtained, 3) organ consented but not recovered, 4) organ recovered for reason other than transplant, 5) organ recovered for transplant but not transplanted, and 6) organ transplanted. In summary, codes 4, 5, and 6 indicate that the kidney was recovered from the donor (i.e., procured).

In addition, there are two deceased donor classifications to specify the quality of a donated kidney: *i*) expanded criteria donors (ECD) and *ii*) standard criteria donors (SCD). SCD donors often have fewer risks associated with graft failure whereas ECD organs typically relate to higher risks of earlier graft loss (Metzger et al. 2003, Pascual et al. 2008). All candidates are eligible to receive SCD kidneys; however, ECD kidneys are allocated only to candidates who have indicated

a willingness to accept them.[9]



(a) Top 85% Quality Kidneys.

(b) Bottom 15% Quality Kidneys.

Figure 1: Fraction of kidneys procured as a function of donor per patient arrival rate.

The recipient data contains information regarding transplants (living and deceased donor types) and listings on the kidney, pancreas, and kidney/pancreas waitlists prior to September 3, 2010. Detailed demographic and health information of the recipient and the donor (if there is any) is available in this data set. An entry consists of a listing, a transplant, or both (if the listing resulted in a transplant).

4.2 Data Trends

This section presents summary statistics of the data to highlight certain aspects of and trends in the kidney allocation system. Figure 1 shows that the organ procurement rate increases with the congestion in the DSA, which is captured by the ratio of the patient and organ arrival rates. This relationship is more pronounced for the bottom 15% quality kidneys[10] (Figure 1(b)). As illustrated by Figure 2, while the number of deceased donors has remained relatively flat over the span of time our data covers, there has been a marked increase in the additions to the waiting list. This indicates not only that there is a substantial gap between the supply and demand for kidneys but that the gap is rapidly expanding. Figure 3(a) shows the percentage procured and not procured donors by SCD-ECD breakdown and the proportion of ECD kidneys procured has grown. However, Figure 3(b) appears to show that there are similar numbers of not procured donors in

[9]These patients are not required to accept ECD kidney offers, and can turn them down with no penalty.

[10]More specifically, the procurement rate is concave increasing with the congestion. Please see Section 6 for our definition of bottom 15% donors in terms of kidney quality.

each category (in absolute terms), so it is not simply that only inferior organs will be added to the supply. Collectively, over the 2000-2009 period, these two non-procured elements appear to be a growing new source of kidneys for transplantation.

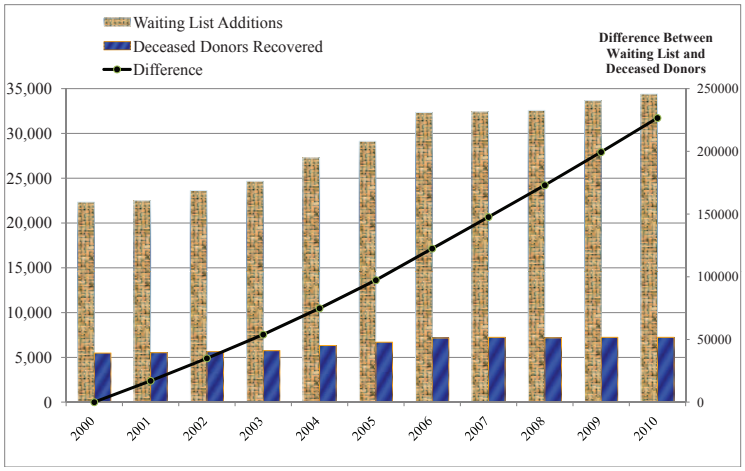
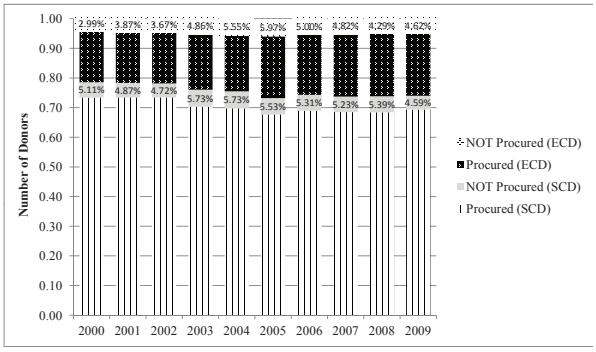
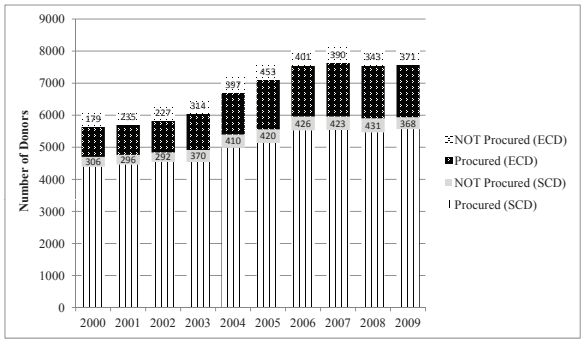


Figure 2: Demand outstripping supply.



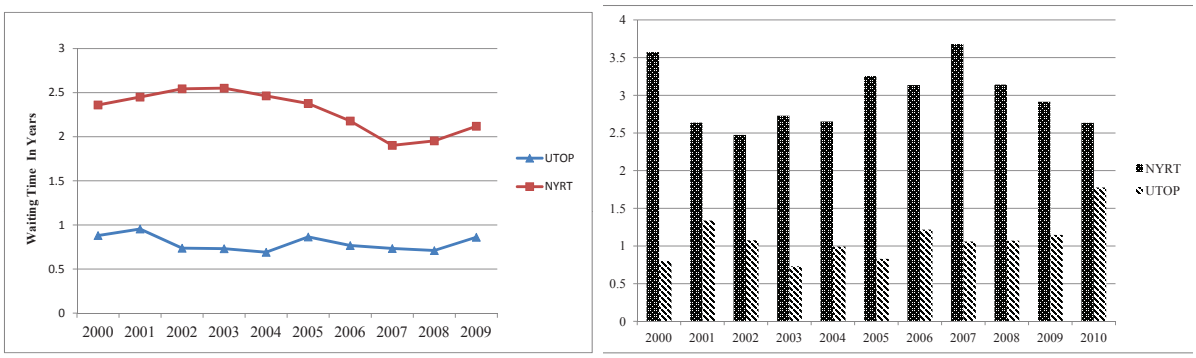
(a) Numbers of donors by SCD-ECD breakdown (percentage).



(b) Numbers of donors by SCD-ECD breakdown (absolute numbers).

Figure 3: Kidneys procured and not procured from 2000 to 2009.

Figure 4 illustrates the geographical heterogeneity. In Figure 4(a) we see there is a large and consistent difference in median waiting time for recipients in geographically different DSAs. The median waiting time in NYRT (New York Organ Donor Network) consistently exceeds two years while it is less than a year in UTOP (Intermountain Donor Services), a DSA based in Utah. Moreover, we see that the quality of procured organs in these areas can differ markedly. Figure 4(b) shows the lowest quality organ procured in NYRT is consistently lower quality than the highest



(a) Median waiting time.

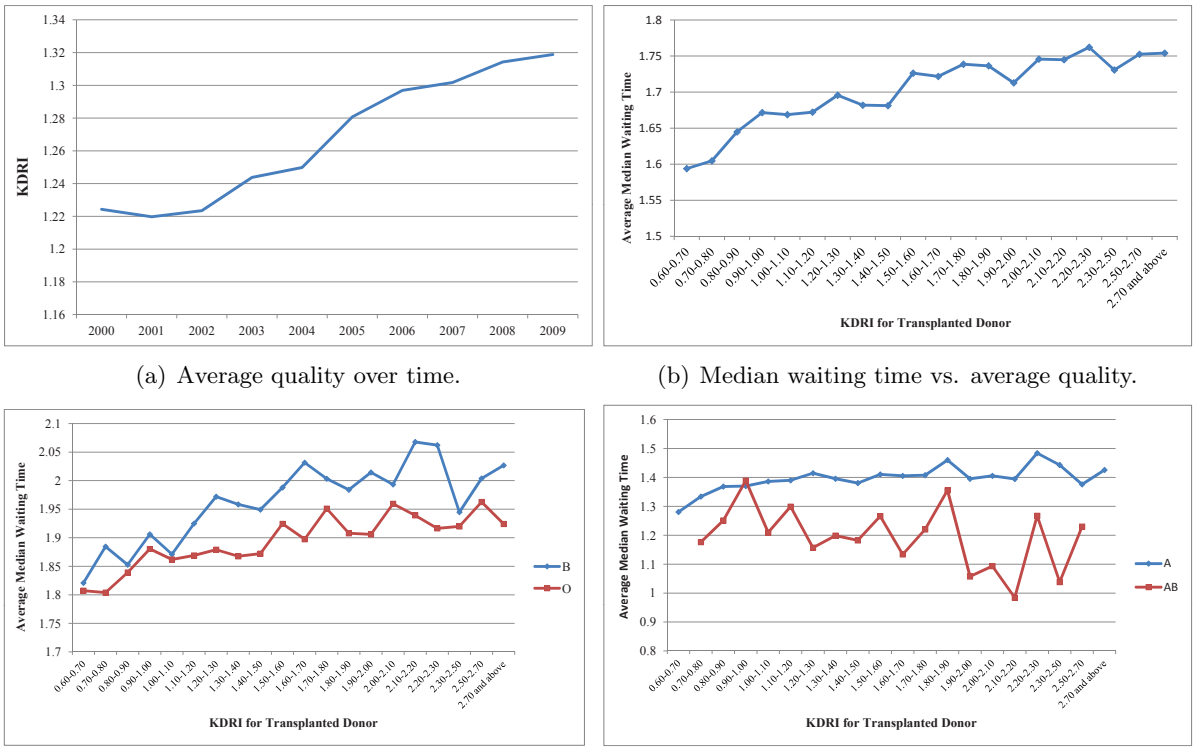
(b) Highest quality not procured in UTOP and lowest quality procured in NYRT.

Figure 4: Median waiting times and organ quality in two OPOs from 2000 to 2009.

quality organ *not* procured in UTOP, in every year of our study.[11] This simple comparison shows that the signal of intent was not being given in UTOP for organs for which intent would have been easily given in NYRT. That is, there could potentially be numerous organs currently not being procured in UTOP which would have been in NYRT. Similar matching stories could appear among all 58 OPOs nationally.

Finally, we observe in Figure 5(a) that the average quality of transplanted kidneys has gradually worsened over time, perhaps reflecting both the increasing willingness of recipients to compromise on quality as waiting times elongate, as well as the increased usage of ECD kidneys in recent years. Figure 5(b) shows a negative correlation between the median waiting time and the mean quality of transplanted organs. That is, we observe over time that as the median waiting time for recipients increases, they seem to be willing to accept lower quality organs. When this is broken down by blood-type, we see that this is most prominently true for blood-types B and O (Figure 5(c)) and type A to a lesser extent (Figure 5(d)); this pattern appears not to be true for type AB (Figure 5(d)), although we also notice that type AB has a consistently lower median waiting time than the other blood-types.

[11] The KDRI quality metric we use, described in Section 5, is reverse-scaled: a high number indicates lower quality than a low number.



(a) Average quality over time.

(b) Median waiting time vs. average quality.

(c) Waiting Time vs Quality for blood-types B and O.

(d) Waiting Time vs Quality for blood-types A and AB.

Figure 5: Waiting time and quality relationships.

5 Empirical Model and Variables

5.1 Variables Affecting the Acceptance Probability of a Kidney

Waiting Time In a DSA. The waiting time is one of the primary determinants of patients' priority and decisions in the kidney allocation system. We calculated the *median* waiting times of all patients waiting for a kidney at each DSA during each quarter (between the first quarter of 2000 and the second quarter of 2010) by blood type ($W_{j,k,t}$); see Appendix B for the details of the calculation of the waiting times and all other relevant variables. As mentioned in Section 1, there are significant variations in the waiting times across different DSAs and different blood types. This difference is especially significant when one compares blood types O and B to A and AB.

Kidney Donor Risk Index. To measure the quality of offered kidneys, we used an index called Kidney Donor Profile Index (KDPI). A brief discussion of how this index was constructed is provided in Section 1. A more detailed explanation is available in Appendix B including the coefficient estimates obtained from the graft survival model of Rao et al. (2009) (Appendix C, Table 6).

KDPI is derived from Kidney Donor Risk Index (KDRI) which is an estimate of the relative risk of a graft failure after transplant of a particular donor compared to the median donor. KDRI has several advantages over the currently used deceased donor classifications (i.e., ECD and SCD). First, KDRI is based on 10 different donor factors, whereas ECD/SCD classification is based on only 4 factors. Second, it is a continuous number which enables more detailed differentiation of donor kidney quality compared to the dichotomous ECD and SCD classification. Third, the proposed policy to substantially revise the kidney allocation uses KDRI as a measure of kidney quality.

Competition Among Transplant Centers. We also explored the effect of competition among transplant centers within a DSA. Different OPOs have varying numbers of transplant centers within their service boundaries (DSAs); see Figure 6. There are 273 transplant centers that belong to one of the 58 DSAs. Under current policy, the vast majority of deceased donor kidneys (more than 70%, see Davis (2011)) are transplanted locally. Hence, we conjecture that the competition may play a role in the procurement decisions and should be controlled for in the regression analyses below. We calculated the patient arrival rate ($\lambda_{j,t}$) and donor arrival rate ($\mu_{j,t}$) to each DSA j during each quarter t. Also, let N_j represent the number of transplant centers in each DSA j. We computed $\frac{\lambda_{j,t}}{\mu_{j,t}} N_j^2$ to account for competition among transplant centers. This competition variable considers all transplant centers that potentially compete with each other for a deceased-donor organ. The ratio of total number of patients divided by total number of donors can be used as a measure for market congestion. We combined this ratio with the square of the total number transplant centers to give more weight to DSAs with greater numbers of transplant centers. The parameter N_j is squared to capture the network effect of competition between the transplant centers in DSA j which is strongly nonlinear in the number of centers.

5.2 Estimating the Probability of Kidney Procurement from a Deceased Donor

In this subsection, we model the probability of procuring a kidney as a proxy for our latent variable (*intent*, as described in Section 1). The outcome of this decision is readily available in our donor data set. Let Y_i represent the observable binary decision to procure a kidney from the deceased donor i: $Y_i = 1$ if the kidney was procured and $Y_i = 0$ otherwise. We assume that the distribution of Y_i depends on a vector of covariates X_i. The response probability is given by

$$\Pr(Y_i = 1|X_i) = F(X_i^T \boldsymbol{\beta})$$

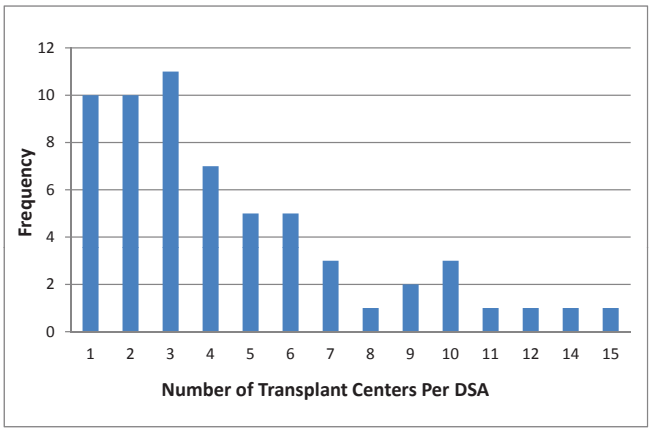


Figure 6: Histogram of the Number of Transplant Centers at each DSA.

where $F(\cdot)$ is a cumulative distribution function and $\boldsymbol{\beta}$ is a $K \times 1$ column vector of the coefficient of the covariates. We further assume that the function F takes the form of the standard logistic distribution. Then,

$$\Pr(Y_i = 1|X_i) = \frac{\exp\left(X_i^T\boldsymbol{\beta}\right)}{1+\exp\left(X_i^T\boldsymbol{\beta}\right)},$$

where $X_i^T\boldsymbol{\beta} = \beta_0 + \sum_{j=1}^{J}\beta_j x_{ij}$.

A Model for the Intent of an OPO. We specify the intent of an OPO as follows:

$$\Pr(Y_i = 1|X_i) = F(\beta_0 + \beta_{KDRI} \times KDRI_i + \beta_W \times W_{j,k,t} + \beta_{Comp} \times \frac{\lambda_{j,t}}{\mu_{j,t}} N_j^2).$$

In this model, we include the kidney quality index ($KDRI_i$) of deceased donor i. The next explanatory variable is the median waiting time ($W_{j,k,t}$) of all patients with blood type k ($k \in \{A, B, AB, O\}$) waiting for a kidney at DSA j ($j \in \{1, \ldots, 58\}$) during quarter t ($t \in \{1 \ldots 42\}$). The last regressor is the competition variable ($\frac{\lambda_{j,t}}{\mu_{j,t}} N_j^2$) as defined above. The results of this model are displayed in Table 2. As can be seen, the kidney quality index, the median waiting time, and the competition variables are significant at 0.01% level. Hence, we find evidence that as the organ quality increases, the probability of recovering a kidney increases because lower KDRI values are associated with increased donor quality. Additionally, the results indicate that as the median waiting time increases, the probability of recovering a kidney from a donor increases as well. Lastly, our data does support the effect of competition on the organ procurement decisions. Particularly,

this result demonstrates that the higher the competition among transplant centers, the higher the intent of an OPO. Therefore, we find support for Hypotheses 1, 2, and 3.

The waiting time of a typical patient is highly dependent on his/her blood type. Our aggregate level of analysis does not reveal much information specific to different blood types. Next, we partition our data by the blood type of a donor and investigate how the impact of each variable varies across different blood types.

The main insight from the results of the intent model for different blood types (see, Table 2) is that donor quality matters for all blood types but waiting time matters only for blood types A, O, and AB. The median waiting times are the highest for patients with blood type B followed by type O and then type A. One would anticipate that the higher the median waiting time for a kidney at a DSA, the higher is the patients' willingness to accept an offer. This in turn may lead to more sensitivity towards the changes of waiting time. Our results support this for blood types A, O, and AB. However, we fail to show a significant relationship between the median waiting time and probability of procurement for blood type B. It may be plausible to think that patients with blood type B have become insensitive to the changes in the waiting time due to their extended duration on the list.

Variable	**Intent Model Parameter Estimate**	**Intent Model Parameter Estimate** (Blood Type=A)	**Intent Model Parameter Estimate** (Blood Type=O)	**Intent Model Parameter Estimate** (Blood Type=AB)	**Intent Model Parameter Estimate** (Blood Type=B)
β_0	4.8008***	4.8917***	4.6753***	4.7068***	4.7089***
	(0.0498)	(0.0820)	(0.0747)	(0.3809)	(0.1487)
β_{KDRI}	-1.8176***	-1.8560***	-1.8065***	-1.9443***	-1.7202***
	(0.0224)	(0.0372)	(0.0317)	(0.1877)	(0.0646)
β_W	0.0903***	0.1105**	0.1204***	0.4915**	0.0593
	(0.0187)	(0.0375)	(0.0274)	(0.1902)	(0.0508)
β_{Comp}	0.0007***	0.0005*	0.0007**	0.0020^{+}	0.0010*
	(0.0001)	(0.0002)	(0.0002)	(0.0012)	(0.0004)
Num. of Obs.	74,951	28,683	36,046	1,566	8,656

Note: Standard errors are in parenthesis.
*** $p < 0.0001$, ** $p < 0.01$, * $p < 0.05$, $^{+}$ $p < 0.10$.

Table 2: Summary of Estimation Models (Intent Model)

A wide spectrum of quality exists among deceased donor organs. We argue that the decisions for lower quality organs may be different from the decisions when all quality levels are considered. Hence, to test this, we stratified the data into two groups: *i*) donors with KDRI less than 1.85 (i.e.,

top 85% quality[12]) and *ii*) donors with KDRI higher than 1.85 (i.e., lowest 15% quality). We again estimated the coefficients using our intent model specification as described above and compared the results of these mutually exclusive groups.

Variable	**Intent Model Parameter Estimate** KDRI >1.85	**Intent Model Parameter Estimate** KDRI <1.85
β_0	4.1900***	5.5008***
	(0.1379)	(0.0838)
β_{KDRI}	-1.5911***	-2.3116***
	(0.0552)	(0.0543)
β_W	0.1545***	0.0598**
	(0.0315)	(0.0230)
β_{Comp}	0.0009***	0.0004**
	(0.0002)	(0.0002)
Number of observations	11,015	63,936

Note: Standard errors are in parenthesis.
*** $p < 0.0001$, ** $p < 0.01$, * $p < 0.05$.

Table 3: Summary of Estimation Models (Intent Model with Bottom 15% and Top 85% Quality Donors.)

Based on the estimated coefficients available in Table 3, for a typical lower quality donor (i.e., $KDRI_i > 1.85$) who has the average values of all three variables (i.e., $KDRI_i = 2.28$, $W_{j,k,t} = 1.72$, and $\frac{\lambda_{j,t}}{\mu_{j,t}} N_j^2 = 81.25$): *i*) a 10% increase in the donor quality (10% reduction in the $KDRI_i$) would result in a 9.63% increase in the probability of recovering his/her kidney; *ii*) a 10% increase in the waiting time would result in a 0.76% increase in the probability of recovering his/her kidney; and *iii*) a 10% increase in the competition variable would result in a 0.21% increase in the probability of recovering his/her kidney. Similarly, for a typical higher quality donor (i.e., $KDRI_i < 1.85$) who has the average values of all three variables (i.e., $KDRI_i = 1.17$, $W_{j,k,t} = 1.67$, and $\frac{\lambda_{j,t}}{\mu_{j,t}} N_j^2 = 73.28$): *i*) a 10% increase in the donor quality (10% reduction in the $KDRI_i$) would result in a 1.22% increase in the probability of recovering his/her kidney; *ii*) a 10% increase in the waiting time would result in a 0.05% increase in the probability of recovering his/her kidney; and *iii*) a 10% increase in the competition variable would result in a 0.01% increase in the probability of recovering his/her

[12]The analysis of the Kidney Transplantation Committee shows that graft survival rate degrades significantly faster after this cut-off, and hence, 85% is a natural choice; see Figure 3 of the Proposal to Substantially Revise the National Kidney Allocation System Document, available at http://optn.transplant.hrsa.gov/PublicComment/pubcommentPropSub_311.pdf.

kidney. It is important to note that the intent for low quality organs is more sensitive to changes in waiting time than for high quality organs. Presumably, this has motivated the proposed policy change of the broader sharing of the lower quality organs. The impact of this proposed policy change is studied in the next section.

6 Counterfactual Analysis

The procurement rates of the deceased-donor kidneys exhibit significant variation across different DSAs. This is illustrated for the OPOs in New York versus in Utah in Figure 7, which provides histograms of the quality (KDRI) of procured kidneys by those OPOs. In particular, the OPO in Utah procures better quality organs than the OPO in New York. To be more specific, the lowest quality organ procured in Utah has KDRI of 2.4; and the organs of lower quality (i.e. higher KDRI) are not procured in Utah whereas such organs are procured in New York, as shown in Figure 7. Therefore, a natural conclusion is that if such organs were (made available) in New York, they could have been procured, increasing the organ supply. Although Figure 7 shows just

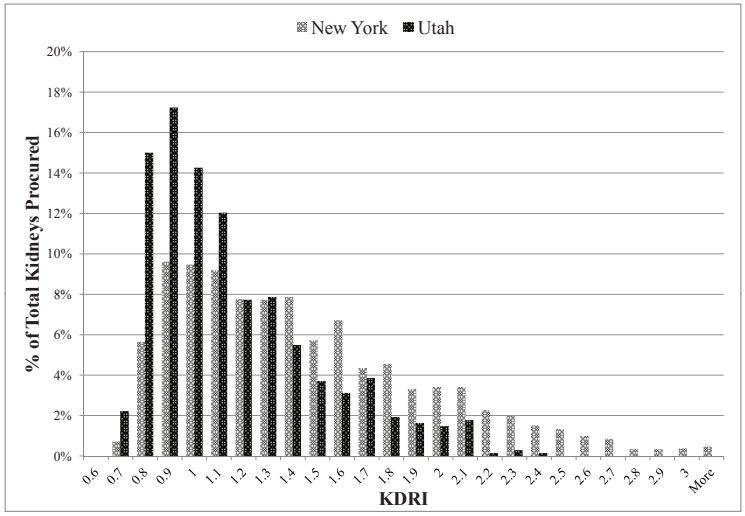


Figure 7: Histogram of Number of Kidneys Procured for Different KDRI.

one pair of OPOs, such disparities are widespread and hence, the opportunity to better utilize lower quality kidneys is likewise widespread in the deceased-donor kidney allocation system. As a matter of fact, as part of the proposal to substantially revise the kidney allocation policy, the Kidney Transplantation Committee is considering possible changes to the allocation policy for lower

quality kidneys. The proposal is to share those kidneys more broadly. That is, instead of following the current geographically-tiered protocol of sharing (i.e. a kidney is first offered in its DSA, then in its region, and then nationally), the proposal is to offer it directly in its region followed by the entire country. One can also consider offering the lower quality kidneys nationally without offering them regionally first.

The specific proposal of the Kidney Transplantation Committee is to share the bottom 15% quality of the organs more broadly. Table 4 displays different KDRI threshold values for each year. Whenever a donor has a KDRI higher than this threshold value,[13] the organ recovered from this donor belongs to the bottom 15%. We ran the logistic regression described in Section 5 with the same variables over the sample of the bottom 15% quality kidneys, separately for each blood type. Then using the estimated probability $\hat{Y}_i$ of procurement[14] for each kidney i in the data, $\sum_{i=1}^{n_k} \hat{Y}_i$ gives the total estimated number of kidneys procured, where n_k is the number of kidneys for blood type k.

The additional number of kidneys procured (the estimated number under the new regional sharing policy minus the actual number under the current policy) for each blood type is reported in the third column of Table 5; the results for an analogous study under national sharing are reported in the last column of Table 5. The additional number of kidneys procured vary by the blood type – highest for blood types O and A. In addition, the gain from this policy change is more conspicuous in more recent years. Moreover, the national sharing leads to significantly higher gains over regional sharing although both lead to significant increases in the supply of deceased-donor organs.

7 Discussion

We attempt to explain some of the heterogeneity in the kidney procurement rates across the different geographies in the United States. The organizations governing the procurement of kidneys are Organ Procurement Organizations. These enterprises are notified when a deceased donor becomes available whereupon they are asked to indicate whether the kidney should be excised. This indication is known as "intent." Each of the nation's 58 Donor Service Areas has a single OPO and their expression of intent varies considerably, dependent upon local circumstances.

[13] There are 11,247 such observations in our data set.

[14] In this calculation, we substituted the largest median waiting time across all DSAs (in each of the eleven UNOS regions during each quarter for each blood type) as the median waiting time.

Year	85 Percentile KDRI
2000	1.725
2001	1.735
2002	1.747
2003	1.798
2004	1.828
2005	1.901
2006	1.886
2007	1.903
2008	1.880
2009	1.888
2010	1.851

Table 4: 85th Percentile of KDRI Variable by each Year

		Regional Sharing	**National Sharing**
		Number of Additional Kidneys Procured Per Year	Number of Additional Kidneys Procured Per Year
2000-2010	A	12.36	29.31
	AB	0.32	1.30
	B	5.79	13.10
	O	29.28	63.03
	Total	**47.75**	**106.74**
2006-2010	A	20.44	47.96
	AB	0.36	1.29
	B	9.82	20.71
	O	25.33	54.18
	Total	**55.96**	**124.13**

Table 5: Bottom 15% Quality Donors Regional and National Sharing

A game theoretic model is formulated and analyzed in section 3. This model captures the dynamics of organs of differing quality arriving in a DSA and establishes the equilibrium strategy regarding the acceptance of organ offers of the homogenous patients in the DSA. This strategy manifests as a non-decreasing threshold function mapping from the patient's waiting time to their acceptable quality. If an arriving organ's quality surpasses this threshold, it will be accepted by the patient. This competitive model within a DSA inspires two hypotheses with a third drawn from the literature. These hypotheses concern how the quality of arriving organs, the waiting time within a DSA, and the degree of competition positively affects the OPO's intent.

Using UNOS' STAR data, we exercise a logistic regression. The dependent variable is the intent

exhibited by the OPO while the independent variables are the quality of the procured organ, the median waiting time in the DSA, and the degree of competition between the transplant centers in the DSA. The quality measure is KDRI proposed by Rao et al. (2009), encapsulating a plethora of donor characteristics. Estimating the logistic regression, we find that increasing quality, median DSA waiting time, and transplant center competition all increase the OPO's probability of intent, with significance at the 0.0001 level. Support for these regressors is preserved when considering individual blood types (albeit at weaker levels), with the exception that patients of blood type B appear to have become oblivious to waiting. This shows strong and robust support for the hypotheses. When we segment the data by quality, we find that longer median waiting times affect the intent more strongly for lower quality organs. This suggests that the longer the waiting time, the greater the likelihood intent will be given for lower quality organs.

Lastly we consider a counterfactual study to investigate the proposal to enhance the availability of procured kidneys. In essence, the proposal intends to make the lowest quality 15% of organs more widely available immediately, rather than follow the geographically cascading hierarchy of the current policies. Initially, we allow these lowest 15% of organs to be made available regionally (rather than just within the DSA) and we find this results in 48 additional kidney transplants per year. When these lowest 15% of organs are made available nationally, this number increases to 107 additional kidney transplants per year. The additional organs come from regions where the OPO would otherwise not have issued intent to procure the kidney. When the same analysis is conducted within the more recent years in the dataset, this effect is even more profound: regionally there will be 56 additional transplants per year and 124 additional transplants per year nationally. Given this greater number of transplants, this indicates the proposal may be an increasingly viable avenue for enhancing the supply of deceased donor kidneys.

This analysis has shown that higher organ quality, longer waiting times in a DSA, and greater transplant center competition all generate greater OPO intent. These characteristics differ markedly across the country. These disparities endow the system with an opportunity to procure more organs if some organs are shared more broadly immediately. Following such a policy nationally is expected to yield 124 additional kidney transplants per year, a number expected to increase as the difference between supply and demand for organs grows. This number reflects an increase of 0.9% of all procured and offered kidneys in 2009, the most recent year in our dataset, and 7.3% of the bottom

15% quality kidneys procured. Moreover, there are 14 of the 58 DSAs in the United States in 2009 with 124 or fewer kidneys available. Therefore, this increase of 124 kidneys reflects the addition of a small- to medium-sized DSA.

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Appendix A: Proofs

Proof of Proposition 1. It follows from (2)-(3) that

$$Q(t) = e^{-\gamma t}\left[\lambda - \int_0^t e^{\gamma s} G'(l(s))\, l'(s) ds\right], \quad t < \tau. \tag{8}$$

Then combining (4) and (8), we see that τ must satisfy

$$e^{\gamma \tau}\Delta G(\bar{L}) + \int_0^\tau e^{\gamma s} G'(l(s))\, l'(s) ds = \lambda. \tag{9}$$

At equilibrium a patient who has waited for t time units must be indifferent between accepting an organ of life years $l(t)$ and waiting. That is, we must have

$$l(t) = W_t + L_t \quad \text{for } t < \tau, \quad l(t) > \underline{L}, \tag{10}$$

where W_t denotes the expected residual waiting time conditional on having waited for t time units, and L_t denotes the expected post-transplant life expectancy associated with waiting (not including the waiting time on the transplant list) of a patient who has waited for t time units.

The following figure shows the various events (and their rates) that can happen to patients who have waited for t time units:

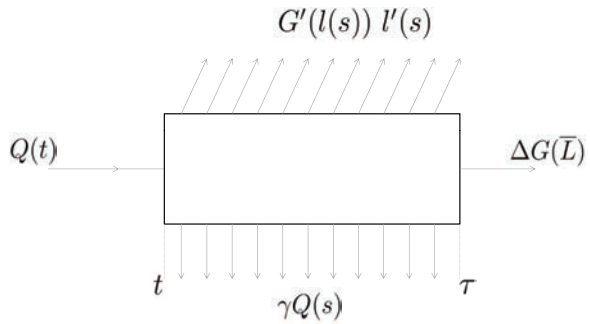

Figure 8: The portion of the transplant waiting list consisting of patients who have waited for t time units or more. Viewing this as a system, patients enter at the rate of $Q(t)$, and can leave the system at time $s \in [t, \tau)$ with rate $G'(l(s))\, l'(s)$ and at time τ with rate $\Delta G(\bar{L})$ by receiving a transplant. Patients can also leave the system by dying at rate $\gamma Q(s)$ (at time s).

Given the system portrayed in Figure 8, we write by Little's Law that

$$W_t = \frac{\int_t^\tau Q(s)ds}{Q(t)}. \tag{11}$$

To compute L_t, consider what happens to the intensity of fluid $Q(t)$ (of those who have been waiting for t time units) as shown in Figure 8, and interpret the fraction served at various times as the probability density (or mass at time τ) of getting transplanted after waiting for $s \geq t$ time units, denoted by $\phi(s)$. Note that

$$\phi(s) = \frac{G'(l(s))\ l'(s)}{Q(t)} \quad \text{for } t \leq s < \tau \quad \text{and } \phi(\tau) = \frac{\Delta G(\bar{L})}{Q(t)}. \tag{12}$$

Then, we write

$$L_t = \int_t^\tau \phi(s) l(s) ds + \phi(\tau)\bar{L}. \tag{13}$$

Substituting (12) into (13) yields

$$L_t = \int_t^\tau l(s)\, \frac{G'(l(s))\ l'(s)}{Q(t)}\, ds + \frac{\Delta G(\bar{L})}{Q(t)}\, \bar{L}.$$

Equivalently,

$$L_t = \frac{1}{Q(t)} \int_{l(t)}^{\bar{L}} u dG(u). \tag{14}$$

Substituting (11) and (14) into (10) gives

$$\int_t^\tau Q(s)ds + \int_{l(t)}^{\bar{L}} u dG(u) = Q(t) l(t) \quad \text{for } t < \tau,\ l(t) > \underline{L}. \tag{15}$$

In what follows, we will first ignore the restriction $l(t) > \underline{L}$ in (15) and solve for $f(\cdot)$ that solves (15). Then, we will observe that $f(\cdot)$ is strictly increasing. Therefore, truncating $f(\cdot)$ at $\underline{L}$ from below yields $l(\cdot)$. To this end, consider the equation

$$\int_t^\tau Q(s)ds + \int_{f(t)}^{\bar{L}} u dG(u) = Q(t) f(t) \quad \text{for } t < \tau.$$

Differentiating both sides with respect to t and substituting for $Q'(t)$ (cf. Equation (3)) gives

$$-1 = -\gamma f(t) + f'(t) \quad \text{for } t < \tau. \tag{16}$$

Also, using the boundary condition that $f(\tau) = l(\tau) = \bar{L}$ gives

$$f(t) = \frac{1}{\gamma} + e^{-\gamma(\tau - t)}(\bar{L} - \frac{1}{\gamma}), \quad \text{for } 0 < t < \tau. \tag{17}$$

Then, the patients' strategy is really the truncated function:

$$l(t) = \max\{\underline{L}, f(t)\} = \underline{L} \vee \left(\frac{1}{\gamma} + (\bar{L} - \frac{1}{\gamma})e^{-\gamma(\tau - t)}\right), \tag{18}$$

which proves (5). Then substituting (18) into (9) and making change of variable $u = l(s)$ gives

$$e^{\gamma\tau} \int_{l(0)}^{\bar{L}} (u - \frac{1}{\gamma}) dG(u) = \lambda(\bar{L} - \frac{1}{\gamma}). \tag{19}$$

Similarly, substituting (18) into (8) and making the same change of variable gives (7), concluding the proof. ■

Appendix B: Details of the Calculation of Variables

Waiting Time In a DSA. Although the donor and recipient data sets do not include such kind of information, we calculated this variable by using two variables in the recipient data: *init_date* and *end_date*. These two variables represent the date on which the patient is added to the waiting list and on which the patient is removed from the waiting list respectively. First, we grouped the data by each DSA during each quarter by blood type. Then, we calculated the waiting time of each patient in the recipient data by finding the time difference between the last day of the observed quarter and *init_date* if this patient was added to the waiting list prior to the beginning of the observed quarter and removed from the list after the last day of the quarter. Finally, the median value (in terms of years) of this variable is calculated for all observations grouped by DSA, blood type, and quarter.

Kidney Donor Risk Index. This index combines a variety of donor factors into a single continuous scale that captures the risk of graft failure after kidney transplant. There are 10 factors considered in calculating the KDPI. These factors are donor age, height, weight, ethnicity, history of hypertension, diabetes status, serum creatinine level, cause of death, Hepatitis C Virus status, and DCD (donation after circulatory death) status. Note that the lower the KDPI of a donor, the higher is the donor kidney quality. KDPI is derived from "Kidney Donor Risk Index" (KDRI) which is an estimate of the relative risk of a graft failure after transplant of a particular donor compared to the median donor. This index was first developed by Rao et al. (2009). Similar to KDPI, lower KDRI is associated with increased donor quality. The KDPI is a mapping of the KDRI and this mapping is based on the profiles of all deceased donors in the U.S. from whom a kidney was recovered during the prior calendar year. In this study, instead of using this type of mapping we calculated the KDRI value for each donor in our data set and used this variable in the following regressions as a proxy for donor kidney quality.Rao et al. (2009) estimated the association between these 10 donor factors and graft survival by using multivariable Cox proportional hazards regression model.

Appendix C: Tables

Donor Characteristic	**Applies to:**	**KDRI Coefficient ("Beta")**	**KDRI "XBeta" Component**
Age (integer years)	All Donors	0.0128	0.0128*(age-40)
	Donors with age < 18	-0.0194	-0.0194*(age-18)
	Donors with age > 50	0.0107	0.0107*(age-50)
Height (cm)	All donors	-0.0464	-0.0464*(hgt-170)/10
Weight (kg)	All donors w/ weight < 80 kg	-0.0199	-0.0199*(wgt-80)/5
Ethnicity	African American donors	0.1790	0.1790
History of Hypertension	Hypertensive donors	0.1260	0.1260
History of Diabetes	Diabetic donors	0.1300	0.1300
Cause of Death	Donors w/ COD=CVA	0.0881	0.0881
Serum Creatinine	All donors	0.2200	0.2200*(creat-1)
	Donors with creat > 1.5 mg/dL	-0.2090	-0.2090*(creat-1.5)
HCV status	HCV positive donors	0.2400	0.2400
DCD status	DCD donors	0.1330	0.1330

Table 6: KDRI Donor Factors Estimated Coefficients