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Enhancing Kidney Supply Through Geographic Sharing in the United States

Mazhar Arıkan*
School of Business, University of Kansas, 1654 Naismith Drive, Lawrence, Kansas 66045, USA, mazhar@ku.edu

Barış Ata
The University of Chicago Booth School of Business, 5807 S. Woodlawn Avenue, Chicago, Illinois 60637, USA, baris.ata@chicagobooth.edu

John J. Friedewald
Feinberg School of Medicine, Northwestern University, 676 N. Saint Clair Street, Chicago, Illinois 60611, USA, jfriedewald@northwestern.edu

Rodney P. Parker
Kelley School of Business, Indiana University, 1309 E. 10th Street, Bloomington, Indiana 47405, USA, rodp@indiana.edu

The deceased-donor kidney allocation system suffers from a severe shortage of available organs. We illustrate a mechanism which can increase the supply of cadaveric kidneys in the United States. This supply increase exploits the fact that under the current organ allocation policy, some kidneys remain unprocured in some procurement areas but would be highly sought in other areas. The current kidney allocation policy procures within a donor service area (DSA) and offers these kidneys first to patients in the DSA; if these offers are not accepted, the kidney will be offered within the region (a cluster of DSAs); if these offers are not accepted, the kidney will be offered nationally. A deceased-donor organ is procured if there is the belief that the offered organ will be transplanted (known as "intent"). We conduct an empirical analysis of the donor and recipient data (at the DSA level) which reveals that the intent increases significantly with organ quality, the median waiting time for a transplant, and higher competition. In particular, it shows that lower quality organs are likely to be procured at a higher rate in DSAs with longer waiting times. Motivated by a new kidney allocation system, we conduct a counterfactual study which shows that geographically broader sharing the bottom 15% quality kidneys leads to stronger intent for the organ, thus increasing the supply of procured organs available for transplantation. The expected increase in procured organs ranges from 58 (an increase of 0.4% of all procured kidneys) to 174 (an increase of 1.2%), depending on regional or national sharing.

Key words: kidney transplantation; discrete choice model; game theory; control function approach
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1. Introduction

The gap between the demand for and the supply of cadaveric kidneys has continued to grow steadily. There are currently over 98,000 End-Stage Renal Disease (ESRD) patients waiting for a transplantation in the United States (U.S.); and the growth of the waiting list of patients continues to outstrip the supply of kidneys.[1] The supply shortage in (deceased-donor) kidneys is a first-order issue. The allocation policy is effectively transformed into a rationing rule due to this shortage, and a large number of deaths result from this shortage every year.[2] Any increase in the supply of procured organs directly improves the well-being of ESRD patients. Therefore, we seek a mechanism to increase the supply of organs for transplantation as our primary research focus. This differs from most of the existing work in the operations research literature which has focused on the demand side of the deceased-donor allocation problem. We focus on the procurement rate of organs from a given set of donors as the source of supply by conducting an analysis at the Donor Service Area (DSA) level, and indeed ultimately find that by making simple changes to the organ allocation policy which encourages a greater sharing of lower quality organs, more kidneys may be procured and supplied for transplantation.

The procurement and transplantation of organs in the United States operates within the Organ

Procurement and Transplantation Network (OPTN) which is governed by the United Network for Organ Sharing (UNOS), authorized by the U.S. Congress. For the purposes of organ transplantation, the United States is divided geographically into 11 regions, which are further divided into 58 DSAs. The procurement of deceased-donor organs within each DSA is administered by a local Organ Procurement Organization (OPO).[3] Just like UNOS, each OPO is a nonprofit entity regulated by the government, although the OPO is directly responsible for arranging the recovery, testing, tissue typing of organs, and packaging and transporting them to transplantation hospitals. The OPO is also responsible for deciding whether to procure an organ when it becomes available within the DSA. The procurement is done according to the Final Rule[4] issued by the Department of Health and Human Services (DHHS). The procurement occurs unless one of the following occurs: (i) the donor does not meet criteria for eligible donor, (ii) 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, (iii) the family does not agree to donate the organ, (iv) the search for a recipient for that organ has ended unsuccessfully prior to the donor's entrance into the operating room. If none of these four conditions is true, the DHHS Final Rule states that "intent" is present and the procurement may proceed. We will refer to this "intent" throughout the remainder of the study as equivalent to procuring the organ.

Unfortunately, not every medically acceptable (deceased-donor) organ is procured and offered for transplantation. 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. Upon hearing of the availability of a cadaveric organ, the OPO must assess that intent is present and if so, the organ is procured. However, if the OPO deems that there will not be a willing recipient, typically because the organ may be of lower quality, the organ may not be procured. The intent is established prior to the donor entering the operating room. If the OPO believes there is at least one patient in the DSA who would seriously consider accepting the organ (after deeming the organ is medically acceptable and the donor's family has given consent), then intent is established and procurement will proceed (i.e., "intent" = "procurement"). Our dataset includes the information of whether or not an organ is procured. Thus, we observe in the data whether intent was expressed for each medically eligible organ.

Our primary research objective is to investigate the extent of additional kidneys which may be procured if some small changes to the UNOS allocation policy are considered. These kidneys are those which are currently not procured due to their marginal quality and are most likely concentrated in some areas of the country (the high quality kidneys are procured throughout the country; it is the lower quality kidneys which may not be procured in some areas). The change to the UNOS policy we study concerns a greater degree of sharing of these lower quality organs to encourage higher levels of procurement of them. To further understand this, in our empirical study, we investigate how the three factors (organ quality, median waiting time in the DSA, transplant center competition in the DSA) affect intent in those different DSAs. The organ quality varies from donor to donor. Moreover, the median waiting times and the degree of transplant center competition vary across different DSAs; so does the intent. The variation in these three factors helps us glean the relationship between the intent and these factors. Building on this analysis, through a counterfactual analysis we then determine the extent of additional kidneys of marginal quality which may be procured under some targeted small changes to the UNOS allocation policy.

UNOS' geographically-based procedure for seeking a recipient for an organ is the following. First, the OPO is obliged to seek a recipient from the waiting list within the DSA; if no willing recipient is found in the DSA, the OPO seeks a willing recipient within the region (but outside the DSA); if there are no willing recipients within the region, the organ may then be offered to patients of the waiting list nationally (i.e., outside the region). Given the limited time until the donor's entrance to the operating room, the intent (procurement) is strongly correlated with the acceptance of the organ (by a recipient in the local DSA). The slight policy modification we are considering is for the OPO to seek recipients for the lower quality kidneys within the region (or the nation) immediately, without seeking them within the DSA first, that is, the broader sharing of lower quality organs.

We first develop and analyze a game theoretical model of a DSA to study the patients' accept/reject decisions for deceased-donor organ offers. In essence, patients decide between accepting an organ offer or waiting for a better quality organ. This model helps us understand how the acceptance probability of a deceased-donor organ (and hence, the intent for it) change with the organ quality and the congestion in a DSA (e.g., median waiting time for a transplant) and helps develop testable hypothesis related to organ quality and waiting time until transplantation. Three hypotheses pertaining to how intent is affected by organ quality, waiting time until transplantation, and competition between transplant centers in a DSA (motivated by the literature) are defined prior to testing in our empirical model. The estimation is done using an

endogeneity-corrected[5] probit model, described in more detail in section 5.

We find that the organ quality is the most important factor determining intent. In particular, the intent (and the procurement rate) increases as the quality improves. We also observe that, when considering all the data, procurement rate in a DSA also increases as the median waiting time until transplantation and the competition among transplant centers in that DSA increase. However, the significance of these two variables (i.e., waiting time until transplantation and the competition) is not kept at all times when we partition the data by organ quality or blood type. Importantly, we find that while the waiting time until transplantation is significant when estimating using only the lower quality organs, it is not significant when considering higher quality organs. This suggests that OPOs with substantial median waiting times are more likely to procure the lower quality organs knowing there is a likelihood that someone in the DSA will accept it.

Using the results of the probit estimation, we then undertake a counterfactual study to consider how the supply of organs may be enhanced by an adjustment of the UNOS allocation policy amongst the lower quality organs. By considering a broader sharing of the lowest quality kidneys (bottom 15%), e.g., regionally or nationally, we observe that more of those organs may be procured under this policy than under the original policy. This policy change is suggested as part of the proposal to substantially revise the kidney allocation policy and the new policy became effective in December 2014.[6] The analysis in section 6 shows that 58 additional organs will be procured per year under regional sharing of the bottom 15% of the organs, increasing the supply of the bottom 15% quality kidneys by 3.3%. Similarly, 129 additional organs will be procured per year under national sharing of the bottom 15% of the organs, which reflects the addition of a small- to medium-sized DSA (a supply increase of 7.3% among the bottom 15% quality kidneys). In addition, to inform policy makers further, we extend the counterfactual study and quantify the impact of varying the quality threshold for broader sharing from 15% to 20%. This further fine-tuning of the quality threshold can increase the supply of procured deceased donor kidneys by 174 per year. This increase is significant and corresponds to an addition of a medium-sized DSA, or an increase of 1.2% of the total kidney supply on average each year.

The remainder of the study is structured as follows. Section 2 provides a literature review. Section 3 develops a game theoretical model of a DSA and describes the transplant center competition by citing the relevant literature, both of which help formulate testable hypotheses. Section 4 describes the data. Section 5 introduces the econometric method and the estimation results. The counterfactual study is undertaken in section 6. Section 7 concludes. Proofs, additional details of the calculations of variables and figures, the details of the endogeneity correction method, additional estimation results and tables are provided in Appendices.

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 the passing of this legislation, UNOS has managed the allocation of deceased donor organs in the United States. 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 Organ Procurement and Transplantation Network (2014a) for details. Su and Zenios (2004) note 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)." The recent work Schummer (2016) explores the welfare implications of increasing the acceptance of lower quality organs by (the highly ranked) patients on the waitlist. The author considers a stylized model where an infinite number of ordered patients are present and make accept/reject decisions. Schummer (2016) shows that not interfering with patients' decisions is Pareto dominant if the patients are risk-neutral or risk-averse and patient. However, when they are impatient the result no longer holds. In particular, there is a trade-off to be made in that case, e.g., highly ranked patients may suffer whereas those with lower rankings may benefit from increasing the acceptance of lower quality organs by the highly-ranked patients. The author also discusses the implications of the result for the "organ spoilage" problem because the organs may spoil during the sequential offer process due to the limited cold ischemia time.

Opelz and Döhler (2007) state that cold ischemia time up to 18 hours does not have much influence on the graft survival rates, but cold ischemia time longer than 18 hours can be detrimental. The 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 DSAs lead to a significant disparity in waiting times and access to transplantation across different DSAs. Davis (2011) notes that "The overall median waiting time to receive kidney transplantation during 2000–2009 varies from 0.93 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 substantial 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) explore the efficiency-equity trade-off and propose a dynamic index policy for deceased-donor kidney allocation. Akan et al. (2012) explore 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. (2013) design a scalable, data-driven allocation policy which incorporates fairness constraints. Ata et al. (2016a) provide an analysis of scoring-based allocation policies taking into account recipient's forward-looking behavior. CONSAD (1995), Pritsker et al. (1995), Zenios et al. (1999), Taranto et al. (2000), Kreke 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 a probabilistic sharing of available kidneys in neighboring DSAs to address the geographic inequities. Ata et al. (2016b) propose 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. Halldorson et al. (2013) consider the effect of competing transplant centers within a DSA and find that liver patients are more likely to accept a donated liver under competition than when no competition exists. 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. (2013).

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 procured deceased-donor organs. Another exception is Arora and Subramanian (2017) who analyze the supply side entities' (i.e., OPO and transplant hospital) decisions on societal outcomes. They show that there exist misalignments between the social planner and supply side players in the cadaver organ donation value chain and propose a pareto-improving contract that achieves socially optimal performance.

Recent strategies to increase the supply of organs in practice include the use of expanded criteria donor (ECD) kidneys[7] 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 factors affect the procurement rate of organs. Thus, it can help increase the supply of deceased-donor organs further.

Our study is also related to the growing body of literature on how workload (provider load or patient waiting time) affects clinical decisions and patient outcomes. KC and Terwiesch (2012) show that at higher levels of intensive care unit (ICU) occupancy, a patient's early discharge probability increases. However, early discharge is associated with increased likelihood of revisiting the ICU in the future. A similar adverse effect of workload is demonstrated in a study by Kuntz et al. (2014) which shows that when occupancy levels exceed a certain tipping point, a patient's mortality risk increases significantly. A recent paper by Freeman et al. (2017) shows that increased levels of workload have varying effects depending on the complexity of a patient's need. In particular, they find that gatekeeper providers display a rationing effect of resource-intensive services for noncomplex cases, whereas they increase the rate of specialist referrals for complex cases. KC and Terwiesch (2009), Kim et al. (2014), Tan and Netessine (2014), Batt and Terwiesch (2017), and Jaeker and Tucker (2016) are other operations management papers in this stream of research. Different from these papers, our study investigates the impact of transplant center congestion on the deceased donor kidney procurement decisions.

3. Hypotheses Development

3.1. A Game Theoretical Model

This subsection develops an overloaded fluid model of an OPO and considers patients' accept/reject decisions for deceased-donor organ offers. The model helps glean insights about what factors affect 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 intent is

not a guarantee that the organ will ultimately be transplanted, but if and only if an OPO shows intent, the organ will be procured; that is, "intent" = "procurement." 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 is willing to seriously consider accepting 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.

Patients may die while waiting for a transplantation. We assume that the hazard rate of time-to-death distribution, denoted by $\gamma(t)$ for $t \geq 0$, is nondecreasing. The expected post-transplant life years associated with an organ takes a value in the range $[\underline{L}, \bar{L}]$, where $\bar{L} > 1/\gamma(t)$ for all $t \geq 0$, which means that patients prefer the highest quality kidney to staying on dialysis at all times.[8] 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 jump at $\bar{L}$, that is,

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

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

We assume that G, λ, and $\gamma(\cdot)$ 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, that is, 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[9] 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[10] $l(\tau) = \bar{L}$.

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 characterize the stationary queue length profile:

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

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

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

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

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*

$$l(t) = \max\left\{\underline{L}, \exp\left\{\int_0^t \gamma(s)ds\right\}\left[\bar{L}\exp\left\{-\int_0^\tau \gamma(s)ds\right\} + \int_t^\tau \exp\left\{-\int_0^s \gamma(u)du\right\}ds\right]\right\}, \tag{5}$$

where τ is the unique solution of the following equation:

$$\int_0^\tau \exp\left\{\int_0^s \gamma(u)du\right\}dG(l(s)) = \lambda. \tag{6}$$

The corresponding stationary queue-length profile is characterized by

$$Q(t) = \exp\left\{-\int_0^t \gamma(s)ds\right\}\left[\lambda - \int_0^t \exp\left\{\int_0^s \gamma(u)du\right\}dG(l(s))\right] \quad \text{for } t < \tau, \tag{7}$$

and $Q(\tau) = \Delta G(\bar{L})$. Moreover, as λ increases, τ increases strictly, that is, patients wait longer and $l(t)$ decreases strictly (unless it equals $\underline{L}$) for all $t < \tau$.

The $l(t)$ curve is the equilibrium solution of all the patients in the DSA, 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 in its DSA and the 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. Proposition 1 shows that as the DSA gets more congested (i.e., λ and τ increase), patients waiting for a transplant are willing to accept a lower quality organ (i.e., $l(t)$ decreases for all t).

The expressions in Proposition 1 simplify as shown in Corollary 1 below if the death rate is constant over time.

COROLLARY 1. *When the death rate is constant, that is, $\gamma(s) = \gamma$, the patients' equilibrium decisions are characterized by the threshold function $l(\cdot)$ given by*

$$l(t) = \max\left\{\underline{L}, \frac{1}{\gamma} + \left(\bar{L} - \frac{1}{\gamma}\right)e^{-\gamma(\tau - t)}\right\}, \; t \in [0, \tau], \quad (8)$$

where τ is the unique solution of the following equation:

$$e^{\gamma\tau}\int_{l(0)}^{\bar{L}}\left(u - \frac{1}{\gamma}\right)dG(u) = \lambda\left(\bar{L} - \frac{1}{\gamma}\right). \quad (9)$$

Moreover, the stationary queue-length profile is characterized by

$$Q(t) = e^{-\gamma t}\left[\lambda - e^{\gamma\tau}\int_{l(0)}^{l(t)}\frac{u - 1/\gamma}{\bar{L} - 1/\gamma}\, dG(u)\right] \quad \text{for } t < \tau. \quad (10)$$

Proposition 1 shows that as the DSA gets more congested, that is, 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 the following two testable hypotheses.

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

This hypothesis is motivated by the nondecreasing 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 until transplantation in a DSA increases, the OPO's intent increases.*

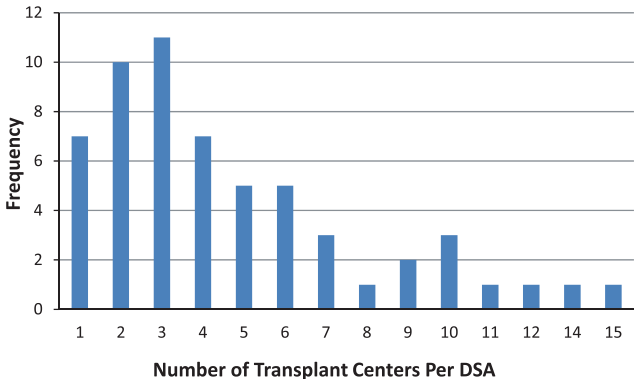
This hypothesis suggests that as the waiting time across all patients in the DSA increases (and hence, congestion increases), the willingness of patients to accept an organ also increases. This hypothesis follows from Proposition 1 and reflects the patients' increased willingness to accept a potentially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

3.2. Transplant Center Competition

There are 272 transplant programs in the United States certified (for each organ type) by the Centers for Medicare and Medicaid Services (CMS) to perform transplants. As mentioned in section 1, the United States is geographically divided into 58 DSAs and each DSA can be composed of one or more transplant centers. There is significant variance in the number of transplant centers across different DSAs; seven DSAs have a single center serving the patients, while some others have ten or more centers competing with each other. Figure 1 displays a histogram of the number of transplant centers in each DSA, showing the heterogeneity of the number of centers.

These transplant centers have varying objectives in terms of transplant volume, costs, and outcomes. In order to cover their fixed costs, transplant centers must perform a minimum number of transplants and maintain their market shares in their DSAs. In addition, they aim to receive an incremental profit with each additional organ they procure. As a result, transplant centers in DSAs with multiple centers can behave more aggressively in terms of patient acceptance and exhibit more demand for lower quality organs. On the contrary, transplant centers with no or

Figure 1 Histogram of the Number of Transplant Centers at Each DSA [Color figure can be viewed at wileyonlinelibrary.com]



little competition can create a greater organ wastage. We elaborate more on this center heterogeneity in section 4 where we highlight certain aspects of and trends in the current kidney allocation system.

The following hypotheses are inspired by Halldorson et al. (2013), Adler et al. (2014), and Cho et al. (2015) all of which analyze the impact of the degree of competition on the transplantation system. In particular, Halldorson et al. (2013) examine the association between competition among transplant centers and post-transplant outcomes, using data from cadaveric liver transplant recipients who underwent transplantation between 2003 and 2009. They find that transplant centers facing higher levels of competition are associated with increased patient access for sicker patients and increased utilization of higher risk (i.e., lower quality) organs in comparison to DSAs without competition. In a similar vein, Adler et al. (2014) demonstrate that higher proportion of riskier kidneys are used in the DSAs with higher competition using data from patients who underwent renal transplantation between 2003 and 2012. Using kidney patient listing data and the number of kidneys transplanted in 2011, Cho et al. (2015) indicate that competition increases the patient access (i.e., higher percentage of patients tend to be listed for transplant). However, Cho et al. (2015) report that the percentage of patients receiving transplants is not different at varying levels of competition among transplant centers. Combining the findings of these papers leads to inconclusive results regarding the intent of an OPO; that is, Halldorson et al. (2013) and Adler et al. (2014) show a positive association between competition and intent, whereas Cho et al. (2015) do not observe a significant impact of competition on the intent. Hence, we test the following two alternative hypotheses regarding competition:

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

Hypothesis 3b. *As the competition within a DSA increases, the OPO's intent does not change.*

We use the Herfindahl–Hirschman Index (HHI) as a measure for competition between transplant centers in the DSA, similar to Halldorson et al. (2013), Adler et al. (2014), and Cho et al. (2015). The HHI is a commonly accepted standard of economic measure of competition among players in a particular industry or market. There are several papers in the operations management literature that measure market competition using HHI in a healthcare setting (see, KC and Staats 2012, Andritsos and Tang 2014, and Lu and Lu 2017). The details of the calculation of the HHI variable is provided in section 5. Next we describe our data sources, the variables, the models, and test the above hypotheses.

4. Data Description

4.1. Data Sources

The data for this study comes from UNOS' Standard Transplant Analysis and Research (STAR) Files. Our dataset 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 United States. 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 use 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_{jt} is the median waiting time (in years) until transplantation in DSA j in quarter t, W_{jkt} is the median waiting time (in years) until transplantation in DSA j for blood-type k in quarter t, and HHI_{jk} is the HHI for blood type k in DSA j. The term HHI_{jk} captures the competition between transplant centers in a DSA. This index is calculated by summing the squares of the market share of each transplant center in a DSA. We define the market share of a transplant center by using the total number of registered patients during our period of study at each DSA for each blood type. The HHI ranges from $1/n$ to 1 where n is the number of transplant centers in a DSA. The closer the HHI gets to zero, the greater the level of competition within a DSA. Our competition variable (HHI_{jk}), the kidney quality variable ($KDRI_i$), and the waiting time variable (W_{jt}) will be discussed further in section 5. The waiting time and the competition variables are defined at the DSA level, and the quality variable is defined at the donor level.

The donor data set contains detailed information regarding each deceased kidney donor such as a

Table 1 Descriptive Statistics of the Dependent and the Independent Variables

Variable	Sample size	Mean	SD	Median
Y_i	76,866	0.90	0.30	1.00
$KDRI_i$	76,399	1.33	0.51	1.21
W_{jt}	2516	1.79	1.00	1.63
HHI_{jk}	244	0.41	0.28	0.33
$W_{jk=\{A\}t}$	2510	1.40	0.79	1.26
$W_{jk=\{O\}t}$	2508	2.03	0.95	1.91
$W_{jk=\{AB\}t}$	1077	1.04	0.89	0.84
$W_{jk=\{B\}t}$	2214	2.25	1.30	2.04

Notes. *i*: index for donor, *j*: index for DSA, *t*: index for quarter, *k*: index for blood type.

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,[11] (4) organ recovered for reason other than transplant, (5) organ recovered for transplant but not transplanted, and (6) organ transplanted. When a donor kidney is assigned codes 1, 2, or 3, then it was not recovered; that is, $Y_i = 0$. The remaining codes 4, 5, and 6 indicate that the kidney was recovered from the donor; that is, $Y_i = 1$. As indicated in Table 1, the mean value of Y_i equals 0.9 which means that 7,687 observations have $Y_i = 0$ (i.e., 10% of the sample size) and the remaining 69,179 observations have $Y_i = 1$.

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 dataset. An entry consists of a listing, a transplant, or both (if the listing resulted in a transplantation).

4.2. Data Trends

This subsection presents summary statistics of the data to highlight certain aspects of and trends in the kidney allocation system. 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. 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 consider them.

Figure 3a shows the percentage procured and not procured donors by SCD-ECD breakdown and the proportion of ECD kidneys procured has grown. However, Figure 3b shows that there are similar numbers of not procured donors in 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 nonprocured elements (ECD and SCD) appear to be a new growing source of kidneys for transplantation.

Figure 4 illustrates an example of geographical heterogeneity. In Figure 4a, we see that there is a large and consistent difference in the median waiting time until transplantation for recipients in two geographically different DSAs. The median waiting time until transplantation in NYRT (New York Organ Donor Network) almost always exceeds two years while it is always 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

Figure 2 Demand Outstripping Supply [Color figure can be viewed at wileyonlinelibrary.com]

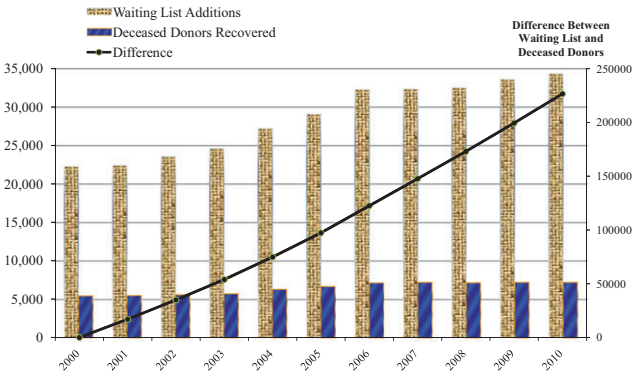


Figure 3 Kidneys Procured and Not Procured from 2000 to 2009. Numbers of Donors By SCD-ECD Breakdown (Percentage: a; Absolute Numbers: b)

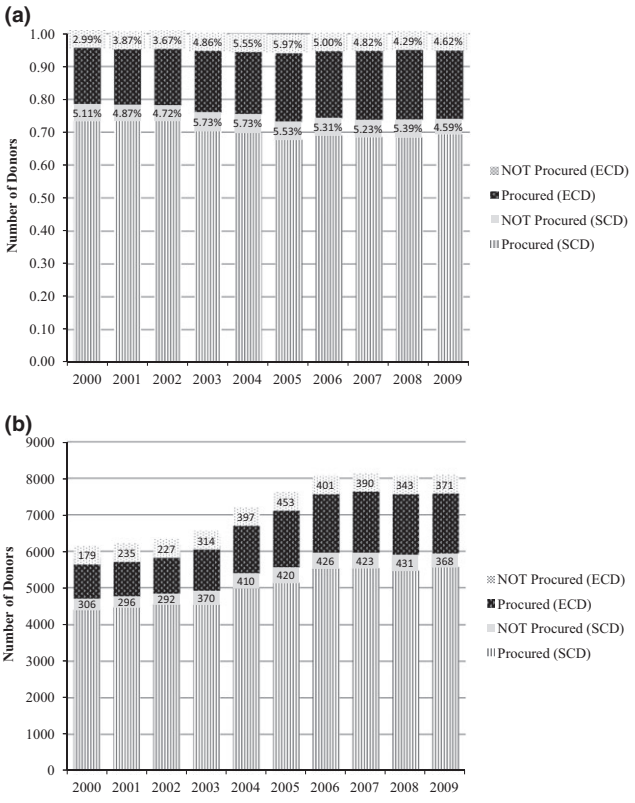


Figure 4 **Median Waiting Times and Organ Quality in Two OPOs from 2000 to 2009. (a) Median Waiting Time Until Transplantation. (b) Highest Quality Organ Not Procured in UTOP and Lowest Quality Organ Procured in NYRT [Color figure can be viewed at wileyonlinelibrary.com]**

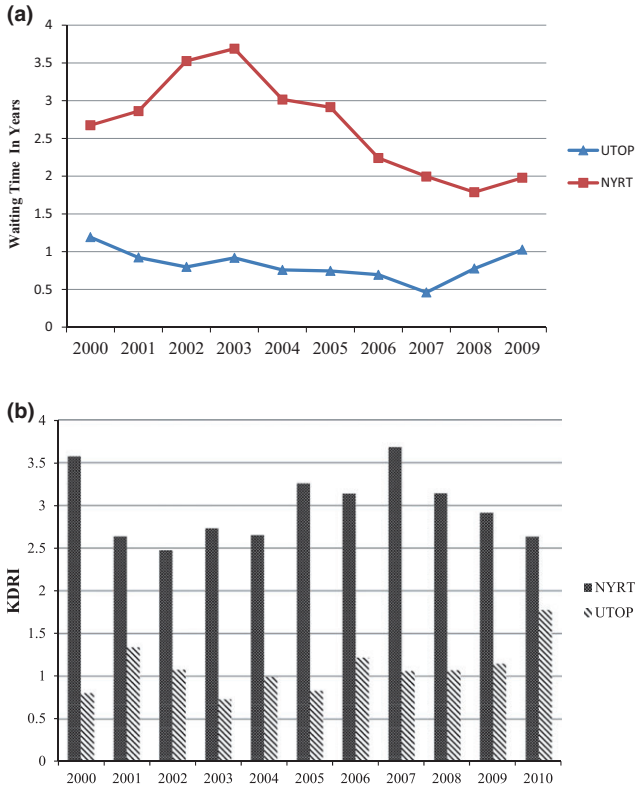
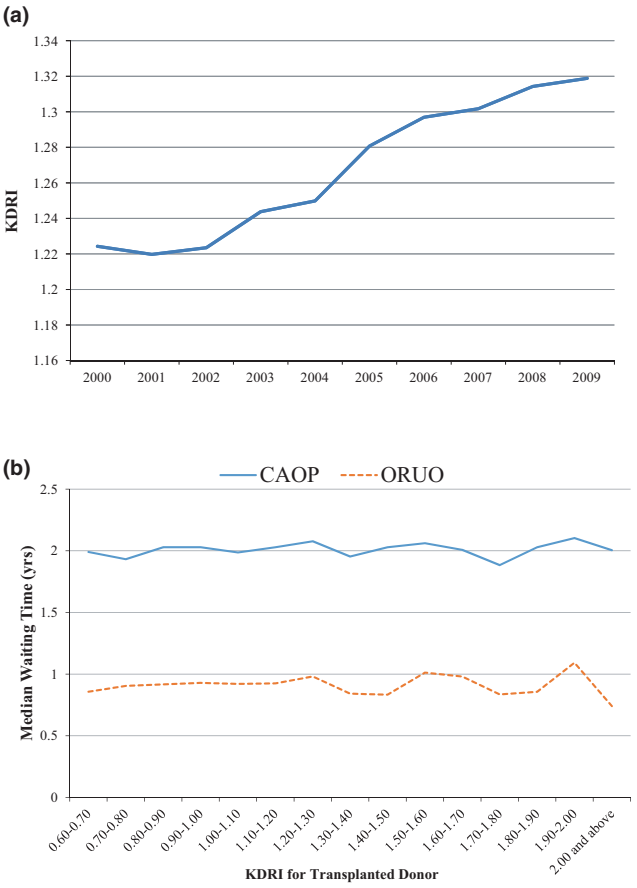


Figure 5 **Waiting Time and Quality Relationship. (a) Average Quality Over Time. (b) Waiting Time Until Transplantation and Quality Relationships in Two OPOs [Color figure can be viewed at wileyonlinelibrary.com]**



can differ markedly. In the remainder of the study, we use the Kidney Donor Risk Index (KDRI) quality metric, which was introduced by UNOS in its most recent kidney allocation policy to fine-tune the binary SCD-ECD donor kidney quality classification system explained above. The KDRI is reverse-scaled: a high number indicates lower quality than a low number.

Figure 4b shows the lowest quality organ procured in NYRT is consistently lower quality than the highest quality organ *not* procured in UTOP, in every year of our study. *This simple comparison shows that there was no intent in UTOP for organs for which intent would have been easily given in NYRT*. That is, there are organs of a quality not being procured in UTOP which would have been readily procured but not necessarily accepted in NYRT since they exceed the lowest quality organs procured in New York. Similar stories appear among several other OPOs nationally.

Next, we observe in Figure 5a that the average quality of transplanted kidneys has gradually worsened over time, perhaps reflecting that demand is progressively outstripping the supply of organs as shown in Figure 2, as well as the increased usage of ECD kidneys in recent years. Figure 5b supports two observations. First, it shows the relationship between the waiting time to transplant and the quality of the accepted organs. Within an OPO, the quality of the kidney received does not appear to be correlated with the median waiting time. Second, Figure 5b illustrates that the waiting time until transplantation for the CAOP OPO (OneLegacy, an OPO based in Los Angeles) is twice as long as for the ORUO OPO (Pacific Northwest Transplant Bank, an OPO based in Portland, Oregon), a heterogeneity reflected across all 58 OPOs. There is also a similar heterogeneity across blood types, with longer average wait times for blood type B and O compared with types A and AB.

Finally, Figure 6 shows the average HHI by year and two blood types of the same two OPOs used in Figure 5b. Traditionally, blood types B and O candidates experience the longest wait time, so we display the time trend of competition for these two blood types. While the competition for organs does not change significantly over time in an OPO, the competition level across different OPOs can be drastically different. We observe in Figure 6 that CAOP OPO kidney transplant market (has four transplant centers) is

Figure 6 Average HHI by Blood Types B and O Over Time in Two OPOs [Color figure can be viewed at wileyonlinelibrary.com]

more competitive than that of ORUO OPO (has three transplant centers). The average HHI at CAOP OPO varies between 0.1 and 0.3; whereas the average HHI at ORUO OPO is always higher (less competition) and varies between 0.3 and 0.8. In addition, there is heterogeneity in competition across blood types within the same OPO. We also observe a similar trend at the aggregate level, the average HHI of all OPOs by year doesn't vary much when the data is broken down by the blood type (varies between 0.5 and 0.65), however there exist differences across blood types. There seems to be slightly more competition for blood type O compared to blood type B (see, Appendix S3, Figure C9).

5. Empirical Model

5.1. Variables Affecting the Acceptance Probability of a Kidney

5.1.1. Waiting Time until Transplantation in a DSA. The waiting time is one of the primary determinants of patients' priority and decisions in the kidney allocation system. We calculate the *median* waiting times of all patients who had transplants at each DSA during each quarter (between the first quarter of 2000 and the second quarter of 2010) by blood type (W_{jkt}); see Appendix S2 for the details of the calculation of these waiting times and all other relevant variables. As mentioned in section 1, there are multiple sources of significant variation in the waiting times including different DSAs and different blood types. This difference is especially significant when one compares blood types O and B to A and AB and also across different DSAs.

5.1.2. Kidney Donor Risk Index. To measure the quality of offered kidneys, we use KDRI following the medical literature. This index and its mathematical model was first developed by Rao et al. (2009); see Organ Procurement and Transplantation Network (2014b) for further details. This index converts a set of donor characteristics into a single number that captures the risk of graft failure after kidney transplant (i.e., an estimate of the relative risk of a graft failure after transplant of a particular donor compared to the median donor). 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 KDRI 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 KDRI. 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. A more detailed explanation is available in Appendix S2 including the coefficient estimates obtained from the graft survival model of Rao et al. (2009) (Appendix S5, Table E8). KDRI has several advantages over the currently used deceased donor classifications (i.e., ECD and SCD). First, KDRI is based on ten different donor factors, whereas ECD/SCD classification is based on only four 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 new kidney allocation policy uses KDRI as a measure of kidney quality.

5.1.3. Competition Among Transplant Centers. We also explore 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 1. Following the results in Halldorson et al. (2013), Adler et al. (2014), and Cho et al. (2015), we conjecture that the

competition may play a role in the procurement decisions and should be controlled for in the regression analyses below. We use the HHI as a measure for competition among transplant centers in the DSA. We first calculate the total number of patients registered at transplant center c by blood type k (λ_{ck}) during the period of our study (January 1, 2000 through June 30, 2010). We also calculate the total number of registered patients at each DSA j for each blood type k by adding the total number of registered patients at its transplant centers ($\sum_{c\in\Omega_j}\lambda_{ck}$ where Ω_j represents the set of transplant centers in each DSA j). The market share of each transplant center by blood type is then $s_{ck}=\frac{\lambda_{ck}}{\sum_{c\in\Omega_j}\lambda_{ck}}$ for transplant center c in DSA j. The HHI is calculated as

$$HHI_{jk}=\sum_{c\in\Omega_j}s_{ck}^2.$$

5.2. Econometric Method

In this subsection, to model the event of procurement (hence, intent), we use the discrete choice model of binary probit, which specifies the probability that a person (in our case, an OPO) chooses one of two alternatives. The probability is expressed as a function of observed variables. In our model, this is the probability of procuring a donor's kidney and the choice set is whether or not the donor's kidney is procured.

Discrete choice models can be derived from utility maximization behavior. We represent the utility that DSA j obtains from procuring a kidney from donor i by $U_{ij}(1)$; the utility from the decision to not procure, denoted by $U_{ij}(0)$, equals to zero. Letting Y_i denote the procurement decision (i.e., $Y_i=1$ if the kidney from donor i is procured, and $Y_i=0$ otherwise), we express the utility function as follows:

$$U_{ij}(Y_i)=\begin{cases}\beta' x_{ij}+\varepsilon_{ij}, & \text{if } Y_i=1;\\ 0, & \text{otherwise,}\end{cases} \tag{11}$$

where x_{ij} denotes the observable variables (e.g., attributes of the kidney from donor i and attributes of DSA j), whereas ε_{ij} denotes the utility from attributes that the researcher does not observe. The vector β denotes the parameters to be estimated. In our analysis, $x_{ij}=(KDRI_i, W_{jkt}, HHI_{jk})'$ where $KDRI_i$ represents the kidney quality index of deceased donor i, W_{jkt} represents the median waiting time until transplantation of all patients with the same blood type k ($k\in\{A, B, AB, O\}$) who had transplants at DSA j ($j\in\{1,\ldots,58\}$) during each quarter t ($t\in\{1\ldots,42\}$), and HHI_{jk} is the competition variable measured by HHI at DSA j for each blood type k. We denote the probability that the organ from donor i in DSA j is procured by P_{ij}, which is given as follows:

$$P_{ij}=\Pr(Y_i=1)=\Pr(U_{ij}(1)>U_{ij}(0))=\Phi(\beta' x_{ij}),$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution since the probit model assumes that ε_{ij} is standard normally distributed.[12]

One potential challenge in estimating the parameters of discrete choice models (e.g., logit or probit models) is the possibility that some component of the utility model that is presumed exogenous is in fact endogenous. In the literature, the term "endogeneity" is used to describe a model in which one (or more) unobservable variable(s) is (are) correlated with observable covariates. Failure to account for this endogeneity in an econometric model results in a violation of the independence assumption which is a necessary condition for obtaining consistent estimates. In our case, there might be unobservable DSA-specific variables which have an impact on the intent of a DSA through some observable covariates. We posit that $KDRI_i$ cannot be an endogenous variable as the quality level of any donor's kidney is most likely independent of DSA-specific factors. However, the two other variables, namely W_{jkt} and HHI_{jk}, may be influenced by unobserved factors that affect the intent of a DSA. These unobserved factors can be financial, managerial, and cultural DSA-specific factors which can have an impact on the procurement decisions at a DSA. For instance, financial burdens can make some transplant centers (and OPOs) be more aggressive in terms of patient selection and perform transplantation for sicker patients. Being more aggressive in patient selection may have direct consequences on the waiting times of patients and the competitive environment in a DSA. Hence, it is not unreasonable to suspect a correlation between W_{jkt} and HHI_{jk} and some unobserved factors that are not captured with our data.

To correct for endogeneity, we use a control function approach. The basic idea of this approach is to construct variables (or, control functions) which would account for the nonzero part of the expected value of the error term conditional on the exogenous variables. It is basically a two-step procedure which utilizes a valid instrumental variable (IV) to control for the part of the error term that correlates with an endogenous variable. We extend the existing control function method described in Rivers and Vuong (1988) and Petrin and Train (2010) to a multivariate context in order to test whether or not our model suffers from endogeneity by exploiting the normally distributed errors in the probit estimation. We find evidence of endogeneity in our specification. The competition variable (HHI_{jk}) is found to be endogenous, whereas the waiting time until transplantation variable (W_{jkt}) turns out to be exogenous. We proceed

with the outline of the estimation procedure followed by the results in section 5.3 provided in Table 2. The details of the implementation of the endogeneity correction method (control function approach) including the results of its two steps (i.e., instrument validity and evidence of endogeneity) and the extension to a multivariate context can be found in Appendix S4. We refer the reader to Petrin and Train (2010) for further details of the control function approach for endogeneity in consumer choice models.

5.2.1. Endogeneity Correction Using the Control Function Approach. The first step of the control function approach is to regress endogenous variables on exogenous instruments (Step 1). In the second step, the residuals from these regressions enter into the probit model as additional covariates (Step 2). By using two separate IVs (one for W_{jkt} and one for HHI_{jk}), we isolate the part of $U_{ij}(Y_i)$ that is not correlated with ε_{ij}.

Let $\widehat{W_{jkt}}$ and $\widehat{HHI_{jk}}$ denote our IVs for the waiting time and competition variables respectively. These IVs are created to reflect the median waiting times and competition in comparable DSAs so that they share similar characteristics of the observed endogenous variables and at the same time they even off the unobserved DSA-specific factors that might be the reason for endogeneity in the model specification. In this way, these IVs would be correlated with the original (suspected) explanatory variables (i.e., W_{jkt} and HHI_{jk}) but not correlated with the error term. To calculate these IVs, we group all 58 DSAs in the United States into 8 clusters based on the average number of transplantations per year and the number of transplant centers. Hence, similar DSAs are placed in the same group, which enables us to average out the unobserved factors affecting the intent. Therefore, we define our two IVs as follows:

$\widehat{\mathbf{W_{jkt}}}$: The average of the median waiting time at DSAs similar in size to DSA j during the same quarter t and for the same blood type k.

$\widehat{\mathbf{HHI_{jk}}}$: The average HHI at DSAs similar in size to DSA j for the same blood type k.

Note that in order not to bias our Hausman-type instrument (Hausman 1996) calculations, we excluded the DSAs in the same region.

5.3. Estimation Results

In this subsection we report the main results from the endogeneity-corrected model, the details of which are provided in Appendix S4.

The results of the Step 1 of the control function approach is provided in Table 6 in Appendix S4. Diagnostics in Step 1 show support for the validity of the chosen instruments. Next, we test the evidence of endogeneity in Step 2 of the control function approach. The results provided in Table 7 in Appendix S4 indicate that the competition variable is endogenous and the waiting time until transplantation variable is exogenous. This implies that an OPO intent model that doesn't control for the endogeneity of the competition variable leads to bias in the model estimation. Hence, in the remainder of the study, endogeneity correction refers to the treatment of the endogenous competition variable and we assume that the waiting time until transplantation variable is an

Table 2 Summary of Estimation Models (Intent Model with Whole Data, Bottom 15%, and Top 85% Quality Donors)

	Dependent variable: Prob(Intent)					
	Whole data		Bottom 15%		Top 85%	
Variable (coefficient)	Parameter estimate†	Average marginal effects‡	Parameter estimate†	Average marginal effects‡	Parameter estimate†	Average marginal effects‡
Constant (β_0)	2.791***		2.761***		2.914***	
	(0.030)		(0.100)		(0.038)	
KDRI$_i$ (β_{KDRI})	−0.989***	−0.143***	−0.971***	−0.310***	−1.133***	−0.130***
	(0.012)	(0.002)	(0.034)	(0.010)	(0.024)	(0.003)
W$_{jkt}$ (β_W)	0.016*	0.003**	0.039**	0.014**	0.012	0.001
	(0.008)	(0.001)	(0.016)	(0.005)	(0.009)	(0.001)
HHI$_{jk}$ (β_{HHI})	−0.101*	0.012	−0.160	0.037	0.044	0.005
	(0.049)	(0.006)	(0.085)	(0.027)	(0.029)	(0.003)
Log-likelihood	−17,917.61		−5539.20		−13,946.01	
Concordance	77.8%		67.5%		70.4%	
Wald $\chi^2(3)$	7,181.67***		771.96***		2300.20***	
Observations	75,778	75,778	11,363	11,363	64,415	64,415

Notes. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.
†Bootstrap standard errors for parameter estimates are in parenthesis.
‡Delta-method standard errors for average marginal effects are in parenthesis.

exogenous variable. In the endogeneity-corrected model, the utility function $U_{ij}(Y_i)$ is given as follows:

$$U_{ij}(Y_i) = \begin{cases} \beta' x_{ij} + (\lambda_C)\zeta_{ij} + \tilde{\varepsilon}_{ij}^C, & \text{if } Y_i = 1; \\ 0, & \text{otherwise}, \end{cases} \quad (12)$$

where ζ_{ij} is the residual from Step 1 regression (using the IV $\widehat{HHI}_{jk}$) that is entered as an additional explanatory variable to the uncorrected utility model Equation (11), the vector β and λ_C denote the parameters to be estimated, and $\tilde{\varepsilon}_{ij}^C$ is the utility from attributes unobservable to the researcher.

The results of this endogeneity-corrected model are displayed in Table 2. As can be seen, the kidney quality index is significant at 0.1% level, and the median waiting time until transplantation variable together with the competition variable are significant at 5% level for the whole data. The Wald χ^2 test statistics yield a p-value less than 0.001 which indicates a significant goodness of fit for the overall model, additionally the concordance of the model is 77.8%.[13]

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, the results give support to the positive association between competition and the probability of recovering a kidney (i.e., higher HHI means less competition). We also report the average marginal effects in Table 2. For instance, considering the whole data, a one unit increase of KDRI leads to an average decrease of 0.143 in the probability that a kidney is procured; in addition, a one year increase in the median waiting time leads to an average increase of 0.003 in the probability that a kidney is procured. The average marginal effect of the competition variable is insignificant.

Therefore, we find support for the hypotheses 1, 2, and 3A. In other words, the results support the first two hypotheses motivated by the game theoretical model and also the hypothesis inspired by the literature which find that competition leads to procuring higher levels of marginal organs (i.e., Halldorson et al. 2013, Adler et al. 2014).[14] Even though our intent variable is defined for all kidneys with varying qualities, our results indicate that transplant centers operating in more competitive markets have an incentive to procure lower quality kidneys. Also, note that, as will be seen below, when the data are analyzed at the lower or higher quality levels, the competition variable is no longer significant.

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 divide the data into two groups: (*i*) donors whose kidney quality falls in the highest 85% quality level based on KDRIs of all donors in that year, that is, top 85% quality; and (*ii*) donors whose kidney quality falls in the lowest 15% quality level based on KDRIs of all donors in that year, that is, bottom 15% quality.[15] We calculate the 85th percentile of KDRI values of all the donors for each year in our dataset. Any donor whose KDRI value higher (lower) than this threshold value is classified as a bottom (top) 15% (85%) quality donor. Table 9 in Appendix S5 displays the different KDRI threshold values for each year.

We again estimate the coefficients and average marginal effects using our endogeneity-corrected intent model specification as described above and compare the results of these mutually exclusive groups (bottom 15% and top 85% quality organs; see the final four columns of Table 2). Note that goodness of fit statistics (log-likelihood, concordance, and Wald χ^2) for these two models, which indicate acceptable fit, are also available in Table 2. It is important to note that the coefficient of the waiting time until transplantation variable is significant for lower quality donors, however the same coefficient is not significant for high quality donors. Hence, the intent for low quality organs is more sensitive to the changes in waiting time than for high quality organs. Presumably, this has motivated the new kidney allocation policy that enables broader sharing of the lower quality organs. The impact of this new kidney allocation policy is studied in the next section (section 6). It is interesting to note that even though the estimated coefficients indicate the opposite ($|\hat{\beta}_{KDRI}^{\text{top }85\%}| > |\hat{\beta}_{KDRI}^{\text{bottom }15\%}|$), the average marginal effects show that the intent for low quality organs is more sensitive to the changes in the quality level of the organ: a one unit decrease in the KDRI (increase in quality) leads to an average increase of 31% in the probability of recovery for low quality organs, whereas a one unit decrease in the KDRI results in an average increase of 13% in the probability of recovery for high quality organs.

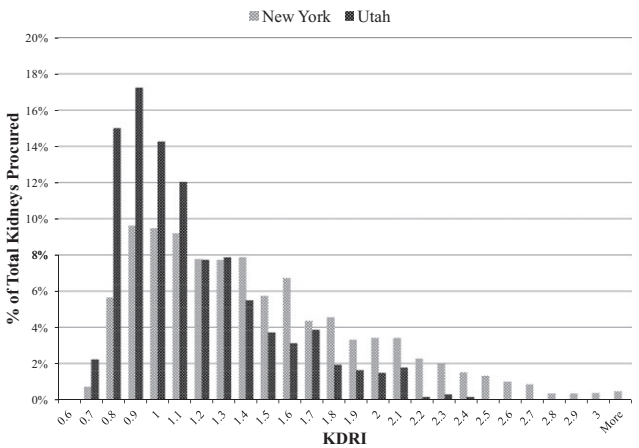
We also report the marginal effects of covariates at the mean values when the value of one covariate changes by 50%. Based on the estimated coefficients available in Table 2, for a typical lower quality donor (bottom 15% quality) who has the average values of all three variables (i.e., $KDRI_i = 2.27$, $W_{jkt} = 1.83$, and $HHI_{jk} = 0.39$): (*i*) a 50% increase in the donor quality (50% reduction in the $KDRI_i$) would result in a 15.1% increase in the probability of recovering his/her kidney; and (*ii*) a 50% increase in the waiting time would result in a 1.2% increase in the probability of recovering his/her kidney. Similarly, for a typical higher quality donor (top 85% quality) who has the average values of all three variables (i.e., $KDRI_i = 1.17$,

W_{jkt} = 1.79, and HHI_{jk} = 0.41): a 50% increase in the donor quality (50% reduction in the $KDRI_i$) would result in a 4.2% increase in the probability of recovering his/her kidney. Both the parameter estimate and the average marginal effect of the waiting time for the top 85% quality sample is insignificant, hence we do not report its marginal effects. Overall, we conclude that the intent for low quality organs is more sensitive to the changes of organ quality than the intent for higher quality organs since the marginal effect of varying the kidney quality by 50% is 15.1% for bottom 15% quality sample and 4.2% for the top 85% quality sample.

6. Counterfactual Analysis

The procurement rates of the deceased-donor kidneys exhibit significant variation across different DSAs. This is illustrated in Figure 7 for the NYRT OPO in New York vs. UTOP OPO in Utah. In particular, UTOP OPO procures better quality organs than NYRT OPO. 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 became available in New York, they could have been procured, increasing the organ supply. Although Figure 7 shows just 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 new kidney allocation system, which became effective in December 2014, lower quality kidneys are shared 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 new policy allows those kidneys to be offered directly in their regions followed by the entire country. One can also consider offering the lower quality kidneys nationally without offering them regionally first.

Figure 7 Histogram of Number of Kidneys Procured for Different KDRI at Two Different OPOs



The specific change in the kidney allocation policy is to share the bottom 15% quality of the organs more broadly (i.e., regionally). This section focuses on the impact of this policy change and quantifies its potential benefits. We also study the impact of sharing the low quality organs nationally and increasing the low quality threshold to 20% from 15%.

We have a total of 11,363 observations in the lowest 15% quality in our data set.[16] We run the endogeneity-corrected probit regression described in section 5 with the same variables over the sample of the bottom 15% quality kidneys, separately for each blood type. Hence, we obtain the estimated coefficients $\hat{\beta}_{0,k}^{\text{bottom15\%}}$, $\hat{\beta}_{KDRI,k}^{\text{bottom15\%}}$, $\hat{\beta}_{W,k}^{\text{bottom15\%}}$, and $\hat{\beta}_{HHI,k}^{\text{bottom15\%}}$ for each blood type k. To estimate the additional number of kidneys procured per year, in our regional sharing analysis, we first substitute the largest median waiting time in donor i's region r for blood type k in quarter t (W_{rkt}^{Max}) as the median waiting time of the donor i. Then, for each donor i and blood type k, we calculate the estimated probability of procurement using the following probit model:

$$\hat{Y}_{i,k}^{\text{Reg}} = \Phi(\hat{\beta}_{0,k}^{\text{bottom15\%}} + \hat{\beta}_{KDRI,k}^{\text{bottom15\%}} * KDRI_i + \hat{\beta}_{W,k}^{\text{bottom15\%}} * W_{rkt}^{\text{Max}} + \hat{\beta}_{HHI,k}^{\text{bottom15\%}} * HHI_{jk}). \tag{13}$$

Therefore, we find the total additional number of kidneys procured per year with regional sharing as follows:

$$\sum_{k\in\{A,B,O,AB\}} \left(\frac{2 * \sum_{i=1}^{n_k} \hat{Y}_{i,k}^{\text{Reg}} - AP_k}{42} * 4 \right), \tag{14}$$

where AP_k is the actual number of blood type k kidneys procured among low quality donors (bottom 15%) during the period of our study, n_k is the number of low quality donors for blood type k. Note that we multiply $\sum_{i=1}^{n_k} \hat{Y}_{i,k}^{\text{Reg}}$ by two since our unit of analysis is a kidney and whenever there is a procurement, two kidneys are procured; in addition, we have 42 quarters during the period of our study. The additional number of kidneys procured per year for each blood type under regional sharing is reported in the third column of Table 3.

We also conduct an analogous study under national sharing. As indicated above, national sharing is not considered in the new kidney allocation system. However, this counterfactual analysis calculates the expected number of additional kidneys which may arise due to a national sharing policy and compares

Table 3 Number of Additional Kidneys Procured Per Year for the Bottom 15% Threshold under Regional and National Sharing

		Regional sharing Number of additional kidneys procured per year [95% confidence Interval]	National sharing Number of additional kidneys procured per year [95% confidence Interval]
2000–2010	A	7.70	19.07
		[7.14; 7.79]	[18.73; 19.36]
	AB	*	*
	B	3.24	6.72
		[3.10; 3.45]	[6.50; 6.85]
	O	28.70	63.07
		[28.63; 29.38]	[62.47; 63.47]
	Total	**39.64**	**88.86**
		[39.24; 40.25]	[88.32; 89.32]
2006–2010	A	23.16	57.82
		[22.56; 23.60]	[56.82; 57.81]
	AB	*	*
	B	5.07	11.56
		[3.10; 3.45]	[11.08; 11.65]
	O	29.38	59.51
		[28.84; 30.10]	[58.38, 59.58]
	Total	**57.60**	**128.89**
		[56.66; 58.43]	[126.85; 128.47]

Notes. *Insufficient sample size for blood type AB to obtain reasonable estimates.

its impact to that of the current regional sharing policy. To estimate the additional number of kidneys procured per year, in our national sharing analysis, we first substitute the largest median waiting time (in the whole nation) for blood type k in quarter t (W_{kt}^{Max}) as the median waiting time of the donor i. Then, similar to the regional sharing estimation above, we calculate the estimated probability of procurement $\hat{Y}_{i,k}^{\text{Nat}}$ for each donor i with blood type k using the probit model. Therefore, the additional number of kidneys procured per year with national sharing is

$$\sum_{k\in\{A,B,O,AB\}} \left(\frac{2 * \sum_{i=1}^{n_k} \hat{Y}_{i,k}^{\text{Nat}} - AP_k}{42} * 4 \right). \qquad (15)$$

The additional number of kidneys procured per year for each blood type under national sharing is reported in the last column of Table 3. We also repeat this analysis using more recent 5 years data for which we run the endogeneity-corrected regressions over the period between 2006 and 2010. The last five rows of Table 3 show the results when the last five years is considered in the estimations. Note that in addition to the point estimates, we report the 95% confidence intervals.[17] 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.

The rest of this section quantifies the impact of adjusting the quality threshold from the lowest 15% (see Table 3) to the lowest 20% (see Table 4). We repeat the analysis of the bottom 15% quality kidneys, using expanded data including all the donors with the lowest 20% quality kidneys. Increasing the quality threshold increases the additional number of kidneys procured for all blood types: the total number of kidneys increases from 58 to 79 under regional sharing and from 129 to 174 under national sharing (these numbers apply to the most recent five years in the sample, 2006–2010). Similar to the results in Table 3, as seen in Table 4, national sharing results in a greater increase of procured kidneys than regional sharing, although the increase of 95 kidneys per year (79 to 174) under 20% is larger than the increase of 71 kidneys (58 to 129) under 15%. The effect of blood type under the policy change is different, which might suggest a more tailored policy change could enhance the total increase. Blood types A and B enjoy a greater increase of procured kidneys when moving from 15% to 20% than type O. Hence, a possible policy adjustment could be that the lowest 20% quality of blood types A and B kidneys be shared more broadly while retaining 15% for blood type O.

We list the percentage supply increases in Table 5. We include the percentage of all procured kidneys and the percentage of the lowest 15% quality (in the time period 2006–2010). While these percentage increases may appear to be modest, they provide a perspective on how the supply (both total and lower quality sources) are affected by the policy changes. We can see that the broader sharing of the lowest 15% quality kidneys nationally increases the supply of all procured kidneys by 0.9% (1.2% for lowest 20% quality kidneys).

Table 4 Number of Additional Kidneys Procured Per Year for the Bottom 20% Threshold under Regional and National Sharing

		Regional sharing Number of additional kidneys procured per year [95% confidence interval]	National sharing Number of additional kidneys procured per year [95% confidence interval]
2006–2010	A	42.14	95.86
		[41.00; 41.16]	[95.68; 96.72]
	B	6.09	16.76
		[5.86; 6.51]	[16.56; 17.20]
	O	30.84	61.73
		[29.93; 31.31]	[60.25, 61.86]
	Total	**79.07**	**174.35**
		[77.41; 79.35]	[173.08; 174.89]

Table 5 Total Number of Additional Kidneys Procured under Regional and National Sharing with Respect to Annual Average Volumes (2006–2010 Data)

	Increase with respect to total number of kidneys procured per year on average between 2006 and 2010 (N = 15,030)	Increase with respect to bottom 15% quality kidneys procured per year on average between 2006 and 2010 (N = 1764)
Bottom 15% regional sharing	58/15,030 = 0.4%	58/1764 = 3.3%
Bottom 15% national sharing	129/15,030 = 0.9%	129/1764 = 7.3%
Bottom 20% regional sharing	79/15,030 = 0.5%	79/1764 = 4.5%
Bottom 20% national sharing	174/15,030 = 1.2%	174/1764 = 9.9%

This represents an increase of 7.3% of these lowest quality kidneys (9.9% for the lowest 20% quality kidneys).

To put the increase of 129 procured kidneys per year (under national sharing of the lowest 15% quality) in perspective, there are 14 of the 58 DSAs in the United States in 2009 with 129 or fewer kidneys available. Therefore, this expected increase of 129 reflects the addition of a small- to medium-sized DSA to the UNOS network.

7. Concluding Remarks

We study how the deceased-donor kidney supply can be enhanced through geographic sharing in the United States. In particular, we examine how demand side pressure affects the supply of deceased-donor organs for transplant. We formulate and test hypotheses to glean the impact of organ quality, waiting time, and competition on organ procurement decisions, that is, the intent. Most importantly, we find that broader sharing of low quality kidneys can lead to a significant increase in the organ supply. To be more specific, both higher organ quality and longer waiting times in a DSA 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 (i.e., sharing lowest 15% quality kidneys nationally) is expected to yield 129 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 around 1% of all procured kidneys per year on average between 2006 and 2010, and 7.3% of the bottom 15% quality kidneys procured annually on average between 2006 and 2010. Moreover, there are 14 of the 58 DSAs in the United States in 2009 with 129 or fewer kidneys available. Therefore, this expected increase of 129 kidneys reflects the addition of a small- to medium-sized DSA.

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Notes

[1]See http://optn.transplant.hrsa.gov/data, accessed on August 10, 2017.
[2]During 2006–2011, more than 4500 patients died each year while waiting for a kidney.
[3]In the remainder of the study, we will refer to the unique geographic area that the OPO serves as the DSA. Also, note that there is one-to-one relationship between an OPO and its DSA.
[4]Department of Health and Human Services (Ruling No: CMS-1543-R, December 21, 2006). Available at http://www.cms.gov/Regulations-and-Guidance/Guidance/Rulings/Downloads/CMS1543R.pdf, accessed on August 10, 2017.
[5]We extend the control function approach advocated by Petrin and Train (2010) to a multi-variate context to correct for endogeneity. This technique is described in detail in Appendix S4.
[6]https://optn.transplant.hrsa.gov/news/revised-national-kidney-transplant-allocation-system-is-now-in-place, accessed on August 10, 2017.
[7]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.
[8]Our analysis only uses the weaker condition that $\bar{L} > 1/\gamma(\tau)$ where τ is the longest waiting time to get a transplant in equilibrium.
[9]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. Consider the scenario where all patients have a strictly decreasing $l(t)$. Now consider two patients who have waited t_1 and t_2 where $t_1 > t_2$. Consequently, $l(t_1) < l(t_2)$. The implication is that patient 1 would accept all the kidneys patient 2 would accept (that is, those with quality l such that $l(t_2) < l$) as well as some kidneys patient 2 would not accept (those kidneys with quality l such that $l(t_1) < l < l(t_2)$), since patient 1's threshold is lower than that of patient 2. Thus, there will never be kidneys of a quality acceptable to patient 2 which will be

offered to patient 2 since they will be already accepted by patient 1 beforehand, in this over-loaded queue setting where demand outstrips supply. Consequently, without loss of generality, we can replace the decreasing $l(t)$ function with a nondecreasing function without affecting the acceptance behavior of patients.

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

[11]Only 0.3% of the observations have the disposition code 3.

[12]The generalized bivariate Probit model only assumes that ε_{ij} follows a normal distribution, however without loss of generality we can assume standard normal distribution in our specification.

[13]Concordance (sometimes called the C-statistic or C-index) is a measure of goodness of fit for a binary outcomes model. It is also equal to the area under the receiver operating characteristic (ROC) curve. We report the in-sample concordance. According to Hosmer and Lemeshow (2000), as a general rule, concordance between 70% and 80% is considered acceptable.

[14]In addition, we divide the data into different groups by blood type and estimate the coefficients in the endogeneity-corrected model. The results of these estimation models are available in Appendix S5.

[15]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 the figure on slide 16 of the Proposal to Substantially Revise the National Kidney Allocation System Document, available at http://www.transplantpro.org/wp- content/uploads/sites/3/Board_06-2013_Kidney_Committee_Actions1.pdf, accessed on August 10, 2017.

[16]Whenever a donor has a KDRI value higher than the 85th percentile of KDRI values of all donors in the observed year (displayed in Appendix S5, Table E9), the organ recovered from this donor belongs to the bottom 15% quality.

[17]Confidence intervals are displayed in brackets. These intervals are obtained through a *bootstrap* approach. In order to obtain the standard errors for the mean value of the total estimated number of kidneys procured, we draw a random sample of size equal to the number of observations for each blood type with replacement (i.e., full sample) where each observation i is sampled subjected to an independent Bernoulli trial with parameter $\hat{Y}_i$ (estimated probability of procurement). Then, the confidence intervals are calculated by finding the mean ($\hat{\mu}$) of the samples and standard errors of the means ($\widehat{\mathrm{SE}}$) for 1000 bootstrap replications for each blood type (separately for regional and national sharing). We obtain repeated samples to calculate the upper ($\hat{\mu} + 1.96 \times \widehat{\mathrm{SE}}$) and lower ($\hat{\mu} - 1.96 \times \widehat{\mathrm{SE}}$) end points of the 95% confidence intervals. The values above the confidence intervals (i.e., point estimates) in Table 3 are calculated directly from the estimated coefficients, so they are not the midpoints of the simulated confidence intervals.

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Supporting Information

Additional supporting information may be found online in the supporting information tab for this article:

Appendix S1: Proofs.
Appendix S2: Details of the Calculation of Variables.
Appendix S3: An Additional Figure.
Appendix S4: Endogeneity Correction Method.
Appendix S5: Additional Tables.