The Role of Kidney Allocation Policy in Addressing Kidney Shortages

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Abstract

Compared to policies intended to increase donations, policymakers have largely ignored the role of allocation policies in addressing current kidney shortages. This paper examines the impacts of prioritizing certain types of candidates for deceased-donor kidney allocation. Using a regression discontinuity design, I find that increased access to deceased-donor kidneys dramatically decreases mortality rates (by 43 percent relative to baseline), while decreasing the likelihood of receiving a living-donor transplant. Both of these effects vary substantially across race, blood type, and dialysis status. The result implies that prioritizing for transplant candidates, who are less prone to crowd-out, in deceased-donor kidney allocation could make policies, designed to increase the number of deceased donors, more effective.

Keywords: transplant, organ allocation, crowd-out, heterogeneity
JEL Codes: D61; H41; I12; I18

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1 Introduction

Kidney transplant is a treatment that prolongs the lives of patients with kidney failure. Although many patients with kidney failure are eager to receive kidney transplants, a large and rapidly increasing excess demand exists because the transplantable kidney supply depends only on altruistic deceased and living donations according to the National Organ Transplant Act (NOTA, 1984), which bans the sale of organs.[1] Figure 1 shows the trends in the kidney transplant market from 1997 to 2016. The number of candidates added to the waiting list for deceased donor kidneys is always greater than the number of candidates receiving kidney transplants, which results in a dramatic increase in the number of candidates remaining on the waiting list each year.

As there is no market that distributes scarce organs using the price mechanism, Organ Procurement and Transplantation Network (OPTN) manages the organ donation and allocation process. According to their strategic plan[2], OPTN aims to achieve "equitable allocation" while also improving transplantation quantity and patient outcomes, specifically mortality. The current kidney allocation system emphasizes equity by placing a high priority on individual waiting time for transplantation. Because allocation based on waiting time does not guarantee the best use of donated kidneys, OPTN has supplemented the allocation system by prioritizing certain types of candidates to improve patient outcomes.[3]

However, to date, the role of the allocation system in increasing transplant quantity has received relatively little consideration. Instead, OPTN has focused on increasing the supply of organ donors. Representative examples of this approach include first-person consent

[1] NOTA (1984) bans the sale of human organs. It states that it is "unlawful for any person to knowingly acquire, receive, or otherwise transfer any human organ for valuable consideration for use in human transplantation". Because allocation based on candidates' willingness to pay is not applicable, the government is obliged to allocate donated kidneys on behalf of the market. In the United States, the Organ Procurement and Transplantation Network (OPTN), established by NOTA, manages donated kidney allocations.

[2] https://optn.transplant.hrsa.gov/governance/strategic-plan/, information access on the web, last accessed on March 27, 2019.

[3] For example, pediatric candidates younger than 18 years of age, whose expected post-transplant survivals are longer than those of adult candidates have received priority for young deceased donor kidneys since 2005. In 2014, OPTN started to include the pre-waitlist registration dialysis time in a transplant candidate's waiting time as the duration of dialysis is highly related to patient survival.

legislation (Levin 2014), the provision of financial incentives for living organ donors such as tax deductions, paid leave (Wellington et al. 2011) and educational programs (Siminoff et al. 2009). Although policies regarding organ supply would be a direct method to increase the number of transplants, designing a kidney allocation system helpful in achieving this goal might be still meaningful under the current large kidney shortages.

In this paper, I ask whether prioritizing certain types of candidates in a kidney allocation system can increase the number of kidney transplants while achieving an improvement in patient mortality. To identify the types of candidates, this paper focuses on the problem of candidates choosing a kidney source between deceased and living donor kidneys. In the U.S., most living donors designate the recipients of their kidneys, while most deceased donors do not designate recipients. Hence, deceased donor kidneys can be matched to all waitlisted candidates based on the kidney allocation policy, while living donor kidneys benefit only the designated recipients. When the chance of receiving a deceased donor kidney increases, some candidates may change their preference from a living donor kidney to a deceased donor kidney (crowd-out) to avoid using kidneys from a known person. However, the living donor kidney cannot be used for other kidney candidates as it is only available for the designated recipient, which limits an increase in the total number of transplants. Hence, if a kidney allocation policy prioritizes candidates who are less likely to be on the margin between a deceased and living donor transplant, then the number of total kidney transplants may increase nearly one-for-one with an increase in the number of deceased donor kidneys.

I also examine the heterogeneous effect of kidney transplantation on the mortality risk of candidates as a measure of patient outcomes.[4] If candidates who are less likely to be crowded out also experience small improvements in mortality in comparison to candidates who are more likely to be crowded out, then overall mortality outcomes would be worsened when we prioritize the former candidates. Hence, an optimal allocation policy would target

[4]In the OPTN strategic plan, reducing waitlist mortality and increasing graft and patient survival are set as key metrics in achieving the improvement of patient outcomes (https://optn.transplant.hrsa.gov/governance/strategic-plan/goal-5/, information access on the web, last accessed on March 27, 2019).

kidney candidates who are less likely to be crowded out and show relatively large mortality improvements in response to positive supply shocks of deceased donor kidneys.

I use restricted-use data from the Scientific Registry of Transplant Recipients (SRTR), which contains detailed information on the universe of kidney transplant candidates, donors, and transplants in the U.S. I focus on the variation in the likelihood of receiving a deceased donor kidney across individuals resulting from a kidney allocation policy - a sensitization point policy - that prioritizes candidates with a highly sensitive immune system. As transplantation is a surgery that replaces a patient's damaged organ with another person's organ, whether the recipient's immune system regards the transplanted organ as a target of removal is important for the success of the surgery. The sensitivity of an individual's immune system is measured by a calculated panel reactive antibody (CPRA) value that ranges from 0 to 100. As it is difficult to find compatible donor kidneys for highly sensitized candidates with high CPRA values, since 2009, OPTN has prioritized candidates with a CPRA value of 80 or greater by assigning them additional kidney allocation points, which increases their rank on the transplant waitlist. Using the plausibly exogenous variation around the CPRA 80 threshold, I compare candidates with CPRA values above and below the sensitization point policy cutoff using a fuzzy regression discontinuity (RD) design.

First, I find that an increase in access to deceased donor kidneys significantly reduces a candidate's likelihood of receiving a kidney from a living donor. My central estimates show that a 10 percentage-point increase in the probability of receiving a deceased donor kidney decreases the likelihood of opting for a living donor kidney by approximately 1.7-1.9 percentage points. This result is similar to those of Fernandez et al. (2013), Howard (2011), and Sweeney (2010), who focus on identifying the trade-offs between kidney sources.[5] To address the endogeneity of the kidney source choice problem, Fernandez et al. (2013) and

[5]Fernandez et al. (2013) show that one additional cadaveric kidney donation reduces living kidney donation by 0.2 to 0.5 units. Howard (2011) find that a decrease of five cadaveric kidney donations is correlated with an increase of one living kidney donation. Sweeney (2010) show that a 10 percentage-point increase in the likelihood of receiving a deceased donor kidney reduces the probability of receiving a living donor kidney by 2-3 percentage points.

Howard (2011) use geographic variation, i.e., traffic safety laws and kidney transplantation wait time, respectively. Regarding the identification strategy, my paper is closely related to that of Sweeney (2010), who examines the trade-offs between kidney sources with RD estimation by exploiting the variation caused by a traditional sensitization point policy in a sample obtained between 1997 and 2006. The prior research, however, focuses only on identifying the existence of overall trade-offs between kidney sources and provides little understanding of the heterogeneity across candidate subgroups and the effect on mortality risks.

Second, I derive the causal effect of the additional chance of receiving a deceased donor kidney in reducing mortality risks. I find that the probability of death before receiving a kidney transplant - known hereafter as "waitlist mortality" - within 2 years decreases by 2.8 percentage points when kidney candidates receive the sensitization point benefits. This is a substantial effect, implying a 43 percent decrease compared to the baseline mortality rate of 6.5 percent. Although OPTN focuses on waitlist mortality, presumably a more important issue for patients is the overall mortality rate, i.e., unconditional on whether they receive a kidney transplant. This effect can be captured when we assess both the waitlist mortality and deaths after receiving a kidney transplant within the same period. I find evidence that the sensitization point benefit is also effective in reducing overall mortality. The overall mortality rate within 2 years[6] decreases by 2.53 percentage points when kidney candidates receive sensitization point benefits, which implies a 34 percent decrease compared to the average mortality rate of 7.4 percent.

Finally, I examine whether the RD estimates on trade-offs between kidney sources and mortality rates differ across candidates with different demographics. Kidney candidates with blood type O, who are African-American, and who are currently receiving dialysis treatment are relatively unlikely to switch kidney sources from living donor kidneys to deceased donor kidneys when access to a deceased donor kidney increases. Also, these candidates groups

[6]Though insignificant, the effect on the overall mortality rate within 1 year (0.7 percentage points) is also sizable and implies a reduction of 26 percent compared to the baseline mortality rate.

show relatively large reductions in waitlist and overall mortality rates when access to deceased donor kidneys increases. These heterogeneous results imply that prioritizing these candidates in deceased donor kidney allocation would result in a larger number of kidney transplants while improving candidate mortality rates.

This paper proceeds as follows. The following section provides background information on the U.S. kidney transplant system and the sensitization point policy. Section 3 describes the data sources, while Section 4 explains the main identification strategy. Section 5 shows the estimation results, Section 6 tests the robustness of the results, and Section 7 concludes.

2 Institutional Details

2.1 Treatments for Patients with Kidney Failure

Kidneys remove waste from the blood and control the body's fluid balance. Kidney damage and improper function (kidney failure[7]) increase the risk of the accumulation of blood wastes in the body, which results in death without treatment. There are two types of treatment, namely, dialysis and kidney transplantation, that enable patients with kidney failure to live prolonged lives. Dialysis treatment filters patients' blood using artificial tools that substitute for the function of their own kidneys.[8] Although it is a relatively low-risk treatment, patients need to receive dialysis at least three times a week permanently, and each treatment takes a long period of time (approximately four hours), which limits patients' quality of life. As the duration of dialysis treatment increases, the risks of infection (Ronco et al. 2006) and mortality (USRDS 2018) also increase.

The other treatment is kidney transplantation. As the transplanted kidney performs the work of the patient's failed kidney, no other treatment for kidney failure is needed except

[7]The status that less than 15 percent of the kidney is working. (National Institute of Diabetes and Digestive and Kidney Diseases, NIDDK)

[8]NIDDK categorizes dialysis into two groups, hemodialysis and peritoneal dialysis, based on the dialysis process (https://www.niddk.nih.gov/health-information/kidney-disease/kidney-failure, information access on the web, last accessed on March 27, 2019).

for the permanent use of immunosuppressants, which reduce the risk of rejection of the transplanted kidney by suppressing the transplant recipient's immune system. There are two sources of transplantable kidneys, living donors and deceased donors. In living kidney donations, donors give one of their two kidneys while they are alive. By contrast, deceased kidney donation is the process of kidney donation at the time of the donor's death. These two kidney donation types also differ in terms of the donor's relationship with the recipient. In most cases, living donors designate the candidates who will receive their kidneys and have a close relationship with the recipients, such as parents, spouses, children, and friends. However, most deceased kidney donors do not designate the recipients of their kidneys.[9] All of the donated kidneys for which recipients are not designated are allocated to patients on the waitlist for deceased donor kidneys using OPTN's allocation rules. Hence, the effect of the allocation rules is highly related to deceased donor kidney transplants.

2.2 A Candidate's Choice between the Two Kidney Sources

In this section, I establish a simple conceptual framework that illustrates that a candidate's kidney choice depends on the transplant benefits and costs of receiving a living donor kidney transplant. Let us assume that a candidate has a potential living donor willing to donate a kidney when it is needed. The kidney candidate chooses whether he will continue waiting for a deceased donor kidney offer on the waitlist or receive a living donor kidney. The net benefits of choosing a living donor kidney instead of waiting for a deceased donor kidney are twofold. First, there is little or no wait time for a living kidney transplant. As time on the waitlist increases, a candidate's quality of life worsens, and the candidate's preference for a living donor kidney with little wait time could increase (Howard 2011; Segev et al. 2007). Moreover, previous studies have shown that the survival outcomes of living donor kidney

[9]Directed deceased donation is legally authorized by the Uniform Anatomical Gift Act (UAGA) and by most states anatomical gift laws. The exact number of directed deceased donations is not available in the SRTR dataset. However, according to OPTN, approximately 100 of the more than 100,000 transplants each year are directed donations (https://optn.transplant.hrsa.gov/news/optn-information-regarding-deceased-directed-donation/, information access on the web, last accessed on March 27, 2019).

recipients are better than those of deceased donor kidney recipients, which implies a higher quality of transplanted kidneys (Roodnat et al. 2003; Weitz et al. 2006). This quality difference does not depend on the candidate's wait time. Hence, the overall net benefits of receiving a living donor kidney transplant increase over the candidate's wait time.

The cost of waiting for a deceased donor kidney includes the expenses of the dialysis treatments. While waiting for a deceased donor kidney, dialysis treatment is an inevitable procedure to prolong the candidate's life. However, when the candidate decides to receive a living donor kidney at a certain time (t), he needs to receive dialysis treatments until that time. Hence, there is no difference in dialysis treatment costs between the two options. Moreover, living donor kidney recipients face "emotional costs" for potential living donors. In contrast to deceased donors, who donate their kidneys after their death, living donors need to undergo a surgery to extract a kidney while they are alive. Although the medical costs are covered by the recipient's health insurance, coverage of lost wages and transportation and lodging costs is not guaranteed. Additionally, as the expected health risks for kidney donors are uncertain (Young et al. 2008; Mjøen et al. 2014; Muzaale et al. 2014) , a candidate would be concerned about a closely related living donor's future health status. If the candidate decides to use a living donor kidney, then emotional costs will always exist, and the amount would be constant over the wait time.

Panel (a) of Figure 2 shows how the net costs and benefits determine the candidate's kidney source choice. The quality benefit and emotional costs of using a living donor kidney are represented as α and β, respectively. The candidate's preference for a living donor kidney transplant relative to waiting for a deceased donor kidney offer increases over the wait time, and he decides to use a living donor kidney at t^*, when the net benefits equal the costs. It is uncertain when a kidney candidate receives an acceptable deceased donor kidney offer, and we assume a bell-shaped deceased donor kidney offer density over the wait time. A candidate who receives an acceptable deceased donor kidney offer before t^* receives a deceased donor kidney transplant (A), but another candidate who does not receive an offer until t^*, switches

to a living donor kidney (B). Unlike panel (a), if a candidate's emotional cost (β) is smaller than the quality benefit of using a living donor kidney (α) at the initial point ($t = 0$), then he will receive a living donor kidney without registering on the waitlist.

Not all kidney candidates have potential living donors when they are waitlisted for deceased donor kidneys as we assumed in the framework. Although I relax this assumption and allow kidney candidates to find their potential living donors while waiting for deceased donor kidneys, these candidates' kidney source choice problem still can be explained (panel (b)). Until they find potential living donors, their only option is waiting for a deceased donor kidney. Hence, the framework can be modified as the initial time ($t = 0$) of the kidney source choice changes to the time when kidney candidates find their potential living donors ($t = t_0$). In that case, the cutoff time when candidates switch kidney sources will increase ($t^* \Rightarrow t^{**}$).

With this framework, we can explain why increased access to a deceased donor kidney crowds out the choice of living donor kidneys. An allocation policy that prioritizes certain groups of waitlisted candidates increases their rank on the waitlist and the probability of receiving a deceased donor kidney offer earlier. Then, the density of receiving a deceased donor kidney offer moves left as shown in panel (c). Some candidates who would choose living donor kidneys without the policy would receive deceased donor kidney offers before t^* under the policy, which implies crowd-out of living donor kidney choices. Hence, the amount of crowd-out depends on the net benefit and cost of choosing a living donor kidney instead of waiting for a deceased donor kidney offer and the availability of potential living donors, which are the key factors that determine t^*.

2.3 Matching Donor Kidneys to Patients

Not all donated kidneys can be transplanted to candidates. Only kidneys donated by compatible donors can be transplanted to the patient, and the compatibility is determined by blood tests, blood type, tissue type, and cross-matching. First, the blood type should be

compatible. There are 4 basic blood types: A, B, O, and AB. A patient with type A blood can receive a kidney from a donor with type A or O blood. A patient with type B blood can receive a kidney from a donor with type B or O blood. A patient with type AB blood can receive a kidney from a donor with any blood type. On the other hand, a patient with type O blood can only receive a kidney from a donor with the same blood type. Second, a donor should have similar body tissue types as a patient. When a patient-donor pair shares many tissue types, the transplanted kidney is more likely to adapt well in the recipient's body. Third, the antibodies of a patient should be less likely to attack a transplanted kidney. This factor is important in minimizing the risk of rejection of the transplanted kidney and medical tests check the sensitivity of a patient's antibodies to a potential donor's tissue types.

When a living donor's kidney is compatible with the characteristics of a designated recipient, he or she receives the donated kidney. In the case of a deceased donor kidney not designated to a certain recipient, OPTN ranks the kidney transplant candidates for the kidney and allocates the kidney to the highest ranked and most compatible candidate. OPTN allocates deceased donor kidneys based on geographical proximity from the transplant center where the kidney is recovered and the kidney points. The distance from the donor hospital is important because a longer period of time between kidney discharge from the donor and transplant surgery might lead to worse transplant results (Salahudeen et al. 2004). For allocation based on geographical proximity, the United States is divided into 58 donor service areas (DSAs), and all transplant centers belong to one of the DSAs. Additionally, there are 11 regions, and each region consists of several DSAs. If a deceased donor kidney becomes available, kidney transplant candidates registered in the DSA where the donor is located receive higher priority. If the kidney is not compatible with any candidate waitlisted in the DSA, candidates registered in the region where the donor DSA is included are matched to the kidney. Lastly, a kidney that could not be accepted by candidates in the region is matched to candidates registered in the U.S. The other factors that rank candidates in each geographical category are the kidney points. The kidney points are determined by each candidate's

age, waiting time, history of prior living donation, and value of sensitization (OPTN 2017). Detailed points are presented in Table 1. Candidates who are younger, better matched, waitlisted longer, and more sensitized are more likely to have higher kidney points.

2.4 Sensitization Points

Among the factors in the kidney points in Table 1, this study focuses on the value of sensitization. Although a kidney transplant is the ultimate treatment for patients with kidney failure, not all transplants are successful because of infection caused by the surgery or failure of the transplanted kidney, i.e., kidney rejection. Kidney rejection occurs when the recipient's immune system recognizes the transplanted kidney as an invader and attacks the kidney.[10] Rejection is more likely to happen for patients with a high level of antibodies, i.e., sensitized candidates. Although the reason for sensitization varies across candidates, OPTN describes representative cases, such as pregnancy, previous transplants, previous blood transfusion, and viral/bacterial infections.[11] Because it is difficult to find kidney donors compatible with sensitized candidates, waiting times for these candidates are likely to be longer than those of candidates with low sensitization. To compensate for this disadvantage, OPTN's kidney allocation system provides sensitized candidates with additional kidney points that increase their rank on the waitlist and allow greater access to deceased donor kidneys.

Figure 3 shows the history of the sensitization measure and sensitization point policy changes. As of October 1, 2009, the panel reactive antibody (PRA), which ranges from 0 to 100, was used to measure the sensitivity of candidates. This value was derived by testing a patient's blood against lymphocytes (white blood cells) obtained from a panel of approximately 100 randomly chosen blood donors.[12] If the test result shows 90 reactions, the likelihood of acute rejection is 90 percent when a donor in the 100 donor pool is available. In

[10] http://columbiasurgery.org/kidney-transplant/organ-rejection-after-renal-transplant, information access on the web, last accessed on March 27, 2019.

[11] https://optn.transplant.hrsa.gov/resources/allocation-calculators/about-cpra/, information access on the web, last accessed on March 27, 2019.

[12] https://optn.transplant.hrsa.gov/resources/allocation-calculators/about-cpra/, information access on the web, last accessed on March 27, 2019.

the PRA era, candidates with a PRA score of 80 or greater received an additional 4 kidney points. According to Table 1, 4 kidney points can be achieved when a candidate waits for 4 years on the kidney transplant waitlist, which implies a large benefit when we consider that the median wait time for kidney transplants is approximately 4 years (USRDS 2018).

The CPRA value has been used as a new sensitization measure since October 1, 2009.[13] Antibodies protect our body by attacking invaders from the outside (antigens). The relationship between an antibody and an antigen is similar to that between a key and a door lock. A certain type of antibody (a key) can only attack antigens with matched tissue types (a door lock). If a candidate has various antibody types, then many tissue types in a transplanted kidney would be matched with the candidate's antibodies and the probability of rejection increases. By comparing a candidate's antigen types with the frequency of the tissue types of more than 12,000 previous donors, each candidate's CPRA value shows how difficult it will be to find donors whose kidneys are less likely to be rejected. Similar to the PRA, this measure has a value ranging from 0 to 100, but the meaning of the value is slightly different. The probability of finding a well-matched donor for the candidate when n donors are considered is $1 - (CPRA)^n$[14] (Keith et al. 2016). Although the sensitization measure was changed in 2009, candidates with a CPRA value of 80 or greater continued to receive an 4 additional kidney points. On December 3, 2014, the sensitization point policy changed to a sliding scale as shown in Table 2.

3 Data

This study used data from the Scientific Registry of Transplant Recipients (SRTR). The SRTR data system includes data on all donor, wait-listed candidates, and transplant recipients in the US, submitted by the members of the Organ Procurement and Transplantation

[13]CPRA was introduced on December 5, 2007, but the original PRA was used in deceased donor kidney allocation until 2009.

[14]If CPRA is 90 percent, then the probability of finding a well-matched donor when the candidate is matched to 100 donors is not 10 percent but rather 99.997 percent.

Network (OPTN). The Health Resources and Services Administration (HRSA), U.S. Department of Health and Human Services provides oversight to the activities of the OPTN and SRTR contractors. The data were extracted on June 2, 2017, and contain individual-level information, such as age, gender, race, blood type, education level, and primary source of insurance. As all the transplant centers' pre-evaluation tests for waitlist registration include blood tests, the dataset includes the initial CPRA values for all candidates placed on the waitlist. However, candidates who receive living donor kidneys without being placed on waitlists do not have CPRA values in the dataset, and I exclude these candidates from the analysis. Each transplant center has its own plan for registered candidates' antibody screening, and candidates' CPRAs are updated whenever transplant centers report the most recent unacceptable tissue types using their antibody type information (OPTN 2017). Hence, the SRTR dataset contains all CPRA values as a history of each candidate. However, the updating term of CPRA varies among transplant centers, as there is no national rule of updating frequency by the OPTN.

To exploit the effect of a sensitization point policy that provides 4 additional kidney points to candidates with CPRA values of 80 or greater, I restrict the sample to candidates registered from October 1, 2009 to December 3, 2014. As the dataset was extracted on June 2, 2017, there is a gap between the end of the analysis period and the end of the dataset. The health outcome status, such as transplant or death, of some candidates registered during the analysis period might have changed during the gap. If I treat these outcomes in the same way as the other outcomes that occurred during the analysis period, the result would be biased, as these outcomes are affected by the new sliding scale sensitization point policy. Hence, this study does not include health outcome changes that occurred after the end of the analysis period.

I exclude candidates who are registered on the waitlist for multiple organs and who are less than 18 years old because they receive additional benefits in the deceased donor organ

allocation.[15] I include only first-time transplant candidates because, all else being equal, the choice between the two kidney sources is similar for candidates without prior transplants as for the other candidates. Additionally, candidates with prior living donor kidney transplants have a different living donor pool compared to a first-time transplant as the donor cannot donate his kidney again.

After the above sample restrictions, there are 152,247 candidates who have ever joined kidney transplant waitlists during the analysis period and more than 68 percent of candidates have zero CPRA. When I estimate the fitted line using RD, this large number of candidates with zero CPRA may drive the estimation results too much. Hence, I exclude the candidates with zero CPRA from the estimation sample. The final sample includes 49,055 kidney transplant candidates. Table 3 shows the summary statistics of the key variables of the sample. In the analysis period, 23 percent of candidates received kidney transplants and 2/3 of transplant recipients received deceased donor kidneys. A total of 18 percent of candidates were removed from the waitlist because of sickness or death before receiving kidney transplants, and the mortality rate increases to 20 percent when I include deaths after receiving kidney transplants. Columns (2) and (3) show the summary statistics of the CPRA subgroups. Unsurprisingly, compared to kidney transplant recipients with a CPRA less than 80 (column (2)), transplant recipients with a CPRA value of 80 or greater (column (3)) are less likely to receive living donor kidneys. This overall difference can be explained by two mechanisms. First, according to the definition of CPRA, it becomes more difficult to find compatible donors when a candidate's CPRA increases, and finding compatible living donors is much more difficult than finding compatible deceased donors as the size of the available living donor pool is smaller than that of deceased donors. Moreover, due to the sensitization point benefit, some candidates with a CPRA value of 80 or greater would switch their kidney source to deceased donor kidneys from living donor kidneys.

[15]Under the deceased donor kidney allocation rules by OPTN, candidates under 18 receive priority in the following ways. (1) pediatric kidney allocation points (Table 1) (2) match classification priority for zero-ABDR mismatches (3) match classification priority for donated kidneys at the local, regional, and national levels.

4 Estimation Strategy

To identify the causal effect of an increase in access to a deceased donor kidney on living donor kidney choice and mortality risk, I exploit the discontinuity at the CPRA 80 resulting from the sensitization point policy. I estimate the effects using the fuzzy RD approach using the CPRA as the running variable.[16] The estimation equation is shown below.

$$Y_i = \alpha + \beta_0 CPRA80_i + f(X_i) + u_i \tag{1}$$

where i denotes a kidney transplant candidate. Y_i is the outcome of interest in the study, the likelihood of receiving a deceased or a living donor kidney and mortality rate. $CPRA80_i$ is a binary variable with a value of one if the CPRA of a candidate i is 80 or greater.[17] X_i is a running variable that measures the difference in CPRA from the threshold. β_0 is the coefficient of interest that shows the discontinuity of the outcomes between the candidates just around the CPRA 80 threshold. As explained in Section 2, each candidate has many CPRA histories that have been measured since their waitlist registration. Hence, the choice of a proper CPRA is important for a precise analysis. In the CPRA era, the eligibility for the sensitization points is determined by the most recent CPRA, and this study also used the most recent CPRA as the running variable. The function $f(X_i)$ represents the relationship between the running variable, CPRA and the outcome variables. In this study, I use the parametric approach, which uses the whole sample in the identification with quadratic polynomials and interactions (see Online Appendix A for details about how I chose the functional form).

The main identification assumption of my RD design is that candidates do not have precise control over the running variable, CPRA (Lee et al. 2008; Lee et al. 2010). When

[16] Lee et al. (2010) showed that the treatment effect in the fuzzy RD design can be interpreted as the local average treatment effect (LATE) in the instrumental variables setting.

[17] According to OPTN (2017), CPRA values are rounded to the nearest one-hundredth percent. Hence, candidates with a CPRA of 79.995 or greater receive the sensitization points. I use the 79.995 threshold to derive the difference from the threshold of the policy.

additional kidney points that increase the likelihood of receiving a deceased donor kidney offer are awarded to candidates with a CPRA value of 80 or greater, candidates placed just below the CPRA threshold have an incentive to manipulate their CPRA to receive the benefit. As explained in Section 2.4, the CPRA value depends on the variety of unacceptable tissue types matched to and likely to be attacked by each candidate's various types of antibodies. However, I argue that manipulating the running variable, CPRA, would be difficult in my context. For CPRA manipulation, candidates must be able to adjust their antibody types precisely rather than adjusting the amount of antibodies, which would be difficult to do. Moreover, a slight adjustment of antibody types may result in a large change in unacceptable tissue types for a candidate and for the CPRA value. Each antibody binds to a specific portion of the tissue, an epitope, when it attacks a tissue. As some tissues share epitopes across tissue types, an antibody can attack multiple types of tissues that share epitopes (Keith et al. 2016). Hence, increasing antibody types precisely for the sensitization point benefit would be difficult, and the benefit could be offset by a large increase in the CPRA value, which would limit the probability of finding compatible donors.

To examine evidence of CPRA manipulation, I plot the distribution of the CPRA values in Figure 4. Panel (a) presents the overall CPRA distribution with a 0.1-bin width. There is a large cluster at the lowest level of CPRA values, although I exclude candidates with a zero CPRA, which implies that most kidney candidates do not face restriction in finding compatible donors. Kidney candidates are also clustered at the highest CPRA values. Since an antibody can be matched to multiple tissue types because tissues share epitopes across types, most tissue types become unacceptable even though a patient does not have all types of antibodies. However, no large cluster is present around the CPRA 80 threshold, which would be evidence of CPRA manipulation for sensitization point benefits. To determine the existence of a cluster around the threshold in detail, panel (b) shows the histogram within a narrower window (bandwidth 3 from the threshold, 0.01 bin width). No large cluster is present at the CPRA 80 threshold, except for a cluster around CPRA 81. Additionally,

Figure 5 presents the mean frequency test results in which each circle is the number of observations in each bin, and the line is the predicted plot. The figure shows no significant discontinuity of observation frequencies at the CPRA 80 threshold.

To further test the validity of the RD design, I examine whether the observed predetermined covariates are similar around the CPRA 80 threshold. As it is difficult to manipulate the CPRA precisely, predetermined characteristics of kidney candidates are unlikely to be discontinuous around the threshold. Table 4 shows the RD estimates of the covariates. Among 18 covariates, there are only 2 characteristics, male and high school education, that show significant discontinuities at the threshold. With a large number of characteristics, it is possible that a few are significantly discontinuous, although candidates located on either side of the threshold have a similar distribution. However, it should be noted that the existence of significant discontinuities can weaken my RD estimation results. One noteworthy result is the RD estimate of gender. In the analysis sample, there exists a highly negative correlation between the share of males and the CPRA value, and this relationship can be explained by the occurrence of pregnancy[18] (Hönger et al. 2013; Hyun et al. 2012). Although pregnancy is effective in increasing the CPRA value, it is difficult to believe that the significant discontinuity in gender covariates is evidence that female kidney candidates with a CPRA value below the threshold become pregnant to achieve the sensitization point benefit. As dialysis treatment for patients with kidney failure changes the status of anemia and hormones, many women of childbearing age may experience irregular menstruation periods and have unhealthy eggs[19], and pregnancy among women on chronic dialysis accounts for only 1-7 percent of dialysis patients (Sachdeva et al. 2017).

Additionally, I test whether the changes in the predetermined characteristics affect the discontinuities of the outcomes at the CPRA 80 threshold. The discontinuous effect may

[18] Approximately 30∼50 percent of women with three or more pregnancies have a high level of antigens, which results in high CPRA (https://optn.transplant.hrsa.gov/resources/allocation-calculators/about-cpra/, information access on the web, last accessed on March 27, 2019).

[19] https://www.kidney.org/atoz/content/pregnancy, information access on the web, last accessed on March 27, 2019.

call into question the causality of the identified results using the RD estimation, because the effect could be driven by changes in the predetermined characteristics. For the test, I use the equation below.

$$Y_i = \alpha + \beta_0 X_i + \beta_1 X_i^2 + \gamma' W_i + u_i \tag{2}$$

where i denotes a kidney transplant candidate. The equation is similar to the identification equation (1). To check the discontinuities of the outcomes driven by the predetermined characteristics, I exclude the binary variable terms, $CPRA80_i$, and include the vector of predetermined characteristics, W_i. After deriving the predicted outcomes, $\widehat{Y}_i$, using the above equation, I plot the predicted outcomes against the CPRA running variables as shown in Figure 6. As I predicted each outcome without using the binary variable terms, $CPRA80_i$, smoothly continuous graphs would be desirable for the validity of the RD design. As expected, all the graphs in Figure 6 show smooth patterns around the CPRA 80 threshold.

5 Results

I show the trade-offs between the two kidney sources in Section 5.1. Section 5.2 shows how a candidate's mortality risk changes as his or her access to deceased donor kidneys increases, while Section 5.3 tests heterogeneity by characteristics of candidates to identify the types of candidates who can be prioritized in the kidney allocation.

5.1 Trade-offs between kidney sources

In this section, I examine whether an increase in access to deceased donor kidneys reduces the likelihood of receiving living donor kidneys. Panel A of Table 5 shows the RD estimates of the probability of receiving deceased donor kidneys, and panel (a) of Figure 7 presents the corresponding figure. There is a positive and significant discontinuity of access to a deceased donor kidney at the CPRA 80 threshold. In column (1) of Table 5, the likelihood of

receiving a deceased donor kidney increases by 23 percentage points just above the CPRA 80 threshold, which implies a 165 percent increase compared to the unadjusted mean probability of receiving a deceased donor kidney (13.9 percent) in the sample below the CPRA 80 threshold. Column (2) shows the RD estimate identified with control variables. The RD estimate with control variables is 0.227, similar to the result in column (1). Although several variables, including gender and education level, show statistically significant discontinuities at the threshold in the validity check, those discontinuities do not substantially affect the RD estimate. For precision, I repeat the estimation that controls the waitlist registration year fixed effects (column (3)) and the waitlisted DSA fixed effects (column (4)). The magnitude of each RD estimate is similar to that of the previous two RD estimates. After the large jump at the threshold, however, the probability of receiving a deceased donor kidney shrinks quickly as the CPRA increases. When a candidate's CPRA increases, the probability of finding compatible donors decreases exponentially. Although the sensitization point provides high-CPRA candidates with priority for deceased donor kidneys, the benefit is focused on candidates with CPRAs just above the threshold, and candidates with very high CPRAs still struggle to receive a deceased donor kidney. This problem illustrates why OPTN modified the sensitization point system to a sliding scale (Table 2) in 2014.

Panel (b) of Figure 7 presents the effect of sensitization points on the probability of receiving a living donor kidney. There is a negative gap at the CPRA 80 threshold, although the gap is smaller than that in panel (a), and the corresponding RD estimate is -0.0399 (Column (1) of Table 5 Panel B), which implies a 43 percent decrease compared to the mean probability of 9.2 percent. The results show evidence of crowding out in the kidney transplant market. Candidates with CPRAs above the threshold are less likely to choose living donor kidneys as their access to deceased donor kidneys increases. The crowd-out effect can be derived by using the fuzzy RD estimation, and the results are shown in column (1) of Table 5 panel C. A 10 percentage-point increase in the probability of receiving a deceased donor kidney reduces the probability of receiving a living donor kidney by 1.73 percentage points,

and the estimate is statistically significant. The fuzzy RD estimates are similar even though I control for predetermined characteristics, year fixed effects, and waitlisted DSA fixed effects in columns (2) to (4), -0.179 to -0.191.

These results show evidence that kidney candidates behave strategically when they choose between two kidney sources: a deceased donor kidney and a living donor kidney. The sensitization points improve the kidney candidate's rank on the waitlist and increases the probability of receiving a deceased donor kidney offer earlier. The fuzzy RD estimates above can be considered as the probability of receiving an acceptable deceased donor kidney offer before the waiting time threshold (t^*) in Figure 2 and switching the kidney source from living donor kidneys to deceased donor kidneys.

5.2 Mortality

The second measure of evaluating a deceased donor kidney allocation policy is the effect on patients' outcomes. In particular, reducing the waitlist mortality of kidney candidates, which indicates the deaths before receiving kidney transplants, has been suggested as a key metric of improving patient outcomes in OPTN's strategic plan.[20] To find the types of candidates who can be prioritized in deceased donor kidney allocation to increase the transplant quantity while improving mortality, understanding the causal effect of increased access to deceased donor kidneys on patient mortality is necessary.

In the waitlist mortality outcome, I include removal from the waitlist due to severe sickness, as these patients also face a high risk of mortality. Table 6 shows the RD estimates of the waitlist mortality analysis, and panels (a) and (b) of Figure 8 present the corresponding figures. As the mortality risk could be highly correlated with the waiting time, I estimate the effect within fixed durations, 1 and 2 years, from the waitlist registration. I exclude candidates whose maximal waiting time by the end of the analysis period, December 3, 2014, is less than the length of each duration. In Figure 8, there are negative discontinuities

[20] https://optn.transplant.hrsa.gov/governance/strategic-plan/goal-5/, information access on the web, last accessed on March 27, 2019.

at the CPRA 80 threshold, and the magnitude of discontinuity increases as the duration increases. The corresponding RD estimate, in column (1) of Table 6 panel A, increases as the duration increases from 1.13 percentage points (1 year) to 2.83 percentage points (2 years).[21] Compared to the baseline waitlist mortality rate of candidates with CPRAs below the threshold, the waitlist mortality rate decreases by approximately 43 percent, a sizable reduction. In columns (2) to (4), which control for covariates, the magnitude of the RD estimates is similar for each duration. Panel B of Table 6 shows the fuzzy RD estimates using the first-stage results in the above section.[22] In column (1), a 10 percentage-point increase in the likelihood of receiving a deceased donor kidney significantly reduces the 1-year waitlist mortality rate by 0.4 percentage points and the 2-year waitlist mortality rate by 1 percentage point. Similar to the reduced-form results, the RD estimates in columns (2) to (4) are not significantly different from the result in column (1).

Although waitlist mortality is a widely used mortality risk measure, it may underestimate kidney candidates' mortality risk from waitlist registration. The measure shows the risk of losing a chance of receiving kidney transplants rather than the risk of death because deaths after receiving kidney transplants are not considered. Hence, when a kidney policy increases access to donated kidneys and reduces waitlist mortality, interpreting the result as evidence of improvement in mortality risk from waitlist registration requires caution.

To address this concern, I examine the overall mortality measure which considers both deaths before receiving kidney transplants and after receiving kidney transplants within 1 and 2 years from waitlist registration. The RD estimates of the overall mortality are shown in Table 7, and related figures are presented in panels (c) and (d) in Figure 8. Compared to waitlist mortality outcomes, the magnitude of discontinuity is relatively small, but the negative discontinuity at the CPRA 80 threshold still increases as the duration increases. In

[21] As the sample size for the mortality analysis in each duration is different, direct comparisons of RD estimates may not accurate. In Online Appendix B, I repeat the RD estimation using the same sample size for each duration.

[22] For each duration, I derived the RD estimates with the same sample restriction as the reduced-form estimation.

panel A of Table 7, baseline overall mortality rates are slightly greater than baseline waitlist mortality rates because people who die after receiving kidney transplants are now considered. Although the RD estimates for 1-year overall mortality analysis are negative, I do not find any significant discontinuity at the CPRA 80 threshold. When I extend the analysis duration to 2 years, the RD estimates become significant. In column (1), I find evidence that kidney candidates who receive sensitization point benefits experience a significant decrease in overall mortality rates by 2.53 percentage points. Compared to the baseline overall mortality rates (7.4 percent), the magnitude of RD estimates implies a roughly 34 percent decrease. The effect on overall mortality is stable controlling for covariates in columns (2) to (4). Panel B presents the fuzzy RD estimates of the overall mortality outcome. I do not find any significant evidence that an increase in the probability of receiving a deceased donor kidney reduces the overall mortality within 1 year (column (1)), but the results become significant for the overall mortality results within 2 years. When the probability of receiving a deceased donor kidney increases by 10 percentage points, the overall mortality rate within 2 years decreases by approximately 0.9 percentage points, and the results are similar controlling for covariates.

5.3 Heterogeneity

I find evidence that an increase in access to deceased donor kidneys partially crowds out kidney candidates' living donor kidney choices and improves both waitlist mortality and overall mortality. It is possible, however, that the magnitude of the effects would be heterogeneous across kidney candidates with the different characteristics. In the kidney source choice problem discussed in Section 2.2, the net benefits or costs of receiving a living donor kidney instead of waiting longer for a deceased donor kidney offer may vary among candidates. In addition, the availability of potential living donors could be different across kidney candidates. When the magnitude of the crowd-out effect is heterogenous across kidney candidates, prioritizing candidates with smaller crowd-out effects would help increase the number

of kidney transplants.

Table 8 shows the fuzzy RD estimates across race for kidney candidates. In column (1), both groups of candidates show a significant crowd-out of living donor kidneys when access to deceased donor kidneys improves; however, the magnitude of the RD estimates is significantly different between the two races. When the probability of receiving a deceased donor kidney increases by 10 percentage points, white candidates are 2.55 percentage points less likely to receive a living donor kidney and the amount of crowd-out decreases to 1.19 percentage points when I restrict the sample to candidates who are African-American. Based on the findings of previous studies, this difference could be caused by knowledge about the net benefit of living donor kidney transplants or the potential living kidney donor pool. Due to relatively limited access to healthcare, African-American kidney candidates tend to have little knowledge about the benefit of living donor kidney transplants compared to white kidney candidates (Purnell et al. 2013). In addition, they are less likely to find potential living donors than white kidney candidates because of a lack of skills to recruit potential donors (Rodrigue et al. 2014; Weng et al. 2010). Both reasons result in a longer cutoff time until kidney candidates switch the kidney source from a living donor to a deceased donor, as shown in Figure 9, and this difference could cause heterogeneity in the crowd-out effect when access to deceased donor kidneys increases. In the effect on mortality outcomes (Columns (2) to (4) in Table 8)[23], African-American kidney candidates show significant RD estimates. When the likelihood of receiving a deceased donor kidney increases by 10 percentage points, the waitlist mortality rate and overall mortality rate decreases by approximately 1 percentage point. However, I do not find any significant effect on the mortality outcomes of white kidney candidates, and the difference in RD estimates is statistically significant for 1-year mortality outcomes. The smaller crowd-out effect but larger mortality reduction of African-American kidney candidates implies that prioritizing African-American candidates would increase the

[23]As the sample size for the mortality analysis in each duration is different, direct comparison of RD estimates may not be accurate. In Online Appendix B, I repeat the RD estimation using the same sample size for each duration.

number of transplants while improving the mortality of kidney candidates.

Another characteristic highly related to the heterogeneous size of the compatible donor pool is blood type. For successful kidney transplantation, the compatibility of blood types between kidney candidates and donors is important. Candidates with blood types A or B can receive donor kidneys with blood type O in addition to donor kidneys with the identical blood type. On the other hand, candidates with blood type O can only receive donor kidneys with the identical blood type. Hence, compared to the other blood types, kidney candidates with blood type O face a restriction in finding potential donors. Using a similar logic with race analysis, limited access to the kidney donor pool results in a longer cutoff time, and we can expect a smaller crowd-out effect for candidates with blood type O(Panel (a) of Figure 10). Table 9 shows the fuzzy RD estimates of the above outcomes across blood types. In column (1), kidney candidates with blood types A and B show large and significant crowd-out in the probability of receiving living donor kidneys. When the probability of receiving a deceased donor kidney increases by 10 percentage points, candidates with blood type A are 2.73 percentage points less likely to receive a living donor kidney (blood type B: 2.82 percentage points). However, as expected, I do not find any significant evidence of crowd-out for kidney candidates with blood type O. In the mortality analysis (Columns (2) to (4) in Table 9), the effect of increased access to deceased donor kidneys is heterogeneous across blood types. I do not find any significant improvement for kidney candidates with blood type A. Blood type B candidates show significant reductions in 2-year mortality outcomes, waitlist mortality (-0.219) and overall mortality (-0.222), and blood type O candidates show significant estimates in waitlist mortality outcomes: 1 year (-0.0713) and 2 years (-0.126). Although the magnitude of the RD estimates for blood type B candidates is larger than that for blood type O candidates, the differences are not statistically significant. Hence, blood type O kidney candidates, for whom a smaller crowd-out effect is observed, can be considered for prioritization.

Finally, I examine the heterogeneity of kidney candidates' dialysis status. Patients with

kidney disease can register on the kidney transplant waitlist even though their kidneys have not failed yet. As the waiting time for deceased donor kidney transplants increases, the risk of kidney failure increases, and candidates would need to start dialysis treatments after failure. Hence, compared to kidney candidates already receiving dialysis treatments, candidates who are not receiving dialysis would place greater value on living donor kidneys, which does not have to wait for an offer, as the waiting time increases. This difference is illustrated by the steeper slope of the net benefit and shorter cutoff time in panel (a) of Figure 10. Hence, we can expect a larger crowd-out effect for candidates who are not receiving dialysis treatment. The heterogeneity results by dialysis status are presented in Table 10. As expected, candidates who are not receiving dialysis treatments are more likely to switch living donor kidneys to deceased donor kidneys. When the probability of receiving a deceased donor kidney increases by 10 percentage points, candidates not receiving dialysis treatments are 3.04 percentage points less likely to choose living donor kidneys, while the result for candidates receiving dialysis treatments is 1.21 percentage points. The results for mortality outcomes show that kidney candidates receiving dialysis treatments can be eligible for prioritization. Although they show a smaller crowd-out effect, the increased access to deceased donor kidneys reduces their waitlist mortality and overall mortality significantly, and I do not find any evidence of a significant mortality effect for candidates who are not receiving dialysis treatments.

6 Robustness Check

This section presents a series of analyses to test the robustness of the main findings. First, in Figure 11, I re-estimate the main results, crowd-out and mortality outcomes using donut-RD models that exclude observations close to the CPRA 80 threshold. The estimation results are stable, which supports the idea that some clusters around the threshold in panel (b) of Figure 4 do not drive the main findings. The magnitudes of the mortality results for 1 year

and 2 years slightly increase at the larger exclusion, but the differences in the donut-RD estimates are insignificant.

Second, if the identified RD estimates are driven by the discontinuity around the CPRA 80 threshold, then the RD estimates that exclude observations far from the threshold are expected to have similar values. In Table 11, I repeat the RD estimation with the samples that exclude 1 percent, 5 percent, and 10 percent of the analysis sample far from the threshold. Column (1) shows the crowd-out effect on the choice of a living donor kidney. Although I exclude the outermost sample, the significance of the RD estimate still holds, and all the results are similar in magnitude. Columns (2) to (4) present effects on candidates' waitlist mortality. In each duration, the RD estimates show similar values. However, in a 1-year analysis, the significance of the RD estimate is removed when I exclude the 5-percent and 10-percent outermost samples. Although insignificant, the coefficient is indistinguishable from the other results with different sample restrictions. In columns (5) to (7), which present the effect on the overall mortality, the magnitudes of the RD estimates are also similar in all durations. However, the effect on the overall mortality within 2 years of registration becomes insignificant when I restrict the 5-percent outermost sample. Although 2 mortality outcomes are insignificant when I restrict the outermost sample, the magnitudes of the RD estimates do not chang substantially, which supports the argument that the identified effects are robust to the outermost sample restrictions.

Finally, the RD estimates focus on the discontinuities of candidates close to the threshold and may not be applied to other candidates. To address this, I re-estimate the effect of receiving the sensitization point benefit assigned to kidney candidates with a CPRA value of 80 or greater using a difference-in-difference (DD) model and compare the results with the RD estimates. Although CPRA was introduced as a new sensitization measure in December 2007, the traditional PRA was used to assign the sensitization point benefit until October 2009. Hence, in the DD framework, I use the sample whose most recent CPRAs are available between December 2007 and December 2014, and the candidates are categorized as shown

in Figure 12. For an accurate analysis using a DD framework, an additional 2 groups of candidates should be excluded from the analysis. First, inclusion of candidates with a traditional PRA of 80 or greater may cause an underestimation of the effect of the sensitization point policy. Kidney candidates with a traditional PRA of 80 or greater (groups III and IV in Figure 12) could receive the sensitization points even though their CPRAs are lower than 80. Hence, I exclude these kidney candidates because they are treated not by CPRA but by the traditional PRA. Second, inclusion of candidates who were registered in the pretreatment period but did not receive kidney transplants until the end of the pretreatment period may also cause an underestimation of the policy effect. They are defined as pretreatment period samples but may receive sensitization point benefits if their CPRAs are 80 or greater because the benefit eligibility is determined by the most recent CPRA. Hence, candidates whose waiting periods overlap between the pre-treatment and post-treatment periods are excluded from the analysis.

In the following regression, β_2 is the coefficient of interest

$$Y_{it} = \alpha + \beta_0 CPRA80_i + \beta_1 postCPRA_t + \beta_2 (CPRA80 \times postCPRA)_{it} + W_{it}\gamma + \eta_t + u_{it} \quad (3)$$

where i denotes a kidney transplant candidate. $postCPRA_t$ is a binary variable with a value of one if candidates are registered on the waitlist in the post-treatment period when the sensitization point benefit is assigned based on the CPRA. $CPRA80_i$ is the same binary variable as the RD estimation, which shows the eligibility for the sensitization point benefit and W_{it} is a vector of predetermined characteristics. I include the waitlist registration year fixed effect (η_t) and standard errors are clustered at the waitlisted DSA level.

Panel A of Table 12 shows the estimates from the DD model. All ot the coefficients are similar to the RD estimates, although the magnitudes become slightly larger. The probability of receiving a deceased donor kidney increases by 24.8 percentage points after the introduction of a sensitization point policy using the CPRA measure. In addition, the probability of receiving a living donor kidney decreases by 4.7 percentage points, which shows

the existence of a crowd-out effect. The DD estimates for mortality, waitlist mortality and overall mortality, are negative and similar in magnitude to the RD estimates. The standard errors of the DD estimates are larger than those of the RD estimates, which results in some insignificant results, even though the level of coefficients is stable. The larger standard errors could be driven by a relatively small sample size in the pretreatment period due to the exclusion of candidates with traditional PRAs greater than 80.

7 Conclusions

Given the absence of the price mechanism due to the stipulations of NOTA in 1984, which bans the sale of organs, the problem of transplantable kidney shortages has become more severe in recent decades. As not all kidney candidates receive transplants in the year of waitlisting, the number of waitlisting candidates increases dramatically every year: roughly 95,000 kidney candidates are currently waiting for kidney transplants on the waitlist.[24] To date, OPTN has mainly tried to reduce organ shortages by increasing kidney donations, but the role of kidney allocation rules in kidney shortages has received much less attention. As kidney candidates choose kidney sources strategically, a change in kidney allocation rules affects candidates' kidney source choices between deceased and living donor kidneys. I propose a model in which kidney candidates choose kidney sources by comparing the net benefit and costs of receiving living donor kidneys rather than waiting longer for deceased donor kidneys. The model implies that an increase in access to deceased donor kidneys could result in the crowd-out of living donor kidney choices only available to designated recipients.

Exploiting the variation in eligibility for kidney sensitization points, which increase access to deceased donor kidneys for candidates with CPRA values of 80 or greater, I find that an increase in access to deceased donor kidneys crowds out the choice of living donor kidneys. When the probability of receiving a deceased donor kidney increases by 10 percentage

[24] https://optn.transplant.hrsa.gov/data/view-data-reports/national-data, information access on the web, last accessed on March 27, 2019.

points, the likelihood of receiving a living donor kidney decreases by approximately 1.7-1.9 percentage points. Additionally, the crowd-out effects are different across demographic subgroups, i.e., races, blood types, and dialysis status. Candidates who are African-American or receiving dialysis treatments are less likely to switch to deceased donor kidneys from living donor kidneys when access to deceased donor kidneys increases. Among the blood type subgroups, blood type A and B candidates show greater crowd-out than blood type O candidates. Using the kidney source choice model, I show that differences in knowledge about the quality difference between deceased and living donor kidneys, the opportunity cost of waiting for deceased donor kidneys, and the availability of potential living kidney donors could be reasons for the heterogeneous crowd-out effects.

The heterogeneous results provide implications for the allocation of deceased donor kidneys. When allocation policies prioritize subgroups that show smaller crowd-out effects, we may expect an increase in the number of overall transplants, thereby ameliorating kidney shortages. In addition, kidney candidates with smaller crowd-out in the choice of living donor kidneys show relatively large improvements in waitlist mortality and overall mortality, which implies that prioritizing these candidates would not worsen the mortality of kidney candidates.

This paper considers only three candidate characteristics because previous research has shown how the net benefits and costs in the choice of kidney sources vary across these characteristics. In order to identify the kidney candidate groups who can be prioritized in deceased donor kidney allocation, further research on the sources of heterogeneity in crowd-out and kidney candidates' mortality is needed. For patients with kidney failure, a kidney transplant is a key treatment to prolong their lives and improve their quality of life. In addition to increasing the supply of altruistic kidney donations, future policies should consider the role of kidney allocation rules in delivering the efficient allocation of donated kidneys.

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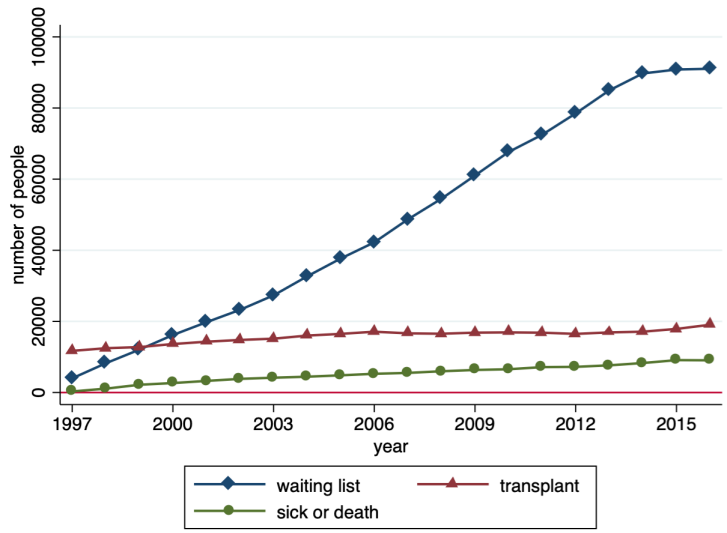
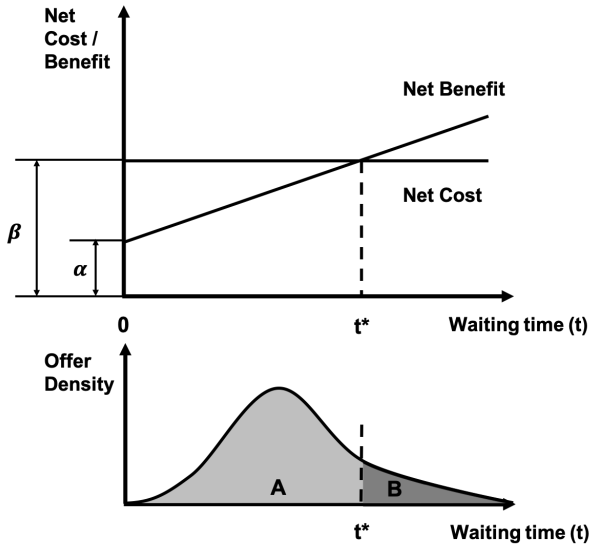
8 Figures

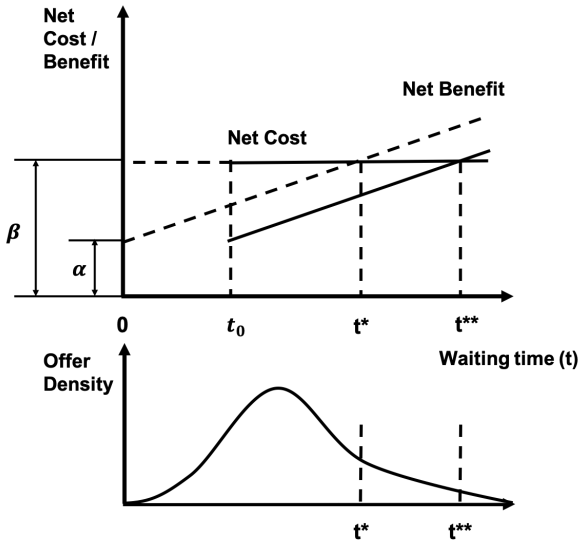


Sources: OPTN database (https://optn.transplant.hrsa.gov/data)
Notes: The OPTN database reports the information on waitlist addition and removal from 1997. The number of waitlisted candidates is calculated by adding the net increase (waitlist addition - removal) to the number of candidates in the previous year. As candidates were already waitlisted before 1997, the real waitlist plot needs to be scaled up. Candidates waitlisted at more than one transplant center or for multiple organs are counted as only one candidate.

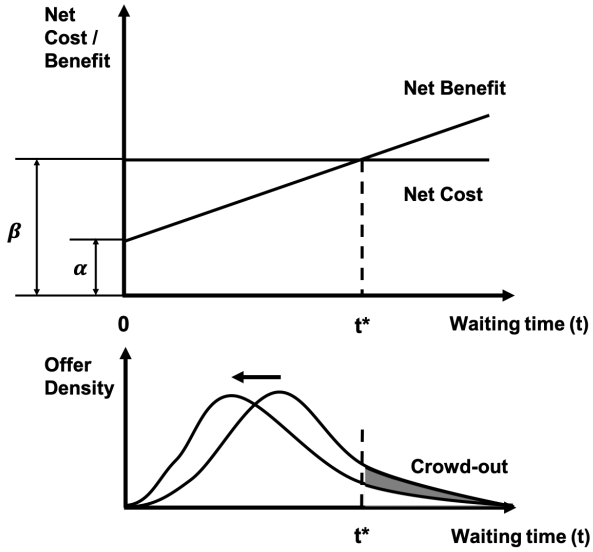
Figure 1: Trends in the kidney transplant market



(a) Kidney source choice



(b) Kidney source choice with relaxed assumption



(c) Crowd-out of living donor kidneys

Notes: The net benefit illustrates the relative benefit of using a living donor kidney compared to waiting for a deceased donor kidney at each waiting time (t). The net benefit consists of the kidney quality gap (α) and preference for a living donor kidney, which increases over waiting time. The net cost illustrates the emotional cost (β) of living donor kidney receipients with a closely related donor. The offer density plots the likelihood of receiving a deceased donor kidney offer at each waiting time (t). Panel (a) illustrates the kidney source choice of kidney candidates who have a potential living donor at the initial time ($t = 0$). Panel (b) illustrates the kidney source choice of kidney candidates who find potential living donors at t_0. Panel (c) shows the crowd-out of living donor kidney choices when the likelihood of receiving a deceased donor kidney increases.

Figure 2: Net costs and benefits of a living kidney transplant

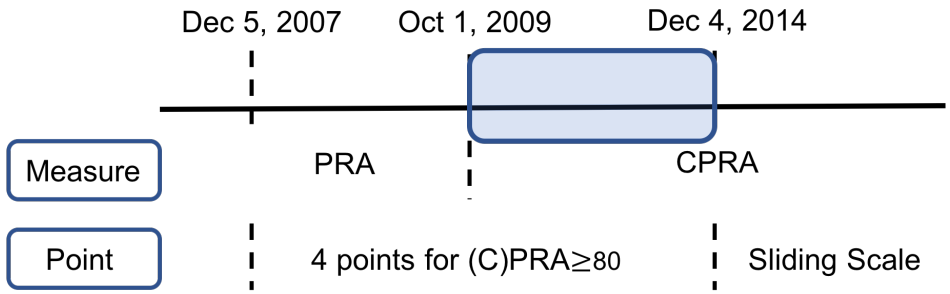
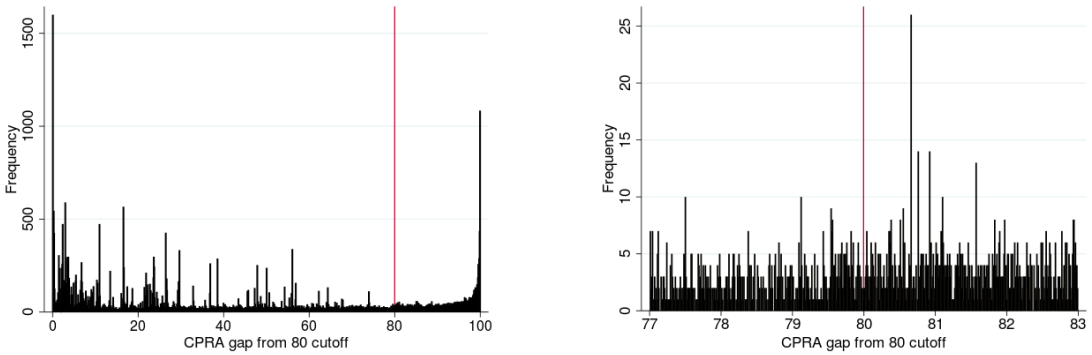


Figure 3: Kidney sensitization measure and sensitization points

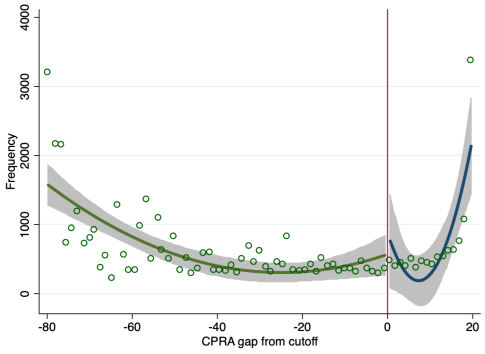


(a) Distribution of CPRA

(b) Distribution of CPRA within bandwidth 3

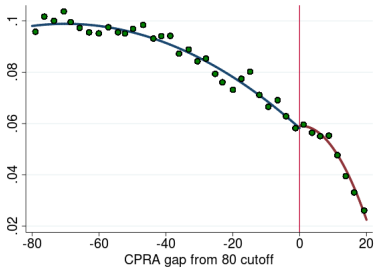
Notes: Panel (a) plots the frequency of CPRA at each 0.1 unit. Candidates with zero CPRA are excluded from the plot. Panel (b) plots the frequency of CPRA at 0.01 units within the bandwidth 3 units from the CPRA 80 threshold.

Figure 4: CPRA distribution

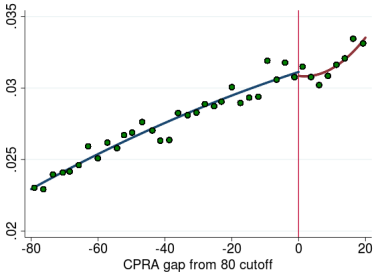


Notes: The figure plots the mean frequency along with quadratic fitted lines (solid lines) and the 95% confidence interval below and above the CPRA 80 threshold.

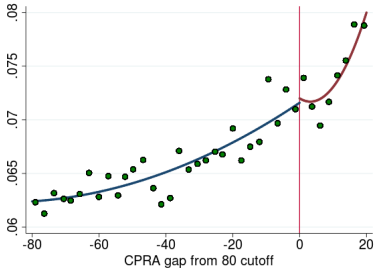
Figure 5: Mean frequency test



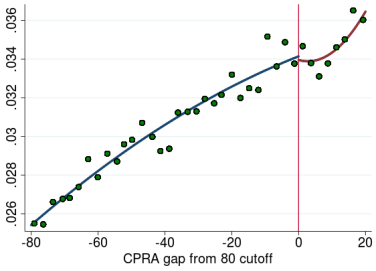
(a) Pr(living tx)



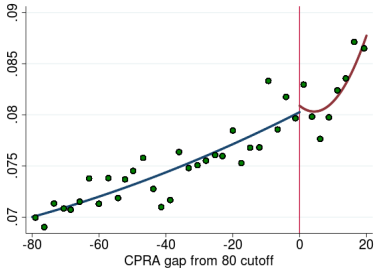
(b) [1 year] Waitlist mortality



(c) [2 year] Waitlist mortality



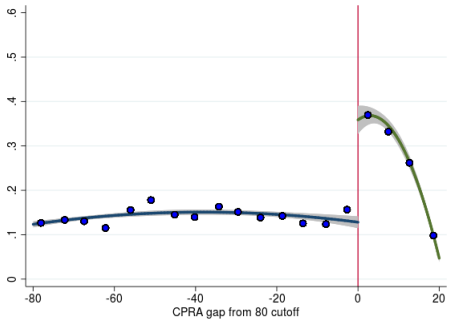
(d) [1 year] Overall mortality



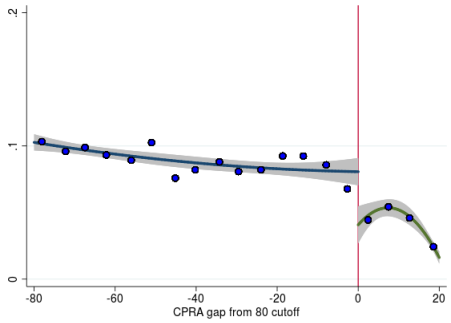
(e) [2 year] Overall mortality

Notes: Panels (a)-(e) plot the mean values of each predicted outcome variable derived from regressions without using the indicator for $CPRA \geq 80$ along with quadratic fitted lines (solid lines) and the 95% confidence intervals below and above the CPRA 80 threshold. The covariates included in each regression are the candidate's age at waitlist registration, blood type, gender, race, education level, payment source, diabetes status, dialysis status, work status, and BMI.

Figure 6: Discontinuities on predicted outcomes



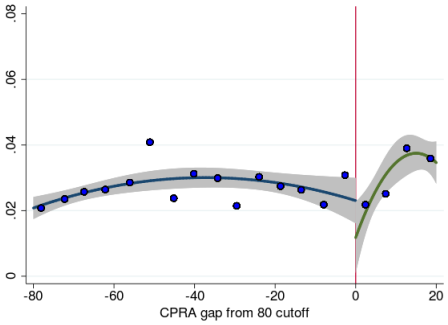
(a) Pr (Deceased)



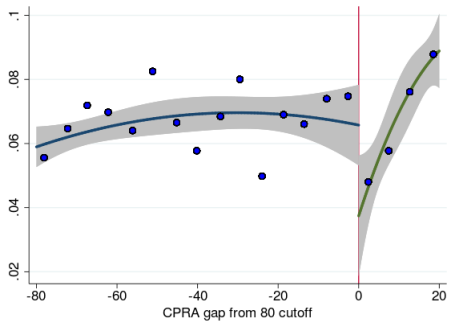
(b) Pr (Living)

Notes: Panels (a)-(b) plot the mean values of each outcome variable along with quadratic fitted lines (solid lines) and the 95% confidence intervals below and above the CPRA 80 threshold.

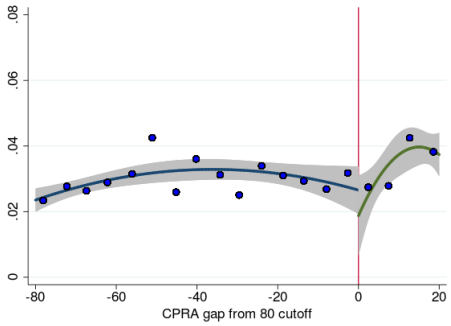
Figure 7: Crowd-out effect on the demand of living donor kidneys



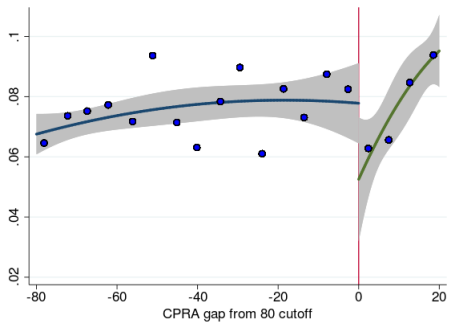
(a) [1 year] Waitlist mortality



(b) [2 year] Waitlist mortality



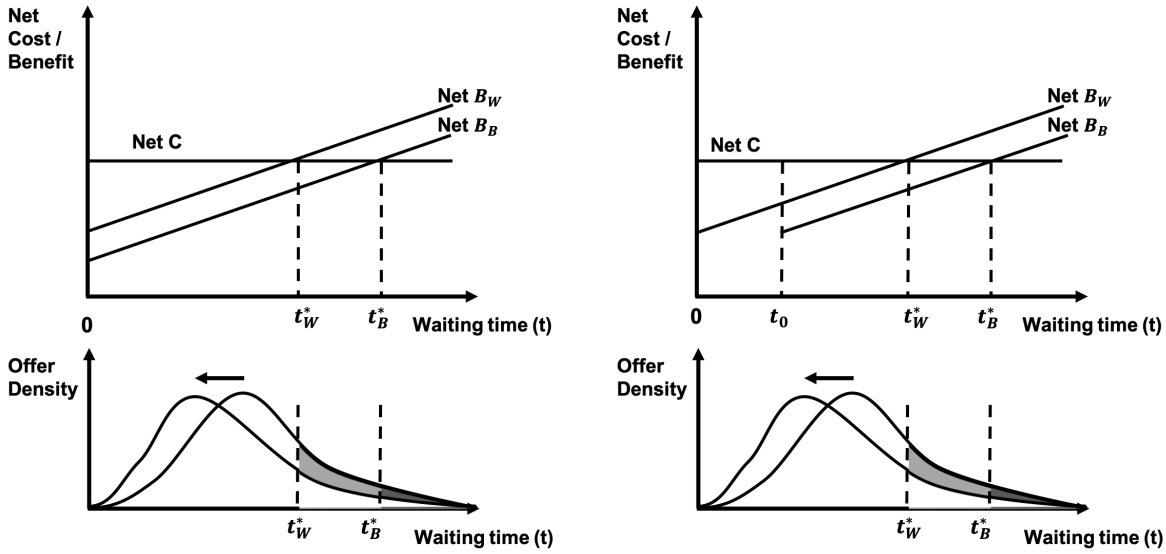
(c) [1 year] Overall mortality



(d) [2 year] Overall mortality

Notes: Panels (a)-(d) plot the mean values of each outcome variable along with quadratic fitted lines (solid lines) and the 95% confidence intervals below and above the CPRA 80 threshold.

Figure 8: The effect on patient mortality

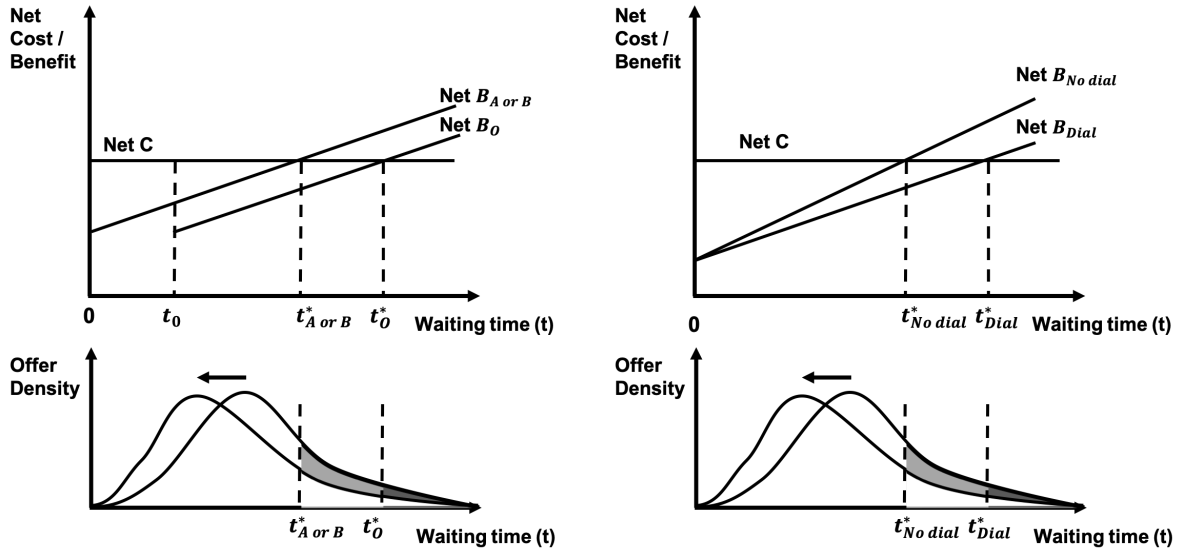


(a) Difference in the knowledge on the net benefit

(b) Difference in the access to potential living donors

Notes: Net B_W and B_B illustrate the relative benefit of using a living donor kidney compared to waiting for a deceased donor kidney at each waiting time (t) for white and black candidates, respectively. Net C illustrates the emotional cost to living donor kidney receipients with a closely related donor. The offer density plots the likelihood of receiving a deceased donor kidney offer at each waiting time (t). An increase in the access to deceased donor kidneys moves the offer density graph to the left. Panel (a) illustrates the heterogeneity in crowd-out effects when the knowledge of the net benefit differs. Panel (b) illustrates the heterogeneity in crowd-out effects when the access to potential living donor kidneys differs. Kidney candidates with limited access to potential donors do not face the kidney source choice problem until they find potential living donors (t_0).

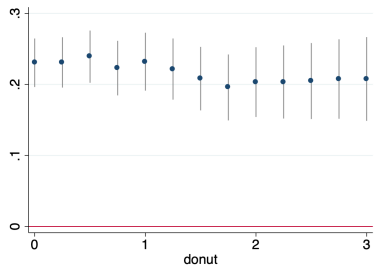
Figure 9: Heterogentiy of the crowd-out effect by candidates' races



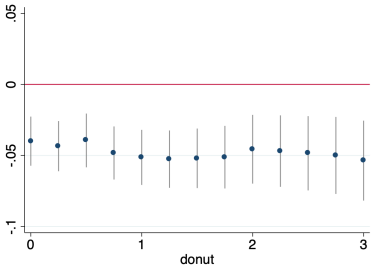
(a) Heterogeneity by blood types (b) Heterogeneity by dialysis status

Notes: Net B illustrates the relative benefit of using a living donor kidney compared to waiting for a deceased donor kidney at each waiting time (t) for white and black candidates, respectively. The net cost illustrates the emotional cost of living donor kidney receipients with a closely related donor. The offer density plots the likelihood of receiving a deceased donor kidney offer at each waiting time (t). An increase in access to deceased donor kidneys moves offer density graph to the left. Panel (a) illustrates the heterogeneity in crowd-out effects when the access to potential living donor kidneys differs. Kidney candidates with limited access to potential donors do not face a kidney source choice problem until they find potential living donors (t_0). Panel (b) illustrates the heterogeneity in crowd-out effects by dialysis status. Kidney candidates who are not receiving dialysis treatment have a steeper Net B over the waiting time to avoid the initiation of dialysis due to longer waiting.

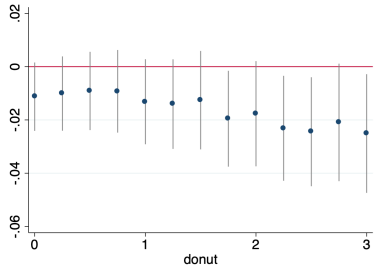
Figure 10: Heterogentiy of the crowd-out effect



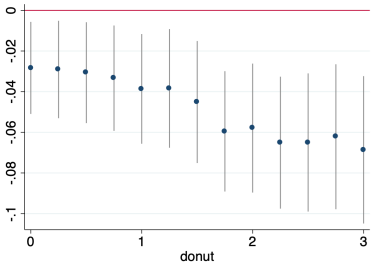
(a) Pr (Deceased)



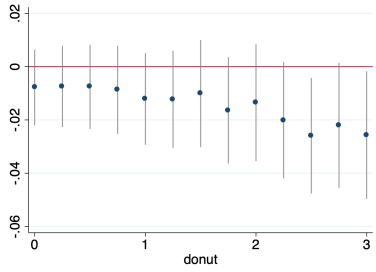
(b) Pr (Living)



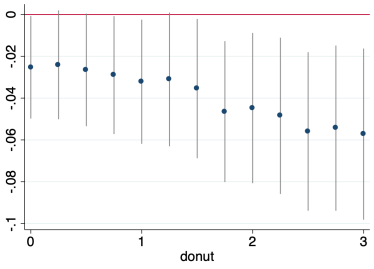
(c) [1 year] Waitlist mortality



(d) [2 year] Waitlist mortality



(e) [1 year] Overall mortality



(f) [2 year] Overall mortality

Notes: Panels (a)-(f) plot point estimates and 95% confidence intervals from the quadratic regression excluding data points around the CPRA 80 threshold; the excluded CPRAs range from +/- 0.25 to +/- 3.

Figure 11: Donut RD estimation

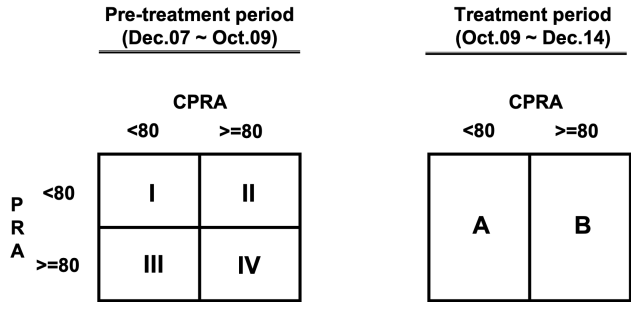


Figure 12: Sample of a difference-in-difference estimation

9 Tables

Table 1: Kidney allocation points

Candidates' condition	Kidney points
Waiting time	1/365 points for each day
Aged 0-10 at time of match Perfect tissue type match	4 points
Age 11-17 at time of match Perfect tissue type match	3 points
A prior living donor	4 points
Sensitized $CPRA \geq 80$	4 points
$\Downarrow$ [Dec 4, 2014]	
Sliding scale	Table 2

Sources: OPTN, "OPTN Policies", (2017), p.79.

Table 2: Scale of sensitization points (From December 4, 2014)

CPRA	Sensitization Point	CPRA	Sensitization Point
0∼19	0	85∼89	4.05
20∼29	0.08	90∼94	6.71
30∼39	0.21	95	10.82
40∼49	0.34	96	12.17
50∼59	0.48	97	17.3
60∼69	0.81	98	24.4
70∼74	1.09	99	50.09
75∼79	1.58	100	202.1
80∼84	2.46		

Sources: OPTN, "OPTN Policies", (2017), p.79.

Table 3: Summary statistics of outcomes

	(1) All	(2) $CPRA < 80$	(3) $CPRA \geq 80$
Transplant	0.23	0.23	0.24
Deceased donor	0.15	0.14	0.21
Living donor	0.08	0.09	0.04
Waitlist mortality	0.18	0.18	0.20
Overall mortality	0.20	0.20	0.22
Observations	49055	37637	11418

Notes: The table shows the mean probability of certain key variables for kidney transplant candidates waitlisted from October 1, 2009 to December 3, 2014. Candidates with zero CPRA are excluded.

Table 4: Balance of covariates

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	A	B	O	White	Black	Asian
$CPRA \geq 80$	0.0113	0.00471	-0.0149	0.0134	-0.0144	0.00554
	(0.0182)	(0.0145)	(0.0194)	(0.0194)	(0.0187)	(0.0104)
mean below cutoff	0.311	0.160	0.492	0.556	0.346	0.075
VARIABLES	Male	Age	$<$ HS	HS	College	Postgraduate
$CPRA \geq 80$	-0.0548	0.00856	0.00253	0.0394	-0.0292	0.00543
	(0.0156)	(0.470)	(0.0105)	(0.0192)	(0.0191)	(0.00898)
mean below cutoff	0.546	52.346	0.070	0.402	0.409	0.069
VARIABLES	Private ins.	Public ins.	BMI	Diabetes	On Dialysis	Work
$CPRA \geq 80$	-0.0114	0.0171	0.0879	0.0312	-0.00362	0.00476
	(0.0190)	(0.0191)	(0.221)	(0.0193)	(0.0157)	(0.0172)
mean below cutoff	0.430	0.541	29.169	0.449	0.795	0.301

Notes: The table shows the estimated discontinuities of predetermined characteristics for kidney candidates. In addition to the indicator for $CPRA \geq 80$, each regression includes a linear spline of the running variables, CPRA. Robust standard errors are reported in parentheses. Public insurance includes Medicare and Medicaid.

Table 5: The effect of sensitization points on kidney source choice

	Baseline	(1)	(2)	(3)	(4)
Panel A. Probability of Receiving a Deceased Donor Kidney (First stage)					
$CPRA \geq 80$	[0.139]	0.230	0.227	0.222	0.215
		(0.0174)	(0.0172)	(0.0167)	(0.0162)
Panel B. Probability of Receiving a Living Donor Kidney (Reduced form)					
$CPRA \geq 80$	[0.092]	-0.0399	-0.0408	-0.0428	-0.0410
		(0.00882)	(0.00861)	(0.00857)	(0.00853)
Panel C: Fuzzy RD estimates					
Pr (Deceased)		-0.173	-0.179	-0.192	-0.191
		(0.0385)	(0.0379)	(0.0380)	(0.0392)
Observations		49,055	49,055	49,055	49,055
Control variables		No	Yes	Yes	Yes
Year		No	No	Yes	Yes
Transplant Center		No	No	No	Yes

Notes: The table shows the estimated results of the effect of receiving sensitization points on the probability of receiving kidney transplants from each kidney source. In addition to the indicator for $CPRA \geq 80$, each regression includes a linear spline of the running variables, CPRA. Robust standard errors are reported in parentheses. The mean probability of each outcome for candidates with CPRAs less than the threshold is presented in the square brackets.

Table 6: The effect of sensitization points on waitlist mortality

		Baseline	(1)	(2)	(3)	(4)
Panel A. Waitlist mortality rate (Reduced form)						
1 year	$CPRA \geq 80$	[0.026]	-0.0113	-0.0109	-0.0109	-0.0115
		{39166}	(0.00655)	(0.00652)	(0.00652)	(0.00655)
2 year	$CPRA \geq 80$	[0.065]	-0.0283	-0.0281	-0.0280	-0.0292
		{29181}	(0.0115)	(0.0115)	(0.0115)	(0.0114)
Panel B: Fuzzy RD estimates						
1 year	Pr (Deceased)		-0.0449	-0.0442	-0.0447	-0.0493
			(0.0260)	(0.0263)	(0.0264)	(0.0279)
2 year	Pr (Deceased)		-0.102	-0.104	-0.103	-0.113
			(0.0410)	(0.0416)	(0.0415)	(0.0435)
Control variables			No	Yes	Yes	Yes
Year			No	No	Yes	Yes
Transplant Center			No	No	No	Yes

Notes: The table shows the estimated results for the effect of receiving sensitization points on waitlist mortality of kidney candidates. In addition to the indicator for $CPRA \geq 80$, each regression includes a linear spline of the running variables, CPRA. Robust standard errors are reported in parentheses. Kidney candidates whose maximal waiting time, the difference between the registration date and December 3, 2014, is less than each analysis period are excluded. The mean probability of each outcome for candidates with CPRAs less than the threshold is presented in the square brackets. The number of observations for each analysis period is presented in the curly brackets.

Table 7: The effect of sensitization points on overall mortality

		Baseline	(1)	(2)	(3)	(4)
Panel A. Overall mortality rate (Reduced form)						
1 year	$CPRA \geq 80$	[0.029]	-0.00779	-0.00743	-0.00750	-0.00797
		{39166}	(0.00725)	(0.00721)	(0.00721)	(0.00724)
2 year	$CPRA \geq 80$	[0.074]	-0.0253	-0.0252	-0.0251	-0.0262
		{29181}	(0.0125)	(0.0123)	(0.0123)	(0.0123)
Panel B: Fuzzy RD estimates						
1 year	Pr (Deceased)		-0.0311	-0.0302	-0.0306	-0.0342
			(0.0289)	(0.0292)	(0.0294)	(0.0309)
2 year	Pr (Deceased)		-0.0913	-0.0931	-0.0925	-0.102
			(0.0447)	(0.0452)	(0.0450)	(0.0472)
Control variables			No	Yes	Yes	Yes
Year			No	No	Yes	Yes
Transplant Center			No	No	No	Yes

Notes: The table shows the estimated results for the effect of receiving sensitization points on overall mortality of kidney candidates. In addition to the indicator for $CPRA \geq 80$, each regression includes a linear spline of the running variables, CPRA. Robust standard errors are reported in parentheses. Kidney candidates whose maximal waiting time, the difference between the registration date and December 3, 2014, is less than each analysis period are excluded. The mean probability of each outcome for candidates with CPRAs less than the threshold is presented in the square brackets. The number of observations for each analysis period is presented in the curly brackets.

Table 8: Heterogeneity of fuzzy RD results by kidney candidates' races

	(1)	(2)	(3)	(4)	(5)
	Living	Waitlist mortality		Overall mortality	
		1 year	2 year	1 year	2 year
White	-0.255	0.0166	-0.0885	0.0508	-0.0694
	(0.0655)	(0.0427)	(0.0611)	(0.0483)	(0.0677)
{27008}	[0.13]	[0.03]	[0.07]	[0.03]	[0.08]
Black	-0.119	-0.123	-0.109	-0.125	-0.0993
	(0.0408)	(0.0365)	(0.0639)	(0.0395)	(0.0678)
{17368}	[0.04]	[0.03]	[0.06]	[0.03]	[0.07]
Difference by races					
W - B	-0.136	0.140	0.021	0.176	0.030
	(0.077)	(0.056)	(0.088)	(0.062)	(0.096)
Observations	49,055	39,166	29,181	39,166	29,181

Notes: The table shows the heterogeneous estimation results for the effect of increased access to deceased donor kidneys on kidney candidates' living donor kidney choices and mortality rates by kidney candidates' races. The results for other races are excluded from the table. In addition to the indicator for $CPRA \geq 80$, each regression includes a linear spline of the running variables, CPRA. Robust standard errors are reported in parentheses. In the mortality analysis, kidney candidates whose maximal waiting time, the difference between the registration date and December 3, 2014, is less than each analysis period are excluded. The mean probability of each outcome for candidates with CPRAs less than the threshold is presented in the square brackets. The number of observations for each analysis period is presented in the curly brackets.

Table 9: Heterogeneity of fuzzy RD results by kidney candidates' blood types

	(1)	(2)	(3)	(4)	(5)
	Living	Waitlist mortality		Overall mortality	
		1 year	2 year	1 year	2 year
A type	-0.273	0.0163	0.00367	0.0144	-0.0127
	(0.0614)	(0.0437)	(0.0644)	(0.0453)	(0.0676)
{15248}	[0.12]	[0.03]	[0.07]	[0.03]	[0.08]
B type	-0.282	-0.0529	-0.219	-0.0839	-0.222
	(0.103)	(0.0609)	(0.104)	(0.0641)	(0.115)
{7804}	[0.08]	[0.03]	[0.06]	[0.03]	[0.07]
O type	-0.0352	-0.0713	-0.126	-0.0141	-0.0863
	(0.0592)	(0.0394)	(0.0657)	(0.0471)	(0.0724)
{24240}	[0.08]	[0.03]	[0.06]	[0.03]	[0.07]
Difference by blood types					
A - B	0.010	0.069	0.222	0.098	0.209
	(0.120)	(0.075)	(0.122)	(0.079)	(0.133)
A - O	-0.238	0.088	0.129	0.029	0.074
	(0.085)	(0.059)	(0.092)	(0.065)	(0.099)
B - O	-0.247	0.018	-0.093	-0.070	-0.136
	(0.119)	(0.073)	(0.123)	(0.080)	(0.136)
Observations	49,055	39,166	29,181	39,166	29,181

Notes: The table shows the heterogeneous estimation results for the effect of increased access to deceased donor kidneys on kidney candidates' living donor kidney choices and mortality rates by kidney candidates' blood types. The results for blood type AB candidates are excluded as the sample size (1764) is too relatively small. In addition to the indicator for $CPRA \geq 80$, each regression includes a linear spline of the running variables, CPRA. Robust standard errors are reported in parentheses. In the mortality analysis, kidney candidates whose maximal waiting time, the difference between the registration date and December 3, 2014, is less than each analysis period are excluded. The mean probability of each outcome for candidates with CPRAs less than the threshold is presented in the square brackets. The number of observations for each analysis period is presented in the curly brackets.

Table 10: Heterogeneity of fuzzy RD results by kidney candidates' dialysis status

	(1)	(2)	(3)	(4)	(5)
	Living	Waitlist mortality		Overall mortality	
		1 year	2 year	1 year	2 year
None	-0.304	0.0256	-0.0625	0.0298	-0.0522
	(0.0768)	(0.0424)	(0.0558)	(0.0446)	(0.0614)
{9669}	[0.21]	[0.02]	[0.05]	[0.02]	[0.06]
Dialysis	-0.121	-0.0737	-0.113	-0.0550	-0.100
	(0.0416)	(0.0328)	(0.0519)	(0.0369)	(0.0567)
{39386}	[0.06]	[0.03]	[0.07]	[0.03]	[0.08]
Difference by dialysis status					
None - Dial	-0.183	0.099	0.050	0.085	0.048
	(0.087)	(0.054)	(0.076)	(0.058)	(0.084)
Observations	49,055	39,166	29,181	39,166	29,181

Notes: The table shows the heterogeneous estimation results for the effect of an increased access to deceased donor kidneys on kidney candidates' living donor kidney choices and mortality rates by kidney candidates' dialysis status. In addition to the indicator for $CPRA \geq 80$, each regression includes a linear spline of the running variables, CPRA. Robust standard errors are reported in parentheses. In the mortality analysis, kidney candidates whose maximal waiting time, the difference between the registration date and December 3, 2014, is less than each analysis period are excluded. The mean probability of each outcome for candidates with CPRAs less than the threshold is presented in the square brackets. The number of observations for each analysis period is presented in the curly brackets.

Table 11: Robustness to the exclusion of outermost observations

	(1)	(2)	(3)	(4)	(5)
	Living	Waitlist mortality		Overall mortality	
		1 year	2 year	1 year	2 year
All	-0.173	-0.0449	-0.102	-0.0311	-0.0913
	(0.0385)	(0.0260)	(0.0410)	(0.0289)	(0.0447)
Observations	49,055	39,166	29,181	39,166	29,181
Drop 1%	-0.170	-0.0446	-0.100	-0.0305	-0.0884
	(0.0383)	(0.0258)	(0.0408)	(0.0287)	(0.0445)
Observations	48,810	38,963	29,035	38,963	29,035
Drop 5%	-0.162	-0.0409	-0.0845	-0.0275	-0.0701
	(0.0379)	(0.0255)	(0.0404)	(0.0284)	(0.0441)
Observations	46,733	37,324	27,820	37,324	27,820
Drop 10%	-0.156	-0.0374	-0.0826	-0.0236	-0.0726
	(0.0375)	(0.0251)	(0.0396)	(0.0280)	(0.0432)
Observations	44,181	35,322	26,409	35,322	26,409

Notes: The table shows the RD estimates for each outcome variable after dropping 1%, 5%, and 10% of kidney candidates far from the CPRA 80 threshold. In addition to the indicator for $CPRA \geq 80$, each regression includes a linear spline of the running variables, CPRA. Robust standard errors are reported in parentheses. In the mortality analysis, kidney candidates whose maximal waiting time, the difference between the registration date and December 3, 2014, is less than each analysis period are excluded. The number of observations for each analysis period is presented in the curly brackets.

Table 12: Difference-in-differences estimates

	(1)	(2)	(3)	(4)	(5)	(6)
			Waitlist mortality		Overall mortality	
VARIABLES	Deceased	Living	1 year	2 year	1 year	2 year
Panel A. DD estimates						
CPRA80*Post	0.248	-0.0474	-0.0166	-0.0366	-0.0169	-0.0332
	(0.0344)	(0.0241)	(0.0168)	(0.0254)	(0.0179)	(0.0239)
Observations	51,584	51,584	41,695	31,710	41,695	31,710
Panel B. RD estimates						
$CPRA \geq 80$	0.230	-0.0399	-0.0113	-0.0283	-0.00779	-0.0253
	(0.0174)	(0.00882)	(0.00655)	(0.0115)	(0.00725)	(0.0125)
Observations	49,055	49,055	39,166	29,181	39,166	29,181

Notes: Panel A shows the difference-in-differences estimates for each outcome. Each regression includes covariates, waitlisted year fixed effects. Standard errors are clustered by kidney candidates' waitlisted DSAs. Kidney candidates who received sensitization points based on their (traditional) PRA are excluded from the control group. Panel B shows the RD estimates for each outcome variable in the analysis period. (October 1, 2009 - December 3, 2014) In addition to the indicator for $CPRA \geq 80$, each regression includes a linear spline of the running variables, CPRA. Robust standard errors are reported in parentheses. In the mortality analysis, kidney candidates whose maximal waiting time, the difference between the registration date and December 3, 2014, is less than each analysis period are excluded.

Online Appendix A Selection of Functional Form

I select the functional form using the F-test approach and the Akaike information criterion (AIC) (Akaike 1974) of model selection. First, the F-test approach (Lee et al. 2010) tests whether the polynomial model fits well with the unrestricted graph. For the test, I add the set of bin dummies and test whether the bin dummies are jointly significant.[25][26] If a polynomial model shows insignificant results on the F-test, then it indicates that the model adequately explains the relationship between the outcome variable and the running variable, CPRA. Row 1 of Online Appendix Table A.1 panel (A) shows the p-values of the F-tests for each polynomial model. The results of models 1 and 3 show that the bin dummies are jointly significant at a 5 percent significance level and imply that the model has the poor goodness of fit. The other prediction models show insignificant results. Second, the AIC shows the trade-off between the bias and the precision. The value of the AIC is derived by using the equation below.

$$AIC \;=\; Nln(\widehat{\sigma^2}) + 2p \tag{4}$$

where $\widehat{\sigma^2}$ is the mean squared error and p is the number of parameters in the regression. A smaller AIC means a better model in explaining the real data. In row 2, the AIC value of model 4 is the smallest. Panel (B) shows the F-test results and AIC values derived with baseline covariates. Models 1 and 3 still show significant results on the F-test. Among the models left, model 4 has the smallest AIC value, similar to the result of the panel (A). Based on the test results above, I choose model 4 with quadratic polynomials and interactions for the identification of the effect on crowd-out and mortality risks.

[25] To avoid the collinearity with the constant and the treatment dummy, CPRA80, I excluded two dummies which is just left and right from the CPRA 80 threshold.

[26] F statistic $= \frac{(R_u^2 - R_r^2)/K}{(1-R_u^2)/(n-K-1)}$, n is the number of observations, K is the number of bins, R_r^2 is the R squared of the regression without bin dummies and R_u^2 is the R squared of the regression with K-2 bin dummies (Jacob et al. 2012). In this study, I grouped candidates into 19 bins (K).

Table A.1: Polynomial model selection

	(1)	(2)	(3)	(4)	(5)	(6)
	Model 1	Model 2	Model 3	**Model 4**	Model 5	Model 6
Panel A. Without covariates						
P-value of F-test	.0004764	.973892	.017061	**.999868**	.8735895	.9985595
AIC	39179.02	37971.27	38564.26	**37866.82**	38065.05	37883.46
Panel B. With covariates						
P-value of F-test	1.32e-11	.7847014	6.55e-06	**.9983431**	.4452405	.9862065
AIC	38394.3	37195.03	37777.64	**37088.96**	37285	37105.46

Note: 1. Functional form of $f(X_i)$ is same as below.
Model 1: $f(X_i) = \beta_1 X_i$
Model 2: $f(X_i) = \beta_1 X_i + \beta_2 CPRA80_i * X_i$
Model 3: $f(X_i) = \beta_1 X_i + \beta_2 X_i^2$
Model 4: $f(X_i) = \beta_1 X_i + \beta_2 X_i^2 + \beta_3 CPRA80_i * X_i + \beta_4 CPRA80_i * X_i^2$
Model 5: $f(X_i) = \beta_1 X_i + \beta_2 X_i^2 + \beta_3 X_i^3$
Model 6: $f(X_i) = \beta_1 X_i + \beta_2 X_i^2 + \beta_3 X_i^3 + \beta_4 CPRA80_i * X_i + \beta_5 CPRA80_i * X_i^2 + \beta_6 CPRA80_i * X_i^3$
2. Included covariates are each candidate's blood type, gender, race, age at waitlist registration, education level, payment source, BMI, type of diabetes, dialysis, and work status.

Online Appendix B Consistency of Mortality Estimates across Duration Restrictions

Table B.1: The effect of sensitization points on patient mortality

	(1)	(2)	(3)	(4)
	Waitlist mortality		Overall mortality	
	1 year	2 year	1 year	2 year
Panel A. Reduced form results				
$CPRA \geq 80$	**-0.0113**		**-0.00779**	
{39,166}	**(0.00655)**		**(0.00725)**	
$CPRA \geq 80$	-0.0135	**-0.0283**	-0.0118	**-0.0253**
{29,181}	(0.00768)	**(0.0115)**	(0.00825)	**(0.0125)**
Panel B. Fuzzy RD estimates				
Pr(deceased)	**-0.0449**		**-0.0311**	
{39,166}	**(0.0260)**		**(0.0289)**	
Pr(deceased)	-0.0487	**-0.102**	-0.0427	**-0.0913**
{29,181}	(0.0276)	**(0.0410)**	(0.0297)	**(0.0447)**

Notes: The table shows the estimated results of the effect of receiving sensitization points on waitlist mortality of kidney candidates with different duration restrictions. For the precise comparison between 1 year and 2 years mortality estimates, 1 year estimates which exclude candidates whose maximal waiting time, the difference between the registration date and December 3, 2014, is less than 2 years are additionally reported in column (1). In addition to the indicator for $CPRA \geq 80$, each regression includes a linear spline of the running variables, CPRA. Robust standard errors are reported in parentheses. The number of observations for each analysis period is presented in the curly bracket.

Table B.2: Fuzzy RD results by candidates' races

		(1)	(2)	(3)	(4)
		Waitlist mortality		Overall mortality	
		1 year	2 year	1 year	2 year
White	Pr(deceased)	**0.0166**		**0.0508**	
	{21,564}	**(0.0427)**		**(0.0483)**	
	Pr(deceased)	0.00682	**-0.0885**	0.0333	**-0.0694**
	{16,062}	(0.0446)	**(0.0611)**	(0.0494)	**(0.0677)**
Black	Pr(deceased)	**-0.123**		**-0.125**	
	{13,979}	**(0.0365)**		**(0.0395)**	
	Pr(deceased)	-0.108	**-0.109**	-0.118	**-0.0993**
	{10,483}	(0.0386)	**(0.0639)**	(0.0394)	**(0.0678)**

Notes: The table shows the heterogeneous estimation results of an increased access to deceased donor kidneys on kidney candidates' mortality rates with different duration restrictions by kidney candidates' races. For the precise comparison between 1 year and 2 years mortality estimates, 1 year estimates which exclude candidates whose maximal waiting time, the difference between the registration date and December 3, 2014, is less than 2 years are additionally reported in column (1). In addition to the indicator for $CPRA \geq 80$, each regression includes a linear spline of the running variables, CPRA. Robust standard errors are reported in parentheses. The number of observations for each analysis period is presented in the curly bracket.

Table B.3: Fuzzy RD results by candidates' blood types

		(1)	(2)	(3)	(4)
		Waitlist mortality		Overall mortality	
		1 year	2 year	1 year	2 year
A type	Pr(deceased)	**0.0163**		**0.0144**	
	{12,226}	**(0.0437)**		**(0.0453)**	
	Pr(deceased)	-0.00867	**0.00367**	-0.0219	**-0.0127**
	{9,069}	(0.0428)	**(0.0644)**	(0.0435)	**(0.0676)**
B type	Pr(deceased)	**-0.0529**		**-0.0839**	
	{6,199}	**(0.0609)**		**(0.0641)**	
	Pr(deceased)	-0.0253	**-0.219**	-0.0370	**-0.222**
	{4,587}	(0.0662)	**(0.104)**	(0.0682)	**(0.115)**
O type	Pr(deceased)	**-0.0713**		**-0.0141**	
	{19,353}	**(0.0394)**		**(0.0471)**	
	Pr(deceased)	-0.0648	**-0.126**	-0.0267	**-0.0863**
	{14,493}	(0.0444)	**(0.0657)**	(0.0500)	**(0.0724)**

Notes: The table shows the heterogeneous estimation results of an increased access to deceased donor kidneys on kidney candidates' mortality rates with different duration restrictions by kidney candidates' blood types. The results of blood type AB candidates are excluded as the sample size (1764) is relatively too small. For the precise comparison between 1 year and 2 years mortality estimates, 1 year estimates which exclude candidates whose maximal waiting time, the difference between the registration date and December 3, 2014, is less than 2 years are additionally reported in column (1). In addition to the indicator for $CPRA \geq 80$, each regression includes a linear spline of the running variables, CPRA. Robust standard errors are reported in parentheses. The number of observations for each analysis period is presented in the curly bracket.

Table B.4: Fuzzy RD results by candidates' dialysis status

		(1)	(2)	(3)	(4)
		Waitlist mortality		Overall mortality	
		1 year	2 year	1 year	2 year
None	Pr(deceased)	**0.0256**		**0.0298**	
	{7,488}	**(0.0424)**		**(0.0446)**	
	Pr(deceased)	0.00454	**-0.0625**	0.00328	**-0.0522**
	{5,616}	(0.0486)	**(0.0558)**	(0.0489)	**(0.0614)**
Dialysis	Pr(deceased)	**-0.0737**		**-0.0550**	
	{31,678}	**(0.0328)**		**(0.0369)**	
	Pr(deceased)	-0.0660	**-0.113**	-0.0562	**-0.100**
	{23,565}	(0.0334)	**(0.0519)**	(0.0366)	**(0.0567)**

Notes: The table shows the heterogeneous estimation results of an increased access to deceased donor kidneys on kidney candidates' mortality rates with different duration restrictions by kidney candidates' dialysis status. For the precise comparison between 1 year and 2 years mortality estimates, 1 year estimates which exclude candidates whose maximal waiting time, the difference between the registration date and December 3, 2014, is less than 2 years are additionally reported in column (1). In addition to the indicator for $CPRA \geq 80$, each regression includes a linear spline of the running variables, CPRA. Robust standard errors are reported in parenthesis. The number of observations for each analysis period is presented in the curly bracket.