ESSAYS ON THE ECONOMICS OF ORGAN TRANSPLANTATION AND HEMODIALYSIS

By

Yeon Choi

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ABSTRACT

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Chapter 1. The Effect of Broader Liver Sharing on Patient Outcomes and Offer Acceptance

This paper evaluates a liver allocation policy known as Share 35, which provides transplant candidates facing high mortality risks with priority for livers obtained from relatively distant geographic areas. Exploiting the variation in the access to liver transplants across transplant candidates, I show that increasing access to liver transplants is an effective way to reduce mortality rates. Although the policy is well-targeted, I find that the policy causes unintended effects on the quality of transplanted livers and transplant candidatesâ liver offer-acceptance incentives. Because the policy promotes liver sharing across areas, targeted candidates receive a lower quality of livers due to longer liver transportation times. However, those candidates receive a compensation on liver quality by receiving livers with better donor characteristics. To further understand the mechanism of the compensation, I develop a strategic liver search model and estimate the model with match-run data that contain offer-acceptance decision histories for all donated livers. I find that the policy enables targeted candidates to be more selective of liver and transfer some of their quality loss to others.

Chapter 2. The Role of Kidney Allocation Policy in Addressing Kidney Shortages

I examine whether prioritizing certain types of transplant candidates in deceased-donor kidney allocation can increase the total number of kidney transplants. Transplant candidates strategically choose one of the two kidney sources, namely, deceased-donor and living-donor kidneys. While deceased-donor kidneys are available for all transplant candidates (similar to public goods), living-donor kidneys are only available for the designated recipients by the donors (similar to private goods). Using a regression discontinuity design, I show that transplant candidates are less likely to choose living-donor kidneys when they have better access

to deceased-donor kidneys, which can be interpreted as a crowd-out effect. Furthermore, I find that the size of the effect varies substantially across race, blood type, and dialysis status of transplant candidates. The result implies that prioritizing 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.

Chapter 3. The Strategic Location Choice of For-profit Hemodialysis Facilities in the U.S.

In the last chapter, I identify key factors related to the location choice of for-profit hemodialysis facilities using a dataset from the United States Renal Data System (USRDS) and structural methods. All patients with kidney failure need to receive hemodialysis treatment regularly and permanently. Because dialysis treatments are homogeneous across facilities, patients are likely to choose a treatment facility based on the distance from their homes. The strategic model introduced by Seim (2006) involves a static and incomplete information game among dialysis facilities for entry and positioning in a market. The estimation results show that in choosing an optimal location, a tradeoff occurs between local demand and competition with potential entrants.

To my parents,
my wife, Hyunjong Jong
and son, Hajin

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The data reported in Chapters 1 and 2 have been supplied by the Minneapolis Medical Research Foundation (MMRF) as the contractor for the Scientific Registry of Transplant Recipients (SRTR). The interpretation and reporting of these data are the responsibility of the author(s) and in no way should be seen as an official policy of or interpretation by the SRTR or the U.S. Government.

The data reported in Chapter 3 have been supplied by the United States Renal Data System (USRDS). The interpretation and reporting of these data are the responsibility of the author(s) and in no way should be seen as an official policy or interpretation of the U.S. Government.

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The Effect of Broader Liver Sharing on Patient Outcomes and Offer Acceptance

1.1 Introduction

A liver transplant is the ultimate treatment for patients whose livers are damaged, potentially leading to better quality of life and improved patient survival. While many patients are desperate for transplants, unfortunately considerable shortage of transplantable livers exists in a system where the sale of human organs is illegal (National Organ Transplantation Act, 1984). More than 12,000 candidates register on the liver transplant waitlists every year, and roughly 1,200 candidates die while waiting for liver transplants because only around 8,000 candidates receive liver transplants in a year[1]. Thus, how to allocate scarce livers is an important issue in the liver transplant market.

A liver transplant recipient is jointly determined by a liver offer via centrally-managed liver allocation rules and a candidate's decision to accept or decline the offer. The current liver allocation rule tries to minimize the mortality risk of transplant candidates while not compromising the quality of donated livers. For the first goal, the sickest patients are prioritized in liver allocation, and the severity of liver disease is measured by either Status 1A condition (the highest severity) or the model of end-stage liver disease (MELD) score, which ranges from 6 (less ill) to 40 (severely ill). However, the severity-based allocation may not guarantee the optimal liver allocation, as livers cannot survive long outside of the body. Thus, the Organ Procurement and Transplantation Network (OPTN) divides the country into 58 geographic allocation units called donor service areas (DSAs), as shown in Figure A.1, and gives priority to transplant candidates registered in the DSA where the donor hospital is located. Finally, if a transplant candidate receives a liver offer based on the allocation rule, he/she strategically decides whether he/she will accept the offer or wait for a higher quality offer.

[1] https://optn.transplant.hrsa.gov/data/view-data-reports/national-data, information accessed on the web, last accessed on September 28, 2019.

In June 2013, the OPTN introduced the Share 35 policy, which awards additional priority to transplant candidates with MELD scores of 35 or higher, to reduce their mortality risks before receiving transplants, which is hereafter termed "waitlist mortality". As shown in Figure A.2, the policy increased the percentage of recipients with MELD scores above 35 from 18 percent in the 4 years before 2013 to 26 percent in the 4 years after 2013. Rather than increasing liver donations, the OPTN loosened the distance-based allocation system explained above; namely, transplant candidates with MELD scores above 35 have increased priority for livers obtained in their regions, which consist of several adjacent DSAs, in addition to their own. Thus, the policy also yields an increase in the share of livers transported to other DSAs from 20 percent in the 4 years before 2013 to 29 percent in the 4 years after 2013. These changes show that the Share 35 policy yields trade-offs between access to liver transplants and the quality of transplanted livers.

This paper examines impacts of the Share 35 policy on the two goals of liver allocation policy, namely, mortality risk and liver quality, and offer-acceptance incentives. Specifically, I first examine whether increasing access to liver transplants is an effective way to reduce mortality risk of transplant candidates. Then, I analyze unintended impacts of the Share 35 policy on the quality of transplanted livers resulting from the promotion of liver sharing across DSAs and liver offer-acceptance incentives of transplant candidates.

To estimate the causal impact of an increase in access to liver transplants on patient mortality risk, I use a fuzzy regression discontinuity (RD) design exploiting the variation around the MELD score 35 threshold, which determines eligibility under the Share 35 policy. After the policy is implemented, transplant candidates with MELD scores just above 35 are 13.6 percentage points more likely to receive liver transplants within 90 days from the waitlist registration compared with those with MELD scores just below 35. Using this result as the first stage, I find that a 10-percentage-point increase in the likelihood of receiving a liver transplant significantly decreases the waitlist mortality rate by 4.4 - 6.5 percentage points. As the policy benefit arises from reallocating donated livers across transplant candidates not a supply shock that might increase the number of liver donations, both transplant candidates with MELD scores

above and below 35 are affected by the policy in an opposite direction. To separate the effect on each candidate group, I use the difference-in-difference (DD) estimation using Status 1A candidates as a control group. DD estimates show that the policy decreases the waitlist mortality rates for transplant candidates with MELD scores above 35 while not causing a significant increase in the waitlist mortality rates for those with MELD scores below 35. Additionally, I analyze the impact on overall mortality rates, which refers to the likelihood of death irrespective of transplant status. Although I do not find any significant impact of an increase in access to liver transplants on the overall mortality rates in the RD design, DD estimates show that the Share 35 policy significantly decreases the overall mortality rates for transplant candidates with MELD scores above 35.

Second, I estimate changes in the quality of transplanted livers and the probability of posttransplant survival using a DD model. I find that transplant recipients with MELD scores above 35 are more likely to receive livers that are obtained from the other DSAs and transported over longer times, which implies lower liver quality. However, I find that those recipients are more likely to receive livers with better donor characteristics which could be interpreted as a compensation for the increased liver travel time. The changes in the quality of transplanted livers result in a decrease in posttransplant survival rates for both transplant recipient groups; MELD scores above and below 35, although the latter group of candidates does not show longer transportation time after the policy implementation.

Finally, to elucidate the mechanism of mixed effect on the quality of transplanted livers for candidates with MELD scores above 35, I examine how the policy affects liver offer-acceptance behavior. I develop a liver search model that explains the strategic liver offer-acceptance behavior of transplant candidates. The model suggests that an increase in access to liver offers for a transplant candidate could increase the minimum quality level of liver offer acceptance. With this model in mind, I estimate the impact of the Share 35 policy on the likelihood of accepting liver offers using a DD specification. DD estimates show that the policy decreases the probability of accepting liver offers for transplant candidates with MELD scores above 35 by 10.2 percentage points, which implies that those candidates become more selective of liver offers. Exploiting the

increased access to liver offers, those candidates could have chosen livers with better donor characteristics although they more commonly received regionally shared livers.

The existing literature on the policy (Massie et al. 2015; Edwards et al. 2016; Annamalai et al. 2015) agrees that the policy increases access to liver transplants for transplant candidats with MELD scores 35 or greater. They show this result by comparing the proportion of liver transplants for candidates with MELD scores above 35 before and after the policy. However, interpreting the results as causal should be careful. Because donated livers are allocated based on the mortality risk of transplant candidates, those with the highest mortality risk experience greater access to liver transplants. Due to the reverse causality, the results in previous literature may not show the causal effect.

The results regarding the impact on waitlist mortality and posttransplant survival are mixed. For example, Massie et al. (2015) and Edwards et al. (2016) found that the Share 35 policy led to a decrease in waitlist mortality of liver transplant candidates with MELD scores above 35 using survival analysis. However, Annamalai et al. (2015) found no significant effect of the policy on waitlist mortality for liver transplant candidates with MELD scores above 35. Similarly, estimates of the effect on posttransplant survival rates are mixed. Edwards et al. (2016) found no significant effect of the Share 35 policy on 1-year posttransplant survival for liver transplant recipients with MELD scores above 35 using the transplant recipient sample within 2 years before and after the policy implementation. However, a recent study of recipients within 3 years before and after the policy implementation revealed that Share 35 increases 1-year posttransplant survival for transplant recipients with MELD scores above 35 (Kwong et al. 2018).

This paper contributes to the related literature in three ways. First, I estimate the causal effect of an increase in access to liver transplants on patient mortality risks. I use a fuzzy RD design that uses the plausibly exogenous variation in access to liver transplants across transplant candidates around the MELD score 35 threshold who have similar characteristics.

Second, I propose a new liver quality model that predicts relatively long-term, that is 5 years, posttransplant survival rates. As the Share 35 policy was not implemented until 2013, currently available data have some limits in estimating the policy

impact on long-term posttransplant survival rates. Thus, the existing literature focuses mainly on 1-year posttransplant survival estimates (Edwards et al. 2016; Kwong et al. 2018). My proposed model uses highly predictive variables for posttransplant survival selected from Machine Learning (ML) algorithms, i.e., the Least Absolute Shrinkage and Selection Operator (LASSO) algorithm. I find that the predicted results show higher prediction power than the widely used Donor Risk Index (DRI) liver quality measure (Feng et al. 2006).

Finally, I find a liver offer-acceptance mechanism through which the Share 35 policy affects the quality of transplanted livers in other ways besides an increase in transportation time. Although the existing literature examines the effect of the Share 35 policy on posttransplant survival, few studies discuss the mechanism. For example, Kwong et al. (2018) explained that transplant recipients with MELD scores above 35 show better posttransplant survival rates after the policy implementation thanks to receiving higher-quality livers. However, they did not present the reason why those variations in liver quality existed across transplant recipients. There are some studies examining the effect of the Share 35 policy on liver offer acceptance. Washburn et al. (2016) and Goldberg et al. (2017) showed that the number of liver offer decline for candidates with MELD scores above 35 increased after the policy implementation. They interpreted the result as an evidence of inefficient liver matching process without discussing the relationship with the quality of transplanted livers.

This paper proceeds as follows. The following section provides additional background information on liver allocation and the Share 35 policy. Section 1.3 describes the data used for estimation, while Section 1.4 discusses the identification strategy. Section 1.5 presents estimates of the access to liver transplants and patient mortality. Section 1.6 and 1.7 investigate estimates of transplantation quality, posttransplant survival, and offer-acceptance behaviors. Section 1.8 provides key robustness and specification checks, and Section 1.9 concludes.

1.2 Institutional Detail

1.2.1 Deceased Donor Liver Allocation Rule

To manage organ shortages and improve organ matching, NOTA established the OPTN, which is responsible for developing the allocation rule and distributing donated organs. The OPTN has been operated by the United Network for Organ Sharing (UNOS), the initial contractor since 1986 (Leppke et al. 2013). Under the OPTN allocation rule, deceased donor livers are distributed based on geographical proximity to the donor hospital and the medical urgency of the candidates[2].

For a successful transplant, the donated liver should be transplanted before the maximum preservation time, which is 8-12 hours[3]. Because of the time limit between organ procurement and transplant, the distance between the donor hospital and the patient's residence is an important component of the liver allocation system. Thus, the OPTN divides the United States into several areas and allocates organs based on geographical proximity. As shown in Figure A.1, the country is divided into 11 regions for organ allocation. Each region consists of several DSAs, and all U.S. transplant centers belong to one of 58 DSAs. Each color in the figure represents a different DSA. The geographical boundaries of DSAs are different from administrative boundaries such as county and state boundaries. Hence, some DSAs include several counties in one state, while others include an entire state or several states. In general, deceased donor livers are allocated according to organ allocation area tiers (DSA $\rightarrow$ Region $\rightarrow$ Nation). Once a liver is recovered from a deceased donor, the DSA administration matches it to candidates listed in the DSA, where it becomes available first. If there is no suitable candidate, it passes to candidates in the region to which the DSA belongs. If a proper candidate cannot be found or the liver is not accepted by offered candidates in the region, nationwide waitlisted candidates have a chance to obtain the liver.

[2]The allocation rule by organ is the same as below. Factors associated with kidney allocation are waiting time, donor/recipient immune system incompatibility, pediatric status, prior living donor status, distance from the donor hospital and survival benefit. Factors associated with heart allocation are medical need and distance from the donor hospital. Factors associated with lung allocation are survival benefit, medical need, waiting time and distance from the donor hospital. (https://optn.transplant.hrsa.gov/learn/about-transplantation/how-organ-allocation-works/, information accessed on the web, last accessed on June 23, 2019)

[3]Maximum organ preservation time for other organs are: heart or lung, 4-6 hours; pancreas, 12-18 hours; kidney, 24-36 hours (https://optn.transplant.hrsa.gov/learn/about-transplantation/how-organ-allocation-works/, information accessed on the web, last accessed on June 23, 2019)

Since February 27, 2002, the medical need of a liver transplant candidate has been measured by the MELD score, which is highly correlated with 3-month mortality of patients without liver transplants[4][5]. OPTN uses the allocation MELD (aMELD) score determined by the calculated MELD (cMELD) score and the exception MELD (eMELD) score (Massie et al. 2011).

$$aMELD = max[cMELD, eMELD] \tag{1}$$

The cMELD score is based on three objective variables, namely, bilirubin, international normalized ratio (INR), and creatinine, which can be obtained by a lab blood test and ranges from 6 (less ill) to 40 (severely ill). The cMELD score is derived by using the equation below and is rounded to the nearest whole number.

$$cMELD = 3.78 * ln[bilirubin] + 11.20 * ln[INR] + 9.57 * ln[creatinine] + 6.43 \tag{2}$$

To predict waitlist mortality risk more accurately, on January 11, 2016, sodium was included as a cMELD score factor for candidates with previous cMELD scores higher than 11 (Biggins 2015). All candidates active on the waitlist at the time of the new policy implementation were affected by this new cMELD score system[6]. The new cMELD score is derived by using the equation below. The new cMELD score is still capped at 40, similar to the previous cMELD score, and rounded to the nearest whole number.

$$cMELD(\_Na) = MELD(i) + 1.32 * (137 - sodium) - 0.33 * MELD(i) * (137 - sodium) \tag{3}$$

where $MELD(i)$ is the cMELD score calculated from the equation (2) and rounded to the nearest whole number.

[4]Wiesner et al. (2003) showed that the 3-month mortality of patients without a liver transplant increases when the MELD score increases. MELD < 9 : 1.9% / 10 - 19 : 6.0 % / 20 - 29 : 19.6% / 30 - 39 : 52.6 % / > 40 : 71.3%

[5]Liver transplant candidates less than 18 years old at the time of registration are prioritized by the Pediatric End-stage Liver Disease (PELD) score.

[6]Candidates who were Status 1A at the time of policy implementation were not affected. In addition, inactive candidates were not affected. (https://www.transplantpro.org/news/technology/policy-and-system-changes-adding-serum-sodium-to-meld-calculation/, information accessed on the web, last accessed on June 23, 2019)

However, it has been shown that the cMELD score does not accurately reflect candidates' need for liver transplants when they have certain liver-related diseases. To solve this problem, OPTN assigns the eMELD score for certain recognized exceptional diagnoses (RED), such as Cholangiocarcinoma and Cystic Fibrosis. (Table A.8).

The only measure of medical needs considered regardless of the aMELD score is the Status 1A condition, which is assigned to patients with fulminant liver failures and whose life expectancy without a liver transplant is fewer than 7 days. Since December 2010, the OPTN has provided them the benefit of regional sharing for donated livers to reduce the mortality risk of Status 1A candidates. That is, all the Status 1A candidates receive the same priority in the liver allocation process irrespective of their DSAs if they are registered in the same region.

1.2.2 Regional Share 35 Policy

Sharma et al. (2012) found that the waitlist mortality of transplant candidates with aMELD scores 35 or greater is similar to that of Status 1A candidates. To promote equity in liver allocation, on June 18, 2013, an extended regional liver sharing policy, Share 35, was implemented. Figure A.3 shows the mechanism of the Share 35 policy. Let us assume that Region 1 consists of three DSAs (A, B, and C) and a deceased donor liver is recovered from DSA A. Regardless of Share 35 policy implementation, Status 1A candidates registered in the Region 1 have priority for the liver over non-Status 1A candidates. Under the allocation rule before Share 35, the liver, which was not accepted by Status 1A candidates, was offered to candidates in DSA A based on their aMELD scores. If the liver was not matched to candidates in DSA A, candidates registered in different DSAs (B and C) received liver offers. Since the implementation of the Share 35 policy, however, the liver is offered to candidates with an aMELD score of 35 or higher registered in Region 1 before it is offered to other candidates with aMELD scores below 35 in the DSA A.

1.3 Data and Sample

This study uses data from the Scientific Registry of Transplant Recipients (SRTR). The SRTR data system includes data on all donors, wait-listed candidates, and trans-

plant recipients in the US, submitted by the members of the Organ Procurement and Transplantation 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 include detailed individual-level information such as liver candidate demographics and dates when and transplant centers where each candidate was registered and underwent transplantation. The standard data also contain information on each liver candidate's cMELD and eMELD score histories. All candidates registered on the liver transplant waitlist must have a laboratory blood test regularly to update their aMELD scores. Each test result is reported to SRTR, and this dataset contains all historical records.

When liver candidates receive donated liver offers, they can decline the offers because of various reasons, such as their health status or donated liver quality without any risk of penalty for the next liver offer. Hence, the standard data, which contain only the information on the final acceptance that results in liver transplant, have limits in the analysis of a liver candidate's liver offer acceptance. To overcome this limitation, I use the potential transplant recipient data, which contain information on match runs conducted for all the donated livers. The data include information on the donors who donated livers, the candidates who received the liver offers, and the decision on whether the livers were accepted or declined by the candidates who received the offers. As the data indicate, donors and candidates with unique identifiers can be linked to the standard data, which contain various demographics of donors and candidates.

This study examines adult liver transplant candidates and recipients who were older than 18 years at the time of waitlist registration because the allocation rule for younger candidates uses different medical urgency measure, Pediatric End-stage Liver Disease (PELD). I also restrict the sample to transplant candidates who were registered on the transplant waitlist between January 2011 and June 2017. As explained in Section 1.2.1, the policy that provides the benefit of regional sharing with Status 1A candidates was implemented on December 2010. Therefore, use of the analysis sample, which includes transplant candidates waitlisted before December 2010 may result in mixed results of two different regional priority policies. Finally, I excluded transplant candidates waitlisted for both liver and intestine transplants, because they are affected

by a non-standard liver allocation rule.

1.4 Empirical Framework

1.4.1 Fuzzy Regression Discontinuity

To derive the causal effect of an increase in access to liver transplants on mortality risk, I use a discontinuous change caused by the Share 35 policy. As transplant candidates with aMELD scores just above 35 are prioritized for donated livers in the waitlisted regions, the likelihood of receiving liver transplants would discontinuously change at the aMELD score 35 threshold. If an increase in the access to liver transplants reduces the mortality risk of transplant candidates, we could expect a discontinuous decrease in the mortality rates at the cutoff. To examine this hypothesis, I use the following local linear regression.

$$Y_i = \alpha + \beta_1 Share35_i + \beta_2 X_i + \beta_3 Share35_i \times X_i + u_i \tag{4}$$

where i denotes a liver transplant candidate. Y_i is a binary variable that indicates whether each candidate receives a deceased donor liver transplant (first stage) or dies while waiting for a liver offer or after receiving a liver transplant (reduced form). To minimize the effect of the waitlist time variation across transplant candidates, I focus on the outcomes occuring within a certain period from the waitlist registration. $Share35_i$ is a binary variable equal to one if the aMELD score of candidate i is greater than or equal to 35. X_i is a running variable that measures the difference between the aMELD score of candidate i and the threshold. In the RD design, a continuous running variable is desirable for a precise estimation (Jacob et al. 2012). However, the aMELD score in the SRTR dataset only shows the value rounded to the nearest whole number. Identification with this discrete MELD score variable could make it difficult to derive precise results. To improve precision, I recover a continuous aMELD score using historical records of 4 critical variables (serum bilirubin, INR, serum creatinine and serum sodium) that are included in the cMELD score equation (2) and (3)[7]. The

[7]The reported eMELD is used, as it is originally a whole number. According to equation (1), each candidate's aMELD score is determined by comparing the cMELD and the eMELD scores. However, just deriving each candidate's historical aMELD score by simply comparing those two scores in the dataset is not

coefficient of interest is β_1, and it is reported in the tables with robust standard errors. For bandwidth selection, I use the bandwidth selection method proposed by Calonico et al. (2017), and the optimal bandwidths are reported in the bottom of the column for each dependent variable.

With regard to the running variable, the aMELD score, because candidates regularly have laboratory blood tests, each candidate has many historical records of aMELD scores. Thus, the choice of an appropriate aMELD score is important for obtaining precise estimation results. An intuitive choice could be the last aMELD score valid at the time of transplantation or death. However, it is uncertain which aMELD score should be used for transplant candidates who did not experience the outcomes of interest during the analysis period. To apply consistent criteria across transplant candidates, this paper uses the initial aMELD score, which is measured at the time of waitlist registration, and set a relatively short analysis duration from the registration. Additionally, using the initial aMELD score can minimize the incentive of manipulation, which is the main assumption of the RD design, because transplant candidates have little information about their previous aMELD scores.

For valid identification using the RD design, transplant candidates should be as good as randomly distributed around the cutoff and not able to perfectly manipulate their aMELD scores for the Share 35 benefit. I examine whether any predetermined characteristic of transplant candidates shows discontinuity around the cutoff, and whether the distribution of aMELD scores shows irregular heaps at the cutoff. The detailed results of validity checks are presented in , and I do not find any evidence of violations for the validity assumptions.

1.4.2 Difference-in-Differences Estimation

Although RD design is a well-known identification strategy that elicits the causal effect of a treatment, there are several limitations in evaluating the Share 35 policy effects.

appropriate. Some reported eMELD scores in a certain period are not used in aMELD score calculation for various reasons. To derive the precise aMELD scores, a candidate's exact eMELD scores in each period should be considered. I calculate historical records of aMELD scores using a variable in the SRTR dataset that shows the reason for the difference between the cMELD and the aMELD scores. If the aMELD score calculation is not available for a certain period, I assigned the most recent aMELD score for each candidate up to that period.

First, interpreting RD estimates as the policy effect on the targeted candidates with aMELD scores above 35 should be approached with caution. The Share 35 policy takes livers that would be offered to transplant candidates with aMELD scores below 35 and provides them to transplant candidates with aMELD scores of 35 or greater. Thus, RD estimates, which compare outcomes between transplant candidates with aMELD scores below and above the 35 cutoff, could show aggregated results that combine the positive and negative effects in each candidate group. Second, due to data restrictions, precisely estimating the policy effect on posttransplant outcomes using the RD design is not possible. Posttransplant outcomes can only be identifiable for transplant recipients. Thus, transplant candidates who did not receive transplants are excluded from the analysis sample. In this case, it is desirable to use the last aMELD scores as the running variable, as I do not have to consider the choice of aMELD scores for transplant candidates who did not receive transplants. However, continuous last aMELD scores calculated using the blood test results are poorly matched to reported last aMELD scores in the dataset due to missing information, and this mismatch may result in imprecise RD estimates.

To overcome the above RD design limitations, I employ a DD approach for all the outcomes of interest using the aMELD scores reported in the dataset. As discussed, exploiting the transplant candidates whose aMELD scores are below 35 as a control group is not desirable for studying the policy effect on targeted candidates with aMELD scores above 35. To identify positive and negative impacts on transplant candidates with aMELD scores above or below 35 separately, I exploit transplant candidates with Status 1A condition as an alternative control group and compare them with transplant candidates with aMELD scores above or below 35. Before being offered to transplant candidates with aMELD scores, donated livers are offered to those with Status 1A condition registered at the regions where the livers are obtained (Figure A.3). As the Share 35 policy only reallocates donated livers not accepted by the Status 1A transplant candidates, I can reasonably assume that the Status 1A transplant candidates are not affected by the policy.

To assess the causal effect of the Share 35 policy, I generate the following general DD model:

$$Y_{icy} = \beta_0 + \beta_1 Post_i + \beta_2 Above35_i + \beta_3 Post \times Above35_i + W_i'\Gamma + \sigma_c + \tau_y + \varepsilon_{icy} \quad (5)$$

$$Y_{icy} = \beta_0 + \beta_1 Post_i + \beta_2 Below35_i + \beta_3 Post \times Below35_i + W_i'\Gamma + \sigma_c + \tau_y + \varepsilon_{icy} \quad (6)$$

where i denotes a liver transplant candidate, c denotes the waitlisted transplant center, and y denotes the year of waitlist registration. After dividing the analysis sample into three groups - Status 1A, $aMELD \geq 35$, and $aMELD < 35$ -, I compare Status 1A transplant candidates with the other two treatment groups. Specifically, transplant candidates with aMELD scores below 35 are excluded in the estimation using the equation (5), and those with aMELD scores above 35 are excluded in the other specification. $Post_i$ is an indicator for dates after Share 35 policy implementation in June 2013. $Above35_i$ is a binary variable that is one if the aMELD score of candidate i is greater than or equal to 35, and zero if the candidate has Status 1A condition. $Below35_i$ is a binary variable that is one if the aMELD score of candidate i is below 35, and zero if the candidate has Status 1A condition. W_i is a set of covariates of transplant candidates, including blood types, gender, age, race, education level, and payment sources. A set of year dummies, τ_y, and waitlisted center dummies, σ_c, capture the changes fixed over years and across transplant centers[8].

Summary statistics of the covariates are shown in Table A.1. The table compares the means and standard deviations (SD) of the control group, i.e. transplant candidates with Status 1A condition, and the two treatment groups, i.e. transplant candidates with aMELD scores above and below 35 measured at the time of waitlist registrtation. On average, compared with Status 1A transplant candidates, the table shows that transplant candidates in both treatment samples are older (52 years and 55 years), more likely to be male (63 percent and 65 percent), and more likely to be white (82

[8]For the precise estimation, identification of variable changes by outcomes of interest. (1) For the analysis of the access to transplants and mortality, $Above35_i/Below35_i$ are determined by the initial aMELD scores measured at the time of waitlist registration, and $y$identifies the year of waitlist registration. (2) For the analysis of the posttransplant outcomes, $Above35_i/Below35_i$ are determined by the last aMELD scores measured at the time of liver transplants, and $y$identifies the year of liver transplants. (3) For the analysis of the offer-acceptance behavior, $Above35_i/Below35_i$ are determined by the aMELD scores measured at the time of liver offers, and $y$identifies the year of liver offers.

percent and 86 percent). In the control group, however, the average age is 44 years, the proportion of males is 39 percent, and the proportion of recipients whose race is white is 72 percent. Blood types, education levels, and payment sources of transplant candidates are comparable.

1.5 Access to Liver Transplants and Mortality Rates

1.5.1 Regression Discontinuity Estimates

Panel (a) of Figure A.4 illustrates the likelihood of receiving liver transplants around the aMELD score 35 threshold, which determines the eligibility for Share 35 treatment. The x-axis shows transplant candidates' initial aMELD scores, and the y-axis describes the probability of receiving a deceased donor liver transplant within 90 days from the waitlist registration. Each of the points in the figure shows the average outcome value collapsed into equal-length bins. Consistent with the Share 35 policy benefit, I find evidence of increased access to donated livers for transplant candidates with aMELD scores greater than or equal to 35. Column (1) of Table A.2 Panel A presents RD estimates analogous to the figures. It shows that the probability of receiving a liver transplant discontinuously increases by 13.6 percentage points above the 35 threshold, which implies an approximately 20 percent increase compared with the (baseline) mean probability of 70.4 percent for candidates below the 35 threshold.

In panels (b) to (d) of Figure A.4, I explore the transplant candidates' waitlist mortality rates, which indicates the risk of losing a chance to receive a liver transplant due to death while waiting for a liver offer. As a liver transplant is the ultimate treatment for liver failure, removal from the waitlist due to deteriorating conditions is also considered as waitlist mortality (Massie et al. 2015; Edwards et al. 2016). The figures indicate negative discontinuities at the aMELD 35 threshold, which shows lower waitlist mortality rates for candidates with aMELD scores above 35 compared with those with aMELD scores below 35. Corresponding RD estimates are presented in columns (2) to (4) of Table A.2 Panel A. Although all results are negative, only the estimates of 180-day and 1-year waitlist mortality are statistically significant. The 180-day waitlist mortality rates for candidates with aMELD scores just above 35 is 7.4

percentage points lower than those for candidates with aMELD scores just below 35, which implies an approximately 35 percent decrease compared with the baseline waitlist mortality of 21 percent (column (3)). RD estimates of 1-year waitlist mortality rates, -7.6 percentage points, in column (4) are similar to those of 180-day waitlist mortality rates.

Fuzzy RD estimates that show the causal effect of an increase in the access to liver transplants on waitlist mortality rates using the above RD estimates are presented in Panel B of Table A.2. For every analysis duration, I find a statistically significant relationship between the probability of receiving a liver transplant and waitlist mortality rates. A 10 percentage point increase in the probability of receiving a liver transplant is associated with a decrease in waitlist mortality rates ranging from 4.38 percentage points to 6.5 percentage points. Therefore, liver allocation policies increasing access to liver transplants for transplant candidates facing extremely high waitlist mortality risk could be effective in reducing their waitlist mortality rates.

Although the waitlist mortality rate is a targeted outcome of the liver allocation rule, the welfare of transplant candidates could be highly related to whether they can survive until a certain period regardless of the receipt of liver transplants. As some transplant recipients could die due to various reasons related to transplantation, analysis of overall mortality risks, including deaths after receiving transplants, is also meaningful. I examine the effect of an increase in access to liver transplants on overall mortality rates. In panels (e) to (g) of Figure A.4, there are still negative discontinuities at the aMELD 35 threshold, but the magnitudes are smaller than those of waitlist mortality outcomes. Corresponding RD estimates are presented in columns (5) to (7) in Table A.2 Panel A. In all the analysis durations, transplant candidates with aMELD scores just above 35 show lower overall mortality rates than those with aMELD scores just below 35, but I find little evidence of statistically significant differences. Fuzzy RD estimates that show the causal effect of an increase in the access to liver transplants on overall mortality rates are presented in columns (5) to (7) of Panel B. Compared with the results of waitlist mortality rates, all the fuzzy RD estimates are smaller in magnitude and insignificant.

1.5.2 Difference in Differences Estimates

By applying the DD approach to the same patient outcomes, we can examine the robustness of the RD estimates and separate the different impacts of the Share 35 policy on transplant candidates with aMELD scores above and below 35. Table A.3 shows the effect of the Share 35 policy on donor characteristics related to transplanted liver quality. Eligibility for the Share 35 policy is identified based on initial aMELD scores, and transplant candidates assigned Status 1A condition at the time of waitlist registration are used as a control group for each aMELD score group, $aMELD \geq 35$ and $aMELD < 35$. All columns are estimated with a full set of covariates, namely, transplant candidate characteristics, waitlisted transplant center fixed effects, and waitlist registration year fixed effects.

First, in column (1), I examine the impact of the Share 35 policy on the access to deceased donor liver transplants. As donated livers are allocated based on the waitlist mortality risk, on average, transplant candidates with aMELD scores greater than or equal to 35 are more likely to receive liver transplants within 90 days from the waitlist registration than those with aMELD scores below 35 (0.633 vs 0.301). As the Share 35 policy reallocates donated livers between transplant candidates with aMELD scores above and below 35, the coefficients for each candidate group show similar magnitudes but different signs. Transplant candidates with aMELD scores above 35 are 5.1 percentage points more likely to receive liver transplants after the Share 35 policy implementation. However the policy lowers access to liver transplants of transplant candidates with aMELD scores below 35 by 5.1 percentage points.

Second, columns (2) to (4) present the policy effect on the waitlist mortality rates within different durations from the waitlist registration. On average, transplant candidates with aMELD scores above 35 experience waitlist mortality rates more than twice that of those with aMELD scores below 35. The DD estimates show that the Share 35 policy reduces waitlist mortality rates of transplant candidates with aMELD scores above 35 without causing significant changes in waitlist mortality rates of transplant candidates with aMELD scores below 35. For example, 90-day waitlist mortality rates of transplant candidates with aMELD scores above 35 decrease by 8.4 percentage points after the Share 35 policy implementation, and the coefficient increases to 9.9

percentage points for 1-year waitlist mortality rates. However, I find little evidence of a statistically significant change in waitlist mortality rates of transplant candidates with aMELD scores below 35 after the Share 35 policy implementation.

Unlike the results regarding access to liver transplants and waitlist mortality, with DD estimates similar to findings in RD models, in the full sample, the DD estimates showed a large decrease in overall mortality rates after the Share 35 policy implementation. Ninety-day overall mortality rates of transplant candidates with aMELD scores greater than or equal to 35 decrease by approximately 10 percentage points after the Share 35 policy, and the magnitude increases as the analysis duration increases. However, DD estimates for transplant candidates with aMELD scores below 35 are small in magnitude and only show marginally significant results for 1-year overall mortality outcome. The difference in the coefficients between transplant candidates with aMELD scores above and below 35 is approximately 9 percentage points, which is larger than that of RD estimates.

1.6 Effect on Posttransplant Outcomes

In this section, I assess the impact of broader liver sharing on posttransplant outcomes. As discussed above, providing especially sick transplant candidates with the priority for livers donated from the areas far from the transplant center could be effective in reducing their mortality risk. However, sharing livers in broader areas could worsen the quality of transplanted livers, which could result in lower posttransplant survival rates due to longer transportation time. To examine this hypothesis, this paper focuses on the Share 35 policy to exploit the exogenous variation in the access to livers obtained from areas further away. As posttransplant outcomes are only available for transplant recipients, I limit the analysis sample to transplant recipients. The eligibility for the Share 35 policy is identified based on the last aMELD scores, and transplant recipients assigned Status 1A condition at the time of transplants are used as a control group for each aMELD score group, $aMELD \geq 35$ and $aMELD < 35$.

1.6.1 Transplanted Liver Quality

Table A.4 shows the effect of the Share 35 policy on donor characteristics related to transplanted liver quality. All columns are estimated with a full set of covariates, namely, recipient characteristics, waitlisted transplant center fixed effects, and transplant year fixed effects. First, I examine the donor characteristics directly affected by the Share 35 policy structure, which promotes frequent regional liver sharing across DSAs for transplant candidates with aMELD scores greater than or equal to 35. As expected, I find that the policy yields more liver sharing across DSAs, resulting in longer distance and time of liver transportation. Column (1) shows that the likelihood of receiving a regionally shared liver, donated from different DSAs in the waitlisted region, increases by 35.9 percentage points for transplant recipients with aMELD scores above 35 after the Share 35 policy implementation. The result is consistent with the results regarding distance and time of liver transportation in Columns (2) and (3). Exploiting the location information of transplant centers, the distance and the cold ischemia time (CIT) are 82.8 and 4.7 percent longer for transplant recipients with aMELD scores above 35 than for Status 1A transplant recipients, respectively. However, transplant recipients with aMELD scores below 35 do not exhibit a statistically significant change in those outcomes. DD estimates show that transplant recipients with aMELD scores below 35 are less likely to receive regionally shared livers, and the transportation distance and time decrease after the policy implementation. The above results could be interpreted as the trade-off between improving equity and efficiency in liver allocation. As the current liver allocation policy balances equity and efficiency, improving equity by reallocating donated livers across areas, i.e., loosening the proximity base allocation rule, does not guarantee the best use of donated livers.

Additionally, I examine other donor characteristics pointed out as factors related to worse posttransplant survival in the previous literature. For example, Busquets et al. (2001) find that livers from donors over 70 years old are negatively associated with graft survival. Livers from donors with a body mass index (BMI) over 35 and donated after the cardiac death are also described as factors that result in lower graft survival (Perito et al. 2012; Taylor et al. 2019). Columns (4)-(6) of Table A.4 show whether the above donor characteristics for transplant recipients with aMELD scores above

and below 35 change after the policy implementation. Most DD estimates do not show a statistically significant impact of the Share 35 policy, but the sign of coefficients is different between the two transplant recipient groups. After the Share 35 policy implementation, lower quality livers identified in Columns (4) to (6) are more likely to be transplanted to recipients with aMELD scores below 35 rather than to those with aMELD scores above 35.

1.6.2 Posttransplant Survival

In the liver transplant market, the quality of transplanted livers is meaningful, because it is highly related to the probability of survival without experiencing death or other liver failures after receiving liver transplants, known hereafter as "posttransplant survival". In this section, I examine how the quality changes in transplanted livers after the Share 35 policy implementation affect the posttransplant survival of transplant recipients. Column (1) of Table A.5 shows the impact on the 1-year posttransplant survival rates. Although statistically insignificant, I find that the posttransplant survival rates of transplant recipients with aMELD scores above 35 increase by 3.9 percentage points after the Share 35 policy implementation, while those of transplant recipients with aMELD scores below 35 slightly decrease. Unlike the concern regarding the quality of livers transplanted to recipients with aMELD scores above 35, the impact on posttransplant survival rates is better for those recipients than recipients with aMELD scores below 35.

However, the analysis of 1-year posttransplant survival rates may not be sufficient to show the impact on the overall posttransplant survival rates. Although additional analysis of long-term survival rates is needed for accurate assessment, it is difficult to perform the test using observed posttransplant survival outcome. Because transplant recipients whose maximal posttransplant duration by the end of the data extraction date (June 2, 2017) is less than the analysis duration should be excluded in the estimation, an increase in duration reduces the sample size and weakens the explanatory power of the estimates. Therefore, I supplement the analysis using ex ante liver quality measures highly related to long-term posttransplant survival.

The representative ex ante liver quality measure is the Donor Risk Index (DRI) introduced by Feng et al. (2006). These scholars developed the index using donor characteristics that were highly correlated with posttransplant survival rates; a higher index shows that the donated liver has lower quality and predicts lower survival rates[9]. In Column (2) of Table A.5, I examine the effect of the Share 35 policy on the negative log value of DRI of liver transplant recipients [10]. The estimates show that recipients with aMELD scores above 35 receive a 2.6 percent lower quality of livers than recipients with Status 1A condition after the Share 35 policy implementation. Unlike the results in Column (1), the negative impact of the Share 35 policy on transplanted liver quality is smaller, -0.014, for transplant recipients with aMELD scores below 35. Based on these results, we can expect that the Share 35 policy negatively affects long-term posttransplant survival of both transplant recipients groups, aMELD scores above and below 35, and the magnitude of the impact is larger for the targeted recipients, $aMELD \geq 35$. However, in explaining the long-term posttransplant survival rates, the DRI measure has some limits. Although the likelihood of survival after receiving transplants is affected not only by donor characteristics but also by the status of recipients at the time of transplantation, the DRI measure mainly focuses on donor characteristics. Furthermore, coefficients for DRI factors were derived using the transplant recipient sample who received transplants before the usage of aMELD scores (1998-2002), which has been the most important factor in the current liver allocation rule since 2002.

As an alternative liver quality measure, I propose a new match quality measure that predicts long-term posttransplant survival rates, i.e., 5 years, using the information of both donor and recipient characteristics. In the SRTR dataset, there are approximately 100 available predictors, and the number of variables increases to several thousand when I include interactions between predictors. Among these predictors, some variables may not affect posttransplant survival rates significantly, and adding too many variables in the prediction model could result in overfitting. To reduce the

[9]DRI = exp[(0.154 if 40≤age<50) + (0.274 if 50≤age<60) + (0.424 if 60≤age<70) + (0.176 if race = African American) + (0.126 if race = other) + (0.066((170 - height)/10) + (0.079 if Cause of Death (COD) = Anoxia) + (0.145 if COD = Cerebrovascular accident) + (0.184 if COD = other) + (0.411 if Donation after Cardiac Death) + (0.422 if partial) + (0.010×Cold Ischemia Time) + (0.105 if Regionally shared liver) + (0.244 if Nationally shared liver)]

[10]To avoid confusion in interpreting the sign of coefficients with other survival outcomes in the table, I use the negative sign on the log value of DRI outcome.

dimension of the prediction model, I use an ML algorithm, LASSO, which chooses the variables with the highest predictive power for posttransplant survival rates by adding a penalization term λ to the OLS objective function (Belloni et al. 2014).

$$\hat{\beta} = argmin \sum_{i=1}^{n} (y_i - x_i'\beta)^2 + \lambda \sum_{j=1}^{k} \mid \beta_j \mid \tag{7}$$

To incorporate the effect of aMELD scores on posttransplant survival rates, the sample used for variable selection is restricted to transplant recipients waitlisted after February 2002. Recipients whose maximal time period, i.e., the difference between the date of transplant surgery and the end of data collection in June 2017, is less than 5 years are excluded for precise estimation. The LASSO algorithm selects 40 variables, and the prediction results using these variables show the highest predictive power. (see for details about how variables are selected using LASSO algorithms and prediction performances are compared).

The DD estimates of predicted posttransplant survival rates for different analysis durations are shown in Columns (3)-(5) of Table A.5. The probability of survival after receiving transplants is calculated using the coefficients obtained by taking a logit estimation with LASSO-selected variables. On average, as analysis duration increases from 1 year to 5 years, posttransplant survival rates decrease for both transplant recipient groups. Although average 1-year posttransplant survival rates in Column (3) are similar to those in Column (1), DD estimates for transplant recipients with aMELD scores above 35 are different in sign. In Column (3), predicted 1-year posttransplant survival rates decrease by approximately 0.8 percentage points after the policy implementation. Although the sign is different, both results in Column (1) and (3) suggest that the negative impact on posttransplant survival rates of transplant recipients with aMELD scores below 35 is bigger in magnitude than that of transplant recipients with aMELD scores above 35. This finding is consistent with DD estimates for the 3- and 5-year predicted posttransplant survival rates in Columns (4) and (5). For all analysis durations, transplant recipients with aMELD scores below 35 are around 1 percentage point less likely to survive after receiving transplants, and all results are statistically significant.

When we consider the Share 35 policy structure, negative impacts of the Share 35 policy on transplanted liver quality and posttransplant survival rates for transplant recipients with aMELD scores above 35 could be intuitive. However, explaining negative and even larger impacts on those outcomes for recipients with aMELD scores below 35 could be difficult. To further elucidate the mechanism, I hypothesize that transplant candidates with a higher chance of receiving liver offers become more selective of liver offers, which could transfer some loss in donor liver quality to other transplant recipients. To examine this hypothesis, I analyze the impact of the Share 35 policy on the liver offer-acceptance pattern in Section 1.7.

1.7 Effect on Liver Offer-Acceptance Behavior

1.7.1 The Liver Search Model

I develop a simple liver search model with an exogenous quality of donated livers in continuous time following the search model proposed by Rogerson et al. (2005). Consider an economy with individuals who are risk-neutral, live infinitely long, and discount the future at rate r. Without receiving a transplant, liver candidates face a high mortality risk. With probability δ, liver candidates die while waiting for a liver offer. Surviving candidates receive donated liver offers at rate λ, and the quality of the liver, q, is randomly drawn from a known distribution function $F(q)$. If a liver offer is accepted, the candidate receives a utility w until he/she experiences a transplanted liver failure. The likelihood of liver failure is a decreasing function of transplanted liver quality, $p(q)$, with $p'(q) < 0$. When not receiving a transplant, the candidate receives a utility b smaller than w. Thus, Bellman equations in discrete time can be defined as

$$V_T(q) = w + \frac{1}{1+r}\{1 - p(q)\}V_T(q) \tag{8}$$

$$V_U = b + \frac{1}{1+r}(1-\delta)[\lambda \int_0^\infty max\{V_U, V_T(q)\}dF(q) + (1-\lambda)V_U] \tag{9}$$

where $V_T(q)$ is the payoff from receiving a donated liver with quality q. V_U is the payoff from searching for a deceased donor liver: earning base payoff, b, and waiting for the next liver offer. When I allow the length of the time period to be $\triangle$ and $\triangle \to 0$, I can

generalize the above two Bellman equations in continuous time.

$$\{r + p(q)\}V_T(q) = w \tag{10}$$

$$(r + \delta)V_U = b + \lambda \int_0^\infty max\{0, V_T(q) - V_U\}dF(q) \tag{11}$$

If $V_T(q)$ is strictly increasing, there is a unique reservation liver quality q_R that makes $V_T(q_R) = V_U$. A liver candidate rejects a liver when $q < q_R$ and accepts it when $q \geq q_R$. Solving equation (10) for $V_T(q)$ and substituting in equation (11) yields the reservation liver quality equation

$$p(q_R) = [\frac{b}{(r + \delta)w} + \frac{\lambda}{r + \delta} \int_{q_R}^\infty \{\frac{1}{r + p(q)} - \frac{1}{r + p(q_R)}\}dF(q)]^{-1} - r. \tag{12}$$

In this model, an increase in the rate of a liver offer, λ, yields a higher reservation liver quality, q_R, which makes a liver candidate more selective. The Share 35 policy increases the chance of receiving liver offers for transplant candidates with aMELD scores greater than or equal to 35 by providing them with the regional priority. Based on the above liver search model, we can expect that transplant candidates treated by the Share 35 policy would become more selective, and show lower offer-acceptance rates given the quality of liver offers.

1.7.2 Results

As not all livers are accepted at the first offer, some transplant candidates have multiple liver offer histories and a different aMELD score for each offer. I treat each liver offer of a transplant candidate as a distinct observation to consider the incentive changes resulting from a different aMELD score. As a candidate's offer-acceptance decisions could be related to each other, standard errors clustered at the individual level are reported. I limit the analysis sample to transplant candidates who received at least one liver offer while waiting since liver offer-acceptance outcome is only avaiilable when transplant candidates receive liver offers. Additionally, I limit the sample to liver candidates ranked in the top 5 positions for each liver offer (Goldberg et al. 2017).

Candidates ranked in a very low position could refuse liver offers due to their ranks rather than the quality of offered livers. Refusals from other candidates with higher rank may present a bad signal about the condition of the offered liver and yield lower acceptance regardless of the quality of livers.

First, I examine whether transplant candidates with aMELD scores greater than or equal to 35 are more likely to receive liver offers after the Share 35 policy implementation. Identifying the causal effect of the policy on the access to liver offers is difficult because the change in offer-acceptance rates after the policy implementation also affects the access to the liver offer. When a liver becomes available, a transplant candidate ranked in second position can receive a liver offer only if the top-ranked candidate declines the offer. If transplant candidates become more selective and decline liver offers more due to an increased access to liver offers, access to liver offers for transplant candidates ranked in a lower position would also increase. Thus, an overall increase in the access to liver offers in the analysis sample, which includes transplant candidates ranked in the top 5 positions, may overestimate the causal effect of the Share 35 policy. Although restrictive, we can avoid the effect of change in offer-acceptance rates and guess the change in access to liver offers by focusing on the first liver offers matched to top-ranked transplant candidates. Figure A.5 shows the frequency of first liver offers for each aMELD score at the time of liver offers, and I find that the Share 35 policy increases liver offers for transplant candidates with aMELD scores above 35 and reduces offers for those with aMELD scores below 35.

Table A.6 presents the DD estimates for the impact of the Share 35 policy on the likelihood of liver offer acceptance. The eligibility for the Share 35 policy is identified based on the aMELD scores at the time of liver offers, and transplant candidates assigned Status 1A condition at the time of liver offers are used as a control group for each aMELD score group, $aMELD \geq 35$ and $aMELD < 35$. All columns are estimated with a full set of covariates, namely, donor and candidate characteristics, waitlisted transplant center fixed effects, and year of liver offer fixed effects. Column (1) shows the DD estimates without donor characteristics. Transplant candidates with aMELD scores greater than or equal to 35 are 12.4 percentage points less likely to accept liver offers after the Share 35 policy implementation. The estimate is an approximately

22 percent decrease in the offer-acceptance rate given that the average acceptance rate of candidates with aMELD scores above 35 before the Share 35 policy implementation was 56 percent. However, the result in Column (1) may not show the causal effect of an increased chance of receiving a liver offer (λ in equation (12)) under the Share 35 policy on a liver candidate's offer-acceptance behavior (q_R). If the Share 35 policy changes not only the likelihood of receiving a liver offer but also the quality of the offer ($F(q)$) for the treated candidates, the result in Column (1) could reflect the impact of both changes. In particular, the change in liver quality could be negative, as the Share 35 policy yields more regional liver sharing and longer transportation times. In this case, the results could overestimate the effect of the change in λ, as transplant candidates with lower quality liver offers would be more likely to refuse them. To isolate the effect of an increased chance of receiving a liver offer, I controll for donor characteristics, and the results are presented in Column (2). The offer-acceptance rates for transplant candidates with aMELD scores above 35 decrease by 10.2 percentage points after the Share 35 policy implementation. As expected, the magnitude of the estimates in Column (2) is smaller than that in Column (1).

As shown in Figure A.5, the Share 35 policy reduces access to liver offers for transplant candidates with aMELD scores below 35. Thus, we can expect that those candidates would be more likely to accept liver offers after the Share 35 policy implementation. However, although statistically insignificant, DD estimates in Columns (1) and (2) for transplant candidates with aMELD scores below 35 are negative in sign, which implies more declines of liver offers. The results that differed from expected results could be explained by the forward-looking behavior of transplant candidates. As transplant candidates update their aMELD scores regularly, some candidates with aMELD scores just below 35 could expect that they will be eligible for the Share 35 policy in the next aMELD score update and decline liver offers based on expectations rather than current aMELD scores. Because each candidate's expectation of aMELD score is unobserved, I use various aMELD score update frequencies across transplant candidates as a proxy. A transplant candidate's aMELD score update frequency is regulated by OPTN's rule. Transplant candidates with aMELD scores ranging from 15 to 18 are updated every 3 months, and those with aMELD scores ranging from 19 to 24

are updated every month. If a transplant candidate has an aMELD score greater than 25, his/her aMELD score should be updated every week. As transplant candidates with aMELD scores close to the aMELD score 35 cutoff update their aMELD scores more frequently, we can expect that those candidates could be more forward looking and become more selective of liver offers. Columns (3) - (5) show the estimates for different subgroups based on the aMELD scores at the time of liver offer. In Column (3), transplant candidates whose aMELD scores ranging from 25 to 34 are 3.8 percentage points less likely to accept liver offers, representing a statistically significant difference. As aMELD scores are farther from the aMELD score 35 cutoff, DD estimates imply that transplant candidates are less likely to become selective of liver offers after the Share 35 policy implementation. As shown in Column (5), transplant candidates with aMELD scores ranging from 15 to 18 are around 0.8 percentage points more likely to accept liver offers. As a result, the negative estimates, that we observed in Columns (1) and (2) could be a result of transplant candidates who become selective of liver offers due to their forward-looking behaviors although their aMELD scores are less than 35.

1.8 Robustness and Specification Check

1.8.1 Placebo Tests

In the analysis of access to liver transplants and patient mortality (Section 1.5), I assume that the observed discontinuities in the outcomes are caused by the Share 35 policy. If similar discontinuities exist at the aMELD score 35 threshold in the pre-Share 35 periods, it would be difficult to argue that the RD estimates are caused by the policy. To address this concern, I repeat the RD estimation using transplant candidates waitlisted before the Share 35 policy implementation. I define the pre-Share 35 sample as candidates whose registration was completed between January 2011 and June 2013[11].

The placebo test results for the access to liver transplants within 90 days from the waitlist registration are shown in Column (1) of Table A.7. Unlike the positive

[11]If I only define the Pre-Share 35 sample with the date of registration, there could be an overlap of candidates between Pre- and Post-Share35 periods, as I am interested in the transplant outcomes within the analysis period (90 days from registration). To avoid this overlap, I exclud candidates whose 90th day from registration exceed June 18, 2013.

and statistically significant results in the post-Share 35 period, transplant candidates with aMELD scores greater than or equal to 35 are 8.4 percentage points less likely to receive liver transplants within 90 days compared with candidates with aMELD scores below 35. The results for waitlist mortality rates and overall mortality rates are shown in Columns (2)-(4) and Columns (5)-(6), respectively. For both outcomes, although the magnitude of RD estimates for 90-day and 180-day outcomes is large, they have opposite signs to those of the results in the post-Share 35 period, with statistically significant differences. However, RD estimates for 1-year waitlist mortality rates are relatively small in magnitude. The above results with the opposite sign suggest that the significant effect on access to liver transplants and waitlist mortality rates found in the post-Share 35 period could be caused by the Share 35 policy implementation.

1.8.2 Sensitivity to Bandwidth and Polynomials

As a specification check, I examine whether the RD estimates in Table A.2 are sensitive to bandwidths and the degree of the polynomials. Figure A.6 and A.7 present the RD estimates and point-wise 95 percent confidence intervals for the estimated coefficients based on all bandwidths from 1 to 4 in 0.25 aMELD score increments. The vertical red line in each figure shows the data-driven optimal bandwidths (Calonico et al. 2017). Additionally, I compare the local linear estimates with estimates using quadratic polynomials. In all figures, the distance between the upper and lower bounds decreases as the bandwidth increases, which indicates an increase in precision due to an increase in sample size. Panels (a) and (b) in Figure A.6 present the results of the likelihood of receiving a liver transplant within 90 days from the waitlist registration. They show that the RD estimates are robust to the bandwidth selection and the degree of the polynomials. The results of the waitlist mortality rates are shown in panels (c) - (h), and those of the overall mortality rates are shown in panels (a) - (f) in Figure A.7. Overall, the figures suggest that the RD estimates for mortality outcomes are not sensitive to the bandwidth choices and the degree of polynomials.

1.8.3 The Assumption of a Common Trend

For the causal interpretation of the estimates driven from a DD estimation strategy, a parallel pre-trend assumption is needed. Under the assumption, the change in outcomes of transplant candidates with aMELD scores above 35 or below 35 would have been the same as that of Status 1A transplant candidates in the absence of the Share 35 policy. I use an event study approach to assess whether the DD estimates in this paper correspond to this the assumption. For the event study analysis, I add interaction terms of a treatment dummy variable and the series of a time dummy variable using the year prior to the time of Share 35 policy implementation in the DD equation. If the assumption holds, I would expect insignificant coefficients for interactions terms before the Share 35 policy implementation.

Figure A.8 displays the estimates from the event study model for access to liver transplants and mortality rates for transplant candidates with aMELD scores greater than or equal to 35. Most figures support the parallel pretrend assumption, but I find a positive and statistically significant results for the 90-day overall mortality rates, panel (e), at the 10 percent significance level. Figure A.9 shows the estimates for the same outcomes for transplant candidates with aMELD scores below 35. 90- and 180-day overall mortality outcomes show positive and statistically significant pretrends at the 5 percent signficance level. The results suggest that we need to be cautious in interpreting the causality of the impact on the overall mortality rates based on the DD estimates.

Figures A.10 and A.11 show the event study results of posttransplant outcomes for transplant recipients with aMELD scores above 35 and below 35, respectively. Regarding the outcomes of transplant recipients with aMELD scores greater than or equal to 35, I do not find any evidence of a violation in the parallel pretrend assumption. However, in Figure A.11 for transplant recipients with aMELD scores below 35, there are three outcomes that have statistically significant estimates at the 10 percent significance level: the likelihood of receiving regionally shared livers (panel (a)), the likelihood of receiving livers from donors whose BMI is over 35 (panel (e)), and the negative log value of DRI (panel (h)).

Finally, the event study results for liver offer-acceptance rates for transplant candidates with aMELD scores above and below 35 are shown in Figures A.12 and A.13. None of the figures show statistically significant estimates before the implementation of the Share 35 policy, which supports the parallel trend assumption of the DD estimates.

1.9 Conclusion

As the price mechanism, which allocates scarce resources based on willingness to pay, does not exist in the liver transplant market, every donated liver is distributed by the allocation rule of the OPTN. Following the Final Rule (2000)[12], the current liver allocation rule prioritizes medically urgent candidates while trying to maintain the quality of donated livers. To improve access to liver transplants for transplant candidates who have similar mortality risk to Status 1A transplant candidates, in June 2013, the OPTN implemented the Share 35 policy. Under the policy, transplant candidates with aMELD scores above 35 are prioritized for livers donated in their regions over local candidates with aMELD scores below 35 registered in the same DSA as the donor hospital.

This paper studies the impact of the Share 35 policy on transplant outcomes and transplant candidates' liver offer acceptances. Using the variation in the eligibility for the policy at the aMELD score 35 threshold, I found that waitlist mortality rates decrease significantly when the access to liver transplants increases, although the significance of the impact on the overall mortality rates is not clear in the RD results. Additionally, I found that the Share 35 policy could result in several unintended impacts on posttransplant outcomes and offer-acceptance incentives of transplant candidates. The policy could worsen liver quality by increasing transportation time, but some amount of the quality loss is transferred to untargeted recipients with aMELD scores below 35. DD estimates suggest that the negative impact on posttransplant survival rates is larger for untargeted recipients with aMELD scores below 35 than targeted recipients. To explain the compensation for the transplanted liver quality loss for the targeted recipients, I propose a mechanism in which the Share 35 policy affects the

[12] https://optn.transplant.hrsa.gov/governance/about-the-optn/final-rule/, information accessed on the web, last accessed on June 23, 2019.

liver offer-acceptance behavior of transplant candidates. With a proposed liver search model, I found that transplant candidates with MELD scores above 35 become more selective of liver offers when the likelihood of receiving a liver offer increases under the Share 35 policy and choose livers of better quality.

Currently, the OPTN is preparing a new liver allocation system that allocates donated livers based on the distance from the donor hospitals regardless of previous geographic boundaries, DSA and Region[13]. Although the areas of distribution according the new allocation rule will change dramatically from those in the Share 35 policy, the liver-sharing model used to prioritize targeted candidates in the Share 35 policy still remains. For example, under the new allocation rule, transplant candidates with MELD scores of 37 or greater registered at transplant centers within 250 nautical miles (nm) of the donor hospital are prioritized under the new allocation rule over those with MELD scores below 37 registered at transplant centers within 150 nm[14]. Although there are active discussions about the new allocation system, the topic is mainly focused on how many donated livers each DSA or region will lose or gain. As shown above, changes in areas where donated livers will be shared will also cause changes in donated liver quality and strategic offer-acceptance behavior of transplant candidates. Therefore, the results found in this study could also be meaningful for evaluating the possible impact of the new allocation rule before its implementation.

[13] https://unos.org/policy/liver-distribution/, information access on the web, last accessed on June 23, 2019.

[14] This allocation rule is applied for livers from non-DCD donors younger than 70. Livers from DCD donors older than 70 are allocated to candidates with MELD scores of at least 15, first within 150 nm, then within 250 nm, then within 500 nm (https://unos.org/policy/liver-distribution/, information accessed on the web, last accessed on June 23, 2019).

Chapter 2

The Role of Kidney Allocation Policy in Addressing Kidney Shortages

2.1 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.[15] Figure B.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[16], 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.[17]

[15] 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.

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

[17] 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.

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 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.[18] If candidates who are less likely to be crowded out also experience small improvements in mortality in comparison

[18]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).

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 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.[19] To address the endogeneity of the kidney source choice

[19]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.

problem, Fernandez et al. (2013) and 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[20] 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 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

[20]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.

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 2.3 describes the data sources, while Section 2.4 explains the main identification strategy. Section 2.5 shows the estimation results, Section 2.6 tests the robustness of the results, and Section 2.7 concludes.

2.2 Institutional Details

2.2.1 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[21]) 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.[22] 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 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

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

[22]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).

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.[23] 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.

2.2.2 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 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

[23]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).

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 B.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^*.

2.2.3 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 B.1. Candidates who are younger, better matched, waitlisted longer, and more sensitized are more likely to have higher kidney points.

2.2.4 Sensitization Points

Among the factors in the kidney points in Table B.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.[24] 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.[25] 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 B.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.[26] 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 the PRA era, candidates with a PRA score of 80 or greater received an additional 4 kidney points. According to Table B.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.[27] 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

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

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

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

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

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 $1 - (CPRA)^n$[28] (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 B.2.

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 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

[28]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.

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.[29] 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 B.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

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

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.

2.4 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.[30] The estimation equation is shown below.

$$Y_i = \alpha + \beta_0 CPRA80_i + f(X_i) + u_i \tag{13}$$

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.[31] 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

[30] D. S. 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.

[31] 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.

2.2, 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 Appendix E 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 (**lee2008regression**; D. S. Lee et al. 2010). When 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 2.2.4, 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 B.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 B.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 B.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[32] (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,

[32]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).

many women of childbearing age may experience irregular menstruation periods and have unhealthy eggs[33], 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 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.

$$Y_i = \alpha + \beta_0 X_i + \beta_1 X_i^2 + \gamma' W_i + u_i \tag{14}$$

where i denotes a kidney transplant candidate. The equation is similar to the identification equation (13). 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 B.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 B.6 show smooth patterns around the CPRA 80 threshold.

2.5 Results

I show the trade-offs between the two kidney sources in Section 2.5.1. Section 2.5.2 shows how a candidate's mortality risk changes as his or her access to deceased donor kidneys increases, while Section 2.5.3 tests heterogeneity by characteristics of candidates to identify the types of candidates who can be prioritized in the kidney allocation.

2.5.1 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 B.5 shows

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

the RD estimates of the probability of receiving deceased donor kidneys, and panel (a) of Figure B.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 B.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 B.2) in 2014.

Panel (b) of Figure B.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 B.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 B.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 B.2 and switching the kidney source from living donor kidneys to deceased donor kidneys.

2.5.2 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.[34] 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 B.6 shows the RD estimates of the waitlist mortality analysis, and panels (a) and (b) of Figure B.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 B.8, there are negative discontinuities at the CPRA 80 threshold, and the

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

magnitude of discontinuity increases as the duration increases. The corresponding RD estimate, in column (1) of Table B.6 panel A, increases as the duration increases from 1.13 percentage points (1 year) to 2.83 percentage points (2 years).[35] 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 B.6 shows the fuzzy RD estimates using the first-stage results in the above section.[36] 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 B.7, and related figures are presented in panels (c) and (d) in Figure B.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 panel A of Table B.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

[35] As the sample size for the mortality analysis in each duration is different, direct comparisons of RD estimates may not accurate. I repeat the RD estimation using the same sample size for each duration and the results are shown in Table B.14.

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

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.

2.5.3 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 2.2.2, 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 B.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 B.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 B.8)[37], 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 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

[37]As the sample size for the mortality analysis in each duration is different, direct comparison of RD estimates may not be accurate. I repeat the RD estimation using the same sample size for each duration and the results are shown in Table B.15 - B.17.

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 B.10). Table B.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 B.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 B.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 B.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.

2.6 Robustness Check

This section presents a series of analyses to test the robustness of the main findings. First, in Figure B.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 B.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 B.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 B.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 B.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

$$Y_{it} = \alpha + \beta_0 CPRA80_i + \beta_1 postCPRA_t + \beta_2 (CPRA80 \times postCPRA)_{it} + W_{it}\gamma + \eta_t + u_{it} \tag{15}$$

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 B.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.

2.7 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 trans-

plants on the waitlist.[38] 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 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

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

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.

Chapter 3

The Strategic Location Choice of For-profit Hemodialysis Facilities in the U.S.

3.1 Introduction

The kidneys are a pair of organs in the human body that remove waste from the blood and control the body's fluid balance. When both kidneys fail, blood wastes accumulate in the patient's body and the risk of death increases. Two representative treatments for patients with kidney failure are kidney transplants and dialysis. Unlike transplants, which place a healthy kidney in a patient's body, dialysis uses a machine that substitutes the work of the kidneys. Due to the high shortage of transplantable kidneys, in 2016, more than seventy percent of 726,331 patients with kidney failure were dependent on dialysis treatment for survival (United States Renal Data System 2018). As depicted in Figure C.1, with the steady increase in the incidence of kidney failure and demand for dialysis treatment, the dialysis industry has expanded. In 2016, there were approximately 7,100 dialysis facilities in the United States, four times the number of facilities in 1988. Furthermore, because Medicare covers nearly all populations with kidney failure regardless of age, the financial burden of the government for supporting those patients is high. According to United States Renal Data System (2018), although less than 1 percent of patients covered by Medicare had kidney failure in 2016, these patients accounted for approximately 7 percent of Medicare fee-for-service coverage.

Despite the fast growth of the dialysis industry and the huge financial burden on Medicare, little is understood about how dialysis facilities decide whether to enter a certain market and where to locate within the market. In the general market, profit-maximizing firms wish to differentiate their products by lowering prices or improving quality to appeal to consumers and gain more profits. However, the dialysis industry has characteristics that make product differentiation difficult. First, the price of dialysis is fully controlled by the government because most patients with kidney failure are eligible for Medicare. Additionally, the performance of dialysis treatment is somewhat

homogeneous across facilities because most of the dialysis process is performed using a dialysis machine. Therefore, the location of dialysis facilities could be the most important factor allowing for product differentiation.

The goal of this paper is to identify key factors that affect dialysis facilities' strategic decisions for market entry and location choice by using a structural model. First, dialysis facilities are likely to choose a location where the demand for dialysis treatment is high. However, they also need to consider the expected competition with other facilities that might choose the same location. Because of the limited options for differentiating the product, namely, dialysis treatment, across facilities in the same location, higher competition will lower a facility's expected profits.

This paper applies the structural methods from modern industrial organization to study dialysis facility behaviors. The analysis of firm entry and location decisions is based on the literature on discrete entry games proposed by Bresnahan et al. (1991) and Berry (1992). These studies show that the level of competition affects the entry decision of firms because an additional entrant in a market reduces profits in an oligopolistic market structure. More recent studies (Mazzeo 2002; Seim 2006) extend this literature by incorporating the product differentiation concept. In Mazzeo (2002)'s model, firms not only determine whether to enter a market but also select product types under the complete information assumption. That is, firms do not have the information on the profit shocks of the other competing firms. On the other hand, in Seim (2006)'s model, video rental stores determine their market entry and their location under the assumption of homogeneous product type and incomplete information status. I contribute to this literature by examining the dialysis industry using the estimation model of Seim (2006).

To date, literature on the hospital competition has focused on the effect of competition on the quality of health care services. In many situations, prices for health care services are administered by regulators such as Medicare. Hence, hospitals are likely to compete for quality and empirical studies support this. Kessler et al. (2000) find higher one year mortality rates for Medicare patients with acute myocardinal infarction (AMI) and lower expenditures in less concentrated markets. Two studies (Cooper et al. 2011; Gaynor et al. 2013) also find similar results and identify lower

mortality rates among AMI patients in less concentrated markets by using a reform in the English National Health Service (NHS) that promotes competition among hospitals. Using the same set of data from the English NHS, Propper et al. (2010) find that having more local competitors has a large impact on hospital management quality based on Bloom et al. (2007). I contribute to this literature by suggesting that facility location could also be a factor that allows health care providers, i.e., dialysis facilities, to differentiate their quality.

Several studies have analyzed the spatial competition in the dialysis industry. Wilson (2016) studied differences in the entry and exit patterns of for-profit and non-profit dialysis facilities. Exploiting 20 years of longitudinal data on dialysis facilities in the U.S., this author finds that for-profit facilities are quicker to enter growing markets and slower to exit declining ones compared to non-profit facilities. Additionally, the existence of for-profit facilities in a market has a larger impact on the entry and exit of competitors. Eliason (2017) estimates an entry game where dialysis facilities choose both the capacity and quality, and he finds that dialysis facilities can compete more effectively in terms of capacity rather than quality because increasing quality is very costly to dialysis providers and patients may not be responsive to the quality. Although these studies consider the market entry decision of dialysis providers, they do not consider location selection upon entry in their estimation models. Wilson (2016) uses counties as their market unit, and Eliason (2017) exploits Core-Based Statistical Areas as a market definition. This paper contributes to this literature by analyzing the location choice problems in a census tract-level assuming that competing dialysis facilities are symmetric.

Detailed information on the dialyis market in the United States is obtained from the United States Renal Data System (USRDS). The data contain the exact locations of dialysis facilities and the demographic characteristics of patients with kidney failure, including their zip code-level residence information. Information on the socio-economic status of each census tract-level location, such as the per capita income, education level, median gross rent, etc., is obtained from the 2015 American Community Survey (ACS).

The estimation results show that dialysis facilities are usually located in areas with a larger number of patients with kidney failure. A 10 percent larger number of

patients with kidney failures increases the location choice probability by 2.01 percent. In terms of competition, I find that the expected probability of having competitors in the location reduces profits significantly and makes firms avoid locations in which high competition is expected. This result supports the idea that dialysis facilities use spatial differentiation to differentiate their products.

When dialysis facilities consider future local demand more than the current demand, the effect of local demand variables increases while the competition effect shrinks. I use the number of population with age 65 years and above and socioeconomic status as the measures of future local demand and find that a 10 percent increase in the elderly population increases the location choice probability by 3.85 percent. As socioeconomic status is negatively related to kidney failure incidence, the estimation results show that dialysis facilities prefer locations with lower socioeconomic status.

This evidence of the strategic location choice of dialysis facilities is meaningful for the discussion on the relationship between profit status and patient outcomes. Previous literature (D. K. Lee et al. 2010; Brooks et al. 2006) finds longer hospital days per patient but no evidence of an effect on patient mortality in for-profit dialysis facilities. To address the possible bias in a patient's choice of dialysis facility, those studies use an instrumental variable regression method with the relative proximity of dialysis facilities to the patient's residence as the instrument. The evidence of strategic location choice of for-profit dialysis facilities implies that the relative distance instruments may not fully address the selection biases. For-profit dialysis facilities are more likely to be located in areas with low socioeconomic status, and patient outcomes in those areas could be different from those in the other areas.

The rest of the paper is organized as follows. The following section provides background information on dialysis and the dialysis industry. Section 3.3 describes the data used for the estimation, while Section 3.4 discusses the estimation model. Section 3.5 presents the parameter estimates of key factors that affect the location choice of dialysis facilities. Section 3.6 provides key robustness factors, and Section 3.7 presents the conclusions.

3.2 Background

3.2.1 Treatments for Patients with Kidney Failure

When a person's kidneys are no longer able to work on a permanent basis, he/she is diagnosed with the end-stage renal disease (ESRD)[39]. As shown in Figure C.2, the number of ESRD occurrences has increased steadily from 1988 to 2016. In 1988, there were 28,927 incidences of patients newly diagnosed with ESRD in the United States, although this figure increased to 101,334 in 2016[40]. The figure shows that the increase in ESRD incidences is driven primarily by people aged 65 and older. This result could be related to an increasing number of elderly people thanks to medical advances (Administration on Aging 2018). Figure C.3 shows the share of primary causes among patients with ESRD. The most common causes of ESRD are diabetes (48%, 2016) and hypertension (29%, 2016). Stevens et al. (2010) shows that the prevalence of these conditions is higher for elderly individuals than for middle-aged adults[41].

ESRD patients need to receive either a kidney transplant or dialysis treatments to prolong their lives. A kidney transplant is a surgery that places another person's kidney into the ESRD patient's body. Unlike patients with other organ failures, ESRD patients can survive by undergoing dialysis treatments without receiving a kidney transplant. Dialysis is a treatment that filters ESRD patients' blood using a machine that performs the work of the kidneys. As blood wastes and fluids continuously accumulate after each dialysis, ESRD patients regularly need to receive dialysis, which takes approximately 4 hours, and is usually performed three times a week. Previous studies have shown that patients who receive kidney transplants may have better outcomes in terms of survival and quality of life on average than those who continue receiving dialysis (Schold et al. 2014; Wolfe et al. 1999; Overbeck et al. 2005). However, Figure C.4 shows that most ESRD patients choose dialysis and do not even register for kidney transplant waitlists. The share of patients who are waitlisted for deceased donor

[39] https://www.cms.gov/Medicare/Coordination-of-Benefits-and-Recovery/Coordination-of-Benefits-and-Recovery-Overview/End-Stage-Renal-Disease-ESRD/ESRD

[40] This paper excludes ESRD occurrences in U.S. territories - Puerto Rico (PR), Virgin Islands (VI), Guam (GU), Northern Mariana Islands (MP), American Samoa (AS) -, and with unknown age, race, sex, zip codes, and profit status of the dialysis center.

[41] Approximately 11% of middle-aged adults have diabetes and 33% have hypertension, with the prevalence of these conditions increasing to 23% and 66%, respectively, by age 60.

kidneys or receive living donor kidneys within 1 year after ESRD diagnosis is less than 10 percent.

3.2.2 Medicare and the Dialysis Industry

If the cost of dialysis treatment is high[42], many patients will not receive the treatment and the mortality risk of ESRD patients will increase. In the United States, Medicare plays an important role in financing dialysis treatment. The Social Security Amendments of 1972 provided Medicare coverage to nearly the entire U.S. population with ESRD regardless of age[43]. On December 31, 2015, more than 80 percent of ESRD-prevalent patients were receiving dialysis treatments covered by Medicare (Kirchhoff 2018). Since 2011, Medicare has reimbursed the dialysis facilities using a prospective payment system (PPS) that provides a bundled amount of money per patient per treatment for dialysis and necessary support, such as tests and medications (Collins 2012). As the amount of the reimbursement is determined in advance (the base rate in 2020 is \$239.33[44][45]), and beneficiaries pay coinsurance equal to 20 percent of the Medicare-approved amount; the price of dialysis treatment for the majority of ESRD patients is stable across dialysis facilities.

As the number of ESRD patients has increased, with certain Medicare payments, the number of dialysis facilities has steadily increased since 1988. Figure C.5 shows that there were approximately 1,800 dialysis facilities in 1988, and this figure increased to approximately 7,100 in 2016[46]. Dialysis facilities can be classified as either hospital-based or freestanding units, i.e., units not affiliated with a hospital (Center for Medicare and Medicaid Services 2019). Additionally, the facilities are operated on either for-profit or not-for-profit bases, similar to other health care providers. The growth in

[42]Childers et al. (2019) found that the cost of dialysis varies across insurers of ESRD patients. For-profit dialysis facilities charge \$248 per treatment when the government is the insurer, compared with \$1,041 per treatment for private insurance.

[43]When a patient enrolls in Medicare based on ESRD, Medicare coverage usually starts at 90 days from the ESRD diagnosis (https://www.medicare.gov/manage-your-health/i-have-end-stage-renal-disease-esrd).

[44]https://www.federalregister.gov/documents/2019/11/08/2019-24063/medicare-program-end-stage-renal-disease-prospective-payment-system-payment-for-renal-dialysis

[45]Actual amount of reimbursement is driven by adjusting multiple factors, such as patient characteristics, facility-level characteristics, etc. Detailed information on the reimbursement amount calculation is available in Kirchhoff (2018).

[46]This paper counts only Medicare-certified hospitals and outpatient dialysis facilities and excludes facilities with unknown for-profit status.

the number of dialysis facilities in each category is shown in Figure C.5. The figure implies that the major growth in the dialysis industry has been driven by freestanding and for-profit dialysis facilities. The share of this category increased from 51 percent (1988) to 84 percent (2016).

3.3 Data

3.3.1 Market Definition

In the dialysis industry, dialysis treatment is somewhat homogenous. As most ESRD patients are eligible for Medicare coverage, the treatment cost is well controlled by the government and similar across dialysis facilities. Furthermore, the process of dialysis treatment is performed by the dialysis machine, which provides standardized care. To recruit more patients, dialysis facilities tend to compete in terms of amenities, such as TVs and heated chairs. However, as ESRD patients need to receive dialysis regularly (at least 3 times a week) and permanently, they are likely to choose dialysis facilities close to their residences; thus the effect of distance may dominate the effect of amenities. Therefore, dialysis facilities may primarily compete against other facilities located in a local area and choose a location that could be the most profitable. Table C.1 shows these characteristics of the dialysis industry derived from the USRDS data. Column (1) reports that the median distance between their preferred dialysis facility and their residence among patients diagnosed with ESRD from 1988 to 2016 was only 7.404 miles. Columns (2) to (5) show the median distance to different subgroups of dialysis facilities classified according to the profit status or affiliation with a hospital. Although the distance to for-profit and freestanding facilities (7.236 miles) is shorter than that to the other types of facilities (7.636 - 8.269 miles), the difference is not great.

Because ESRD patients are sensitive to the distance from their residence, this paper focuses on mid-sized cities to identify well-defined markets. Using 2015 population data from the United States Census Bureau, this paper focuses on mid-sized cities and groups of small cities close to each other with populations ranging from 50,000 to 300,000. All cities within 5 miles from a city boundary are categorized as the same market, and the distance between cities is calculated using population-weighted centroids

of census tracts[47] located in each city boundary. To minimize the effect of neighboring markets on the dialysis facility choice of ESRD patients, I only include markets whose largest neighboring market within 20 miles had a population below 25,000. After this process, eighty-one markets are defined as the sample markets for the analysis. In Table C.2, the market size by population ranges from 56,548 to 304,016, with an average of 127,485 people. On average, there are 30 census tracts in a market. The smallest market consists of 9 census tracts, and the largest market consists of 70 census tracts. As this paper focuses on the midsized dialysis market, each market contains three facilities on average.

3.3.2 Dialysis Facilities

The data on dialysis facility locations are obtained from the USRDS, which collects information about ESRD patients, their treatments, and treatment provider. The facility data include detailed information on each facility's for-profit status, whether the facility is affiliated with a hospital, the date of certification, etc. I use the facility-level location information for 2015, when the number of dialysis facilities was maximized in the available data periods. Dialysis facilities that closed before or opened after 2015 are not considered in the analysis. This paper focuses on the location decision of freestanding and for-profit dialysis facilities[48], which have increased rapidly as shown in Figure C.5.

For the minimum unit of location decision of dialysis facilities, this paper uses United States census tracts because they are not overlapping and contain various demographic characteristics available in the United States Census data. To match the locations of dialysis facilities to census tracts, the precise location information of facilities is necessary, although the USRDS data provide only zip code-level information. To address these limitations on location information, I use the Dialysis Facility Compare Dataset from the Centers for Medicare and Medicaid (CMS), which contains the exact address of dialysis facilities. Using the address and the geocoding Stata module

[47] https://census.missouri.edu/geography/

[48] Not-for-profit facilities are excluded as their goal of operation may not be the profit maximization that this paper is assuming. Hospital-based facilities are excluded as their location decision may depend on the location of the affiliated hospitals.

- OPENCAGEGEO[49], I derive the precise latitude-longitude coordinates of dialysis facilities. The matched census tract for each dialysis facility is identified through the ArcGIS program.

3.3.3 Local Demand for Dialysis Treatments

The number of ESRD patients in each census tract can be assumed as the local demand for dialysis treatments because all ESRD patients need to receive dialysis immediately and permanently for survival. Patients who received kidney transplants or died before 2015 are excluded from the analysis because they are not active ESRD patients. Because USRDS patient data only include zip code-level residence information, the number of ESRD patients in a census tract is calculated by weighting the percentage of the total population of each zip code in each census tract[50]. Using ESRD patients as the local demand for dialysis treatment is not sufficient because dialysis facilities could determine their locations based on not only current demand but also the long-run expected local demand for dialysis treatments. As the alternative proxy for current and future local demand, I also consider the census tract-level population age 65 and older, which is the major group of ESRD patients (Figure C.2), and compare the estimates with the results using census tract-level ESRD patients. According to the study of Ward (2008), the incidence of ESRD could be affected by the socioeconomic status of the population, such as income and education[51]. These variables are available for census tracts from the Census Bureau's ACS data. As this paper analyzes the location choice of dialysis facilities actively operating in 2015, the 2015 Census of Population data are used for the estimation.

Table C.3 provides descriptive statistics of the variables used to estimate the location choice model. As dialysis treatment is needed by patients with permanent kidney failure, I use the census tract population diagnosed with ESRD or older than 65 years of age rather than the total tract population. I also use per capita income and the share of people with low education (high school or below), which could be

[49] https://fmwww.bc.edu/repec/bocode/o/opencagegeo.pdf

[50] 2010 Zip Code Tabulation Area (ZCTA) relationship files from the United States Census Bureau were used for the calculation.

[51] Ward (2008) found that the socioeconomic status of the population is highly associated with ESRD caused by diabetes mellitus.

highly related to ESRD incidence. From the cost perspective, the property lease cost might be important when each dialysis facility chooses the location. As the Census Bureau does not provide information about commercial rent, I use the median gross rent, which represents the housing cost including contract rent and utilities.

3.4 Model of Dialysis Facility Location Choice

3.4.1 Location Choice

The model in this paper assumes that all dialysis facilities choose their locations simultaneously. Additionally, this choice is structured as an incomplete information game, which is similar to the framework of Seim (2006). That is, dialysis facilities have private information about their profit shocks specific to their own location that may not be observed by other competitors. I define a series of M markets as explained in Section 3.3.1. The set of census tract-level locations is indexed by $l = 0, 1, \ldots, L^m$ in each market m[52]. Let the set of potential dialysis facilities be $f = 1, \ldots, F$. The facilities simultaneously determine whether to enter each market m and where to locate their facility in the market m.

This paper assumes that dialysis facility f's payoff at location l in market m is a linear function of market and location characteristics and competition effects in their own location. Therefore, the payoff function can be written as,

$$\Pi_{flm} = \lambda_m + X_{lm}\beta + \gamma N_{lm} + \varepsilon_{flm} \tag{16}$$

where λ_m is the market-level characteristics of market m, X_{lm} is the characteristics of location l in market m, and N_{lm} is the number of dialysis facilities located at location l in market m. ε_{flm} is the facility-specific unobservable data for dialysis facilities operating at location l in market m. I assume that each facility's ε is private information and independently and identically distributed (i.i.d) from the type-I extreme value distribution. Because the idiosyncratic error of each firm, ε, is private information, each facility will choose the optimal location that maximizes the expected payoff based on the expected location choices of other facilities and the distribution

[52]The decision of no entry is labeled as 0.

of private information, ε. To simplify the solution process, I assume that all dialysis facilities are homogeneous as explained in Section 3.3.1. The expected payoff of a firm at location l in market m is

$$\mathbb{E}(\Pi_{flm}) = \lambda_m + X_{lm}\beta + \gamma\{(\eta_m - 1)p_{lm} + 1\} + \varepsilon_{flm} \tag{17}$$

where $(\eta_m - 1)$ is the total number of competitors that entered market m and p_{lm} is the probability that competing facilities choose location l in market m, $p_{lm} = Pr[\mathbb{E}(\Pi_{lm}) \geq \mathbb{E}(\Pi_{km}),\ \forall k \neq l]$.

Due to the assumption on the distribution of private information, ε, the conditional probability of choosing location l given entry in market m can be simplified as follows:

$$\begin{aligned} p_{lm} &= Pr(locate\ at\ l \mid Entry\ in\ m) \\ &= \frac{exp[\lambda_m + X_{lm}\beta + \gamma\{(\eta_m - 1)p_{lm} + 1\}]}{\sum_j exp[\lambda_m + X_{jm}\beta + \gamma\{(\eta_m - 1)p_{jm} + 1\}]} \\ &= \frac{exp\{X_{lm}\beta + \gamma + (\eta_m - 1)\gamma p_{lm}\}}{\sum_j exp\{X_{jm}\beta + \gamma + (\eta_m - 1)\gamma p_{lm}\}} \end{aligned} \tag{18}$$

In a free market assumption, dialysis facilities will enter the market until they can earn nonnegative profits by providing dialysis treatment. Hence, at equilibrium, an additional entrant in the market will gain negative profit. Based on this idea, I assume that the outside payoff of not entering market m is zero. Given the assumption of private information, ε, the probability of entry in market m can be derived as the combination of the average expected payoff for each location in the market and the outside payoff.

$$Pr(Entry\ in\ m) = \frac{exp(\lambda_m)[\sum_j exp\{X_{jm}\beta + \gamma + (\eta_m - 1)\gamma p_{jm}\}]}{1 + exp(\lambda_m)[\sum_j exp\{X_{jm}\beta + \gamma + (\eta_m - 1)\gamma p_{jm}\}]} \tag{19}$$

Therefore, the expected number of entrants in market m can be derived by calculating the following:

$$\eta_m = Pr(Entry\ in\ m) \times F_m \tag{20}$$

where F_m is the number of potential entrants in market m.

3.4.2 Identification

A joint equilibrium that predicts the probability of location choice and market entry can be derived by using Equations (18) and (20). The system of equations is highly nonlinear and difficult to solve because the market characteristics, λ, are unobserved. To simplify the solution process, I follow the logic of Seim (2006), which assumes that the expected number of entrants in each market is the same as the number of actual entrants observed in the data by adjusting the market characteristics, λ. When we solve equations (19) and (20), market characteristics λ can be derived as a function of location characteristics.

$$\lambda_m = ln(\eta_m) - ln(F_m - \eta_m) - ln[\sum_j exp\{X_j\beta + \gamma + (\eta_m - 1)\gamma p_{jm})] \tag{21}$$

If we substitute the number of actual entrants in η_m of Equation (21), the market characteristic λ equalizes the number of expected entrants as the number of actual entrants. As λ is unobserved in the data, I assume that it is independently and identically distributed and drawn from the normal distribution with mean μ and variance σ^2.

The parameters to be estimated are $\theta = (\beta, \gamma, \mu, \sigma)$ where β captures dialysis facilities' preference over location characteristics, γ shows the competitive effects across firms, and μ and σ determine the distribution of market characteristics. To estimate the model, I nest the fixed-point algorithm in Equation (18) into a maximum likelihood routine. Given the parameters, the fixed point solution, $p_m(X, \beta, \gamma, \eta_m; \lambda_m)$, can be found which shows the structural probability vector of each location choice in market m. When we solve this problem for M markets, the estimation problem maximizes the

following log-likelihood function:

$$lnL = \sum_{m=1}^{M} \sum_{j=1}^{L^m} n_{jm} ln(p_{jm}) - \frac{M}{2}[ln(2\pi) + ln(\sigma^2)] - \frac{1}{2\sigma^2} \sum_{m=1}^{M} (\lambda_m - \mu)^2 \qquad (22)$$

where n_{jm} is the actual number of dialysis facilities at location j in market m. The second part of the log-likelihood function shows the market-level characteristics drawn from the normal distribution.

3.5 Results

Table C.4 reports the parameter estimates of the factors that affect the location of dialysis facilities. I obtain the parameter estimates by maximizing Equation (22) using a pattern search algorithm. Because dialysis facilities might operate differently when the demand is measured by the current ESRD patients than when the demand is measured by the population age 65 and older, I estimate separate models for each local demand measure. I assume that the number of potential entrants, F_m, is twice the actual number of facilities in each market. As depicted in Equation (18), changing the size of the potential entrants does not change the location choice decision of the entrants in each market, and its effect is absorbed by the estimates of market characteristics, λ_m. The table additionally shows marginal effect for each exogenous variable. For each location, I calculate the change in the location-choice probability conditional on the market entry when its exogenous variable increases by 10 percent. The reported marginal effects are derived by averaging the change in location-choice probabilities across all census tracts.

As expected, the parameter estimates show that the attractiveness of a location is affected by two opposing forces; local demand and potential competition. Column (1) shows the parameter estimates using the number of current ESRD patients as the local demand. The number of ESRD patients positively affect the dialysis facility's profit. A 10 percent increase in the number of ESRD patients for a specific location makes dialysis facilities 2.01 percent more likely to choose the location. On the other hand, dialysis facilities are less likely to be located in areas with high property rental costs

because high rent would increase the cost of operating dialysis facilities. A 10 percent increase in the gross rental cost for a location implies 1.17 percent lower probability of the location choice.

The parameter for potentially competing facilities is large and negative. As rivals entering in the same location will reduce profits, dialysis facilities have a strong incentive to avoid competition by choosing locations where the other facilities are not located. When one additional dialysis facility enters a market, the likelihood of choosing the location where it was most preferred decreases in all markets. On average, the probability decreases by 1.61%. However, the change increases the likelihood of choosing the location where it was least preferred by 1.18%, which means that more expected competitors leads to a more even distributino of dialysis facilities among locations.

Column (2) reports the parameter estimates using the population over 65 years and socioeconomic status factors as the measure of the long-run expected local demand of dialysis treatment. Dialysis facilities prefer locations with more at-risk patients who are over 65 years of age and have a lower income per capita and a cheaper property rental cost. When a location's population with age 65 and above increases by 10 percent, dialysis facilities are 3.85 percent more likely to select this location. However, income per capita is negatively related to the location-choice probability. For the same level of change in income per capita, the likelihood of the location-choice decreases by 3.73 percent. With regard to education level, I find that dialysis facilities are less likely to be located in areas with a high share of poorly educated individuals. The negative effect of the gross rental cost is larger in Column (2). A 10 percent increase in the gross rental cost of a location reduces the location-choice probability by 2.97 percent, which is twice as high as the magnitude of the marginal effect in Column (1). The effect of competition still negatively affects the dialysis facility's location choice in Column (2). Although the size of the competition parameter, γ, is smaller in Column (2), the impact of one additional entrant in a market is similar to that in Column (1). When one additional facility enters a market, the probability of choosing the previously most preferred location decreases by 1.2% and the probability of choosing the least preferred location increases by 0.89%.

3.6 Robustness Check

This section presents a series of analyses to test the robustness of the main parameter estimates. First, in Table C.5, I loosen the restrictions on the population size of the largest city within 20 miles from each sample market to include more markets in the analysis sample. In the original sample, I excluded markets where the largest city within a distance of 20 miles has a population greater than 25,000, and the parameter estimates are shown in Columns (1) and (2). Columns (3) and (4) show parameter estimates when I loosen the restriction of the population size to 40,000. With this adjustment, 19 additional markets are included in the analysis sample. Finally, in Columns (5) and (6), I increase the population cutoff to 50,000, which is the minimum population size of the sample market. Although more markets are added in the analysis sample, the sign of most parameter estimates is the same as that of the main parameter estimates of the base model. The magnitudes of the estimates slightly increase as the number of sample markets increases, although the change is not that huge when we consider the standard errors. With regard to the competition effect, the magnitudes of the estimates in Columns (5) and (6) were the largest for both of the dialysis demand assumptions.

Second, I examine whether the main parameter estimates are affected by the size of potential entrants. As shown in Columns (1) and (2) of Table C.6, in the base model, I assumed that the number of potential entrants is twice the number of actual entrants in each dialysis market. In Section 3.4.2, the market characteristics, λ, equalize the number of expected entrants as the number of actual entrants. Hence, the location decision upon market entry should not be affected by the change in the number of potential entrants. For the test, I increased the number of potential entrants by threefold and fourfold, and the estimates are reported in Columns (3) to (6). If a smaller share of potential entrants enter the market, it would mean that the markets are not attractive to potential entrants. This change would be indicated by a lower estimate of the mean market characteristics, μ. This result is not found in the estimates using the number of current ESRD patients as the demand factor. The estimates of μ in Columns (3) and (5) are similar to that in Column (1). On the other hand, the estimates using key factors related to ESRD incidence follow our expectations. The

estimate decreases from -2.0027 in Column (2) to -3.3038 in Column (6). Except for the estimate of μ, the other estimates are similar in magnitude as expected.

3.7 Conclusions

In this paper, I estimate a simultaneous game for the entry and location choice decisions of dialysis facilities. The model is set up as an incomplete information game among potential entrants in the dialysis industry where facilities have private information on their location-specific profit shocks. The results show that dialysis facilities choose their locations strategically and there is a tradeoff between local demand and expected competition. Firms prefer locations with more at-risk people, such as ESRD patients or a high population of individuals with ages over 65, and lower per capita income. From the cost perspective, these firms prefer locations with low property rental costs. In terms of competitive interactions, all firms exert a negative impact on their potential competitors in the same location.

There are several caveats to this paper and directions for future research. First, I consider only the effects of local demand and competitive interactions in the immediate location. The related literature (Seim 2006; Orhun 2006; Zhu et al. 2009; Gowrisankaran et al. 2011) incorporates distance band terms in models to observe how the effects change as distance from the targeted location increases. Because I assume that dialysis facilities consider overall ESRD patients in a market as their demand, this approach would lead to more reasonable parameter estimates. Second, this paper only analyzes entry and location choice decisions of freestanding and for-profit dialysis facilities because the other types of facilities, such as hospital-based or not-for-profit facilities, may have objective functions other than profit maximization. Although the goal of these facilities is different from that of the facilities studied here, the existence of those facilities might exert negative impacts on expected profits and result in a different site selection in a market. Third, the model in this paper might simplify the dialysis industry too much and be not enough to analyze the spatial competition among dialysis facilities. The key assumption of the model used in this paper is that dialysis facilities are symmetric. However, the existence of a dialysis chain could weaken the assumption. In 2012, approximately 76 percent of dialysis facilities are chain-affiliated, such

as Davita and Fresenius (Eliason 2017). Because chain-affiliated facilities could have lower cost of operation, they might not be symmetric with the other dialysis facilities. Additionally, this model does not consider the dynamics in the dialysis industry and focuses on the distribution of dialysis facilities in 2015. Because the USRDS dataset includes all the information on the entry and exit of dialysis facilities in the U.S. and their characteristics, the estimation model that can analyze the longitudinal data will provide valuable insights on the overall dialysis market.

APPENDICES

Appendix A Tables and Figures for Chapter 1

Table A.1 Descriptive statistics for liver transplant candidates

		(1)	(2)	(3)	(4)	(5)	(6)
		$aMELD \geq 35$		$aMELD < 35$		Status 1A	
VARIABLES		Mean	SD	Mean	SD	Mean	SD
Blood type							
	A	0.361	0.480	0.378	0.485	0.338	0.473
	B	0.035	0.185	0.036	0.187	0.043	0.202
	O	0.122	0.327	0.122	0.327	0.136	0.343
Gender							
	Male	0.628	0.483	0.648	0.478	0.387	0.487
Age at transplant							
	Age	52.36	11.06	55.02	10.31	43.70	15.03
Race							
	White	0.824	0.381	0.858	0.349	0.719	0.449
	Black	0.120	0.325	0.095	0.293	0.181	0.385
	Asian	0.041	0.198	0.034	0.181	0.079	0.270
Education							
	High school	0.392	0.488	0.397	0.489	0.361	0.480
	Attend college	0.220	0.414	0.238	0.426	0.231	0.422
	Bachelor	0.146	0.354	0.169	0.374	0.157	0.364
	Grad school	0.061	0.239	0.071	0.257	0.064	0.244
Payment source							
	Private insurance	0.532	0.499	0.533	0.499	0.584	0.493
	Medicare	0.198	0.399	0.254	0.435	0.130	0.337
	Medicaid	0.214	0.410	0.159	0.366	0.190	0.392
Observations		5292		37,125		1,882	

Notes: The table displays the means and standard deviation of transplant candidates categorized by health status at the time of waitlist registration; $aMELD \geq 35$, $aMELD < 35$, and Status 1A

Table A.2 Effect of $aMELD \geq 35$ on patient outcomes, RD estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Transplant	Waitlist mortality			Overall mortality		
	90 d	90 d	180 d	1 yr	90 d	180 d	1 yr
Panel A. First stage and reduced form results							
$aMELD \geq 35$	0.136***	-0.059	-0.074*	-0.076*	-0.026	-0.045	-0.014
	(0.049)	(0.040)	(0.041)	(0.043)	(0.042)	(0.044)	(0.055)
Mean below 35	0.704	0.186	0.210	0.222	0.225	0.261	0.295
Observations	1,399	1,524	1,538	1,589	1,740	1,691	1,249
Bandwidth	1.681	1.852	2.043	2.606	2.161	2.312	2.031
Panel B. Fuzzy RD estimates							
Pr (Transplant)		-0.438**	-0.554***	-0.651***	-0.197	-0.351	-0.114
		(0.204)	(0.192)	(0.202)	(0.282)	(0.281)	(0.418)
Observations		1,524	1,538	1,589	1,740	1,691	1,249
Bandwidth		1.852	2.043	2.606	2.161	2.312	2.031

Notes: The table shows the RD estimates for access to liver transplants and mortality rates. Each regression includes the indicator for $aMELD \geq 35$ and a linear spline of the running variable, aMELD scores. Robust standard errors are reported in parentheses.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table A.3 Effect of the Share 35 policy on patient outcomes, DD estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Transplant	Waitlist mortality			Overall mortality		
	90 d	90 d	180 d	1 yr	90 d	180 d	1 yr
$aMELD \geq 35$	0.051*	-0.084***	-0.095***	-0.099***	-0.010***	-0.119***	-0.147***
	(0.028)	(0.024)	(0.026)	(0.029)	(0.029)	(0.031)	(0.040)
Mean	0.633	0.299	0.302	0.306	0.362	0.381	0.409
Observations	6,724	6,724	6,152	5,018	6,724	6,152	5,018
$aMELD < 35$	-0.051*	0.002	-0.018	-0.032	-7.13e-05	-0.021	-0.051*
	(0.026)	(0.018)	(0.018)	(0.022)	(0.020)	(0.020)	(0.026)
Mean	0.301	0.088	0.135	0.183	0.102	0.162	0.233
Observations	36,008	36,008	33,044	26,819	36,008	33,044	26,819

Notes: The table shows DD estimates for access to liver tranplants and mortality rates. The estimation includes waitlisted transplant center fixed effects, waitlisted year fixed effects, and covariates of transplant candidates (blood type, gender, age at waitlist registration, race, education level, payment source). Standard errors clustered at the waitlisted transplant center level are in parentheses.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table A.4 Effect of the Share 35 policy on transplanted liver quality

	(1) Regional share	(2) Log (Dist)	(3) Log (CIT)	(4) Donor age over 70	(5) BMI over 35	(6) Donation after Cardiac Death
$aMELD \geq 35$	0.359***	0.828***	0.047***	-0.001	-0.004	0.001
	(0.037)	(0.123)	(0.018)	(0.008)	(0.016)	(0.013)
Mean	0.223	3.733	1.952	0.015	0.090	0.026
Observations	9,432	9,432	9,432	9,432	9,432	9,432
$aMELD < 35$	-0.031	-0.109	-0.015	0.003	0.018	0.033***
	(0.037)	(0.136)	(0.018)	(0.010)	(0.015)	(0.012)
Mean	0.177	3.594	1.927	0.038	0.121	0.053
Observations	25,343	25,343	25,343	25,343	25,343	25,343

Notes: The table shows DD estimates for the transplanted liver quality. The estimation includes waitlisted transplant center fixed effects, waitlisted year fixed effects, and covariates of transplant recipients (blood type, gender, age at transplants, race, education level, payment source). Standard errors clustered at the waitlisted transplant center level are in parentheses. "Dist" means the distance between the donor hospital and recipient hospital. "CIT" means the cold ischemia time, which is the time between liver removal from the donor and transplant. "BMI" means the body mass index.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table A.5 Effect of the Share 35 policy on posttransplant survival

	(1)	(2)	(3)	(4)	(5)
	Ex-post	Ex-ante			
	Survival	- Log (DRI)	Predicted survival		
	1 yr		1 yr	3 yr	5 yr
$aMELD \geq 35$	0.039	-0.026***	-0.008*	-0.008	-0.007
	(0.026)	(0.009)	(0.004)	(0.005)	(0.005)
Mean	0.827	-0.977	0.826	0.729	0.656
Observations	7,874	9,432	9,432	9,432	9,432
$aMELD < 35$	-0.006	-0.014*	-0.011**	-0.010**	-0.009**
	(0.019)	(0.008)	(0.004)	(0.004)	(0.004)
Mean	0.899	-1.005	0.876	0.779	0.701
Observations	20,800	25,343	25,343	25,343	25,343

Notes: The table shows DD estimates for the outcomes related to posttransplant survival rates. Columns (1)-(2) include the waitlisted transplant center fixed effect, transplant year fixed effect, and covariates of liver transplant recipients (blood type, gender, age at transplants, race, education level, payment source). As the posttransplant survival prediction model uses specific recipient and donor covariates, Columns (3)-(5) use the set of recipient covariates in Table A.13 along with the same set of fixed effects. Standard errors clustered at the waitlisted transplant center level are in parentheses.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table A.6 Effect of the Share 35 policy on liver offer acceptance

	(1)	(2)	(3)	(4)	(5)
$aMELD \geq 35$	-0.124***	-0.102***			
	(0.022)	(0.022)			
Mean	0.560	0.560			
Observations	21,020	21,020			
			Treatment group by $aMELD$ (M) update frequency		
			$25 \leq M < 35$	$19 \leq M < 25$	$15 \leq M < 19$
			(7 days)	(1 month)	(3 months)
$aMELD < 35$	-0.035	-0.023	-0.038*	-0.010	0.008
	(0.022)	(0.022)	(0.022)	(0.023)	(0.029)
Mean	0.445	0.445	0.446	0.442	0.455
Observations	34,378	34,378	23,050	11,942	4,896
Donor covariates	N	Y	Y	Y	Y
Candidate covariates	Y	Y	Y	Y	Y

Notes: The table shows DD estimates for the liver offer-acceptance rates. Column (1) includes waitlisted transplant center fixed effects, waitlisted year fixed effects, and covariates of transplant candidates (blood type, gender, age at waitlist registration, race, education level, payment source). Columns (2)-(5) addtionally include donor characteristics (age, cause of death, indicator of liver sharing, distance between donor transplant center and waitlisted transplant center, and BMI). Standard errors clustered at the waitlisted transplant center level are in parentheses.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table A.7 [Placebo test] Effect of $aMELD \geq 35$ on patient outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Transplant	Waitlist mortality			Overall mortality		
	90 d	90 d	180 d	1 yr	90 d	180 d	1 yr
$aMELD \geq 35$	-0.084	0.071	0.053	-0.007	0.086	0.038	-0.004
	(0.069)	(0.068)	(0.077)	(0.084)	(0.081)	(0.097)	(0.105)
Mean below 35	0.658	0.227	0.252	0.261	0.300	0.341	0.399
Observations	931	732	614	560	577	441	392
Bandwidth	2.634	2.134	2.051	2.509	1.692	1.513	1.847

Notes: The table shows the RD estimates for access to liver transplants and mortality rates. Each regression includes the indicator for $aMELD \geq 35$ and a linear spline of the running variable, aMELD. Robust standard errors are reported in parentheses.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table A.8 Diagnosis for exception MELD score

Diagnosis	exception MELD	Growth
Cholangiocarcinoma	eMELD 22	10% point increase every 3 months
Cystic Fibrosis	eMELD 22	10% point increase every 3 months
Familial Amyloid Polyneuropathy (FAP)	eMELD 22	10% point increase every 3 months
Hepatic Artery Thrombosis (HAT)	eMELD 40	
Hepatocellular Carcinoma (HCC)	cMELD until 6 months eMELD 28 after then	Increase by 34 every 3 months
Hepatopulmonary Syndrome (HPS)	eMELD 22	10% point increase every 3 months
Portopulmonary Hypertension	eMELD 22	10% point increase every 3 months
Primary Hyperoxaluria	eMELD 28	10% point increase every 3 months

Sources: OPTN Policies (OPTN 2017).
Notes: Exception PELD score is excluded in the table.

Table A.9 Balance of covariates

	(1)	(2)	(3)	(4)	(5)
VARIABLES	A	B	O	Male	Age
$aMELD \geq 35$	-0.002	0.037	-0.081	0.016	0.525
	(0.047)	(0.044)	(0.067)	(0.046)	(0.972)
Mean below cutoff	0.375	0.139	0.465	0.588	53.26
Observations	2,013	1,185	1,107	2,176	2,334
Bandwidth	2.452	1.444	1.291	2.513	2.738
VARIABLES	White	Black	Asian	High school	Attend college
$aMELD \geq 35$	0.056	-0.030	-0.009	-0.101	0.007
	(0.040)	(0.032)	(0.018)	(0.063)	(0.043)
Mean below cutoff	0.832	0.109	0.032	0.412	0.225
Observations	1,561	1,754	1,234	1,158	1,795
Bandwidth	1.765	2.023	1.491	1.389	2.098
VARIABLES	Bachelor	Graduate	Private ins.	Medicaid	Medicare
$aMELD \geq 35$	0.044	-0.012	0.014	-0.013	0.031
	(0.042)	(0.025)	(0.054)	(0.045)	(0.051)
Mean below cutoff	0.152	0.064	0.527	0.204	0.220
Observations	1,518	2,197	1,686	1,584	1,388
Bandwidth	1.722	2.522	1.944	1.797	1.528

Notes: The table shows the estimated discontinuities of predetermined characteristics for transplant candidates. In addition to the indicator for $aMELD \geq 35$, each regression includes a linear spline of the running variable, aMELD. Robust standard errors are reported in parentheses.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table A.10 Effect of $aMELD \geq 35$ on patient outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Transplant	Waitlist mortality			Overall mortality		
	90 d	90 d	180 d	1 yr	90 d	180 d	1 yr
Panel A. Standard RD estimates							
$aMELD \geq 35$	0.136***	-0.059	-0.074*	-0.076*	-0.026	-0.045	-0.014
	(0.049)	(0.040)	(0.041)	(0.043)	(0.042)	(0.044)	(0.055)
Observations	1,399	1,524	1,538	1,589	1,740	1,691	1,249
Bandwidth	1.681	1.852	2.043	2.606	2.161	2.312	2.031
Panel B. Donut RD estimates							
$aMELD \geq 35$	0.129**	-0.055	-0.077*	-0.076*	-0.027	-0.057	-0.015
	(0.052)	(0.043)	(0.043)	(0.044)	(0.044)	(0.047)	(0.056)
Observations	1,182	1,307	1,376	1,476	1,523	1.529	1,177
Bandwidth	1.681	1.852	2.043	2.606	2.161	2.312	2.031

Notes: The table compares the main RD estimates (Panel A) with the donut RD estimates (Panel B) that exclude heaped data at the aMELD scores with whole number units. Each regression includes the indicator for $aMELD \geq 35$ and a linear spline of the running variable, aMELD. Robust standard errors are reported in parentheses.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table A.11 Descriptive statistics for liver transplant recipients

		(1)	(2)	(3)	(4)	(5)	(6)
		$aMELD \geq 35$		$aMELD < 35$		Status 1A	
VARIABLES		Mean	SD	Mean	SD	Mean	SD
Blood type							
	A	0.366	0.482	0.363	0.481	0.335	0.472
	B	0.116	0.320	0.148	0.356	0.141	0.349
	O	0.488	0.500	0.432	0.495	0.473	0.499
Gender							
	Male	0.627	0.484	0.695	0.460	0.382	0.486
Age at transplant							
	Age	53.18	10.93	56.65	9.66	44.14	14.96
Race							
	White	0.844	0.363	0.848	0.359	0.693	0.462
	Black	0.102	0.302	0.099	0.298	0.196	0.397
	Asian	0.040	0.196	0.041	0.198	0.088	0.284
Education							
	High school	0.392	0.488	0.405	0.491	0.355	0.479
	Attend college	0.239	0.426	0.239	0.426	0.240	0.427
	Bachelor	0.154	0.361	0.173	0.378	0.169	0.375
	Grad school	0.064	0.245	0.072	0.259	0.074	0.262
Payment source							
	Private insurance	0.546	0.498	0.561	0.496	0.616	0.487
	Medicare	0.204	0.403	0.253	0.435	0.127	0.334
	Medicaid	0.201	0.401	0.135	0.342	0.172	0.377
Observations		8,208		24,119		1,224	

Notes: The table displays the means and standard deviations of transplant recipients categorized by health status at the time of transplantation; $aMELD \geq 35$, $aMELD < 35$, and Status 1A

Table A.12 Descriptive statistics for liver candidates in the match-run sample

		(1)	(2)	(3)	(4)	(5)	(6)
		$aMELD \geq 35$		$aMELD < 35$		Status 1A	
VARIABLES		Mean	SD	Mean	SD	Mean	SD
Blood type							
	A	0.344	0.475	0.371	0.483	0.347	0.476
	B	0.144	0.351	0.160	0.367	0.165	0.371
	O	0.482	0.500	0.393	0.488	0.433	0.496
Gender							
	Male	0.561	0.496	0.642	0.479	0.354	0.478
Age at registration							
	Age	51.09	12.99	54.64	11.01	43.13	15.59
Race							
	White	0.805	0.396	0.834	0.372	0.671	0.470
	Black	0.135	0.341	0.109	0.312	0.215	0.411
	Asian	0.046	0.209	0.044	0.205	0.092	0.290
Education							
	High school	0.406	0.491	0.397	0.489	0.381	0.486
	Attend college	0.232	0.422	0.234	0.423	0.249	0.432
	Bachelor	0.158	0.364	0.182	0.386	0.139	0.346
	Grad school	0.056	0.230	0.070	0.256	0.065	0.247
Payment							
	Private insurance	0.515	0.500	0.546	0.498	0.591	0.492
	Medicare	0.241	0.428	0.262	0.440	0.150	0.357
	Medicaid	0.200	0.400	0.137	0.343	0.171	0.377
Observations		18,444		31,802		2,576	

Notes: The table displays the means and standard deviations of transplant candidates categorized by health status at the time of liver offer; $aMELD \geq 35$, $aMELD < 35$, and Status 1A

Table A.13 Selected variables by LASSO (40 variables)

Donor characteristics	Count	Recipient characteristics	Count
Share = Regional	5	Age	5
Age	5	Race = Black	5
Height	5	Race = Asian	5
Cause of Death = Cerebrovascular accident	5	Weight	5
History of diabetes	5	Previous transplant	5
Donation after Cardiac Death	5	Previous abdominal surgery	5
Anti-Cytomegalovirus = Positive	5	Medical condition = ICU	5
Cold ischemia time (CIT)	5	Medical condition = Hospitalized not ICU	5
Ethnicity = Latino	4	Hepatic encephalopathy	5
Weight	4	Primary diagnosis = Cholestatic cirrhosis	5
History of cocaine use	4	Primary diagnosis = Malignant neoplasms	5
Death mechanism = Drug intoxication	4	Albumin	5
[Square] CIT	4	On ventilator	5
History of other drug abuse, last 6 month	3	Any previous malignancy	5
Tattoos	3	Acute rejection episodes	5
[Square] Height	3	[Square] Weight	5
		History of Portal Vein Thrombosis	4
		aMELD score	4
		Primary diagnosis = Metabolic disease	4
		[Square] Age	4
		[Square] Albumin	4
		Male	3
		Ethnicity = Latino	3
		[Square] Height	3

Notes: The table displays the variables selected by the LASSO algorithm to predict the 5-year posttransplant survival rates of liver transplant recipients. Only variables selected at least 3 times among 5 estimations using different sample sets as the test sample are included.

Table A.14 Comparison of the predictive power

	(1) 1st	(2) 2nd	(3) 3rd	(4) 4th	(5) 5th	(6) Average
DRI	0.2136	0.2079	0.2015	0.2085	0.2071	0.2077
Variables of DRI	0.2130	0.2074	0.2010	0.2080	0.2062	0.2071
LASSO	0.2084	0.2011	0.1950	0.2027	0.2003	0.2015
LASSO w/ interaction	0.2093	0.2041	0.1990	0.2070	0.2059	0.2050
Observations	8948	8979	8948	8892	8961	

Notes: The table displays the Brier scores, which calculate the mean squared error of the predicted probability, for different prediction models. As the prediction model was tested five times using one of 5 sample sets as the test sample, each prediction model contains five Brier scores. Column (6) shows the average Brier score for each prediction model.

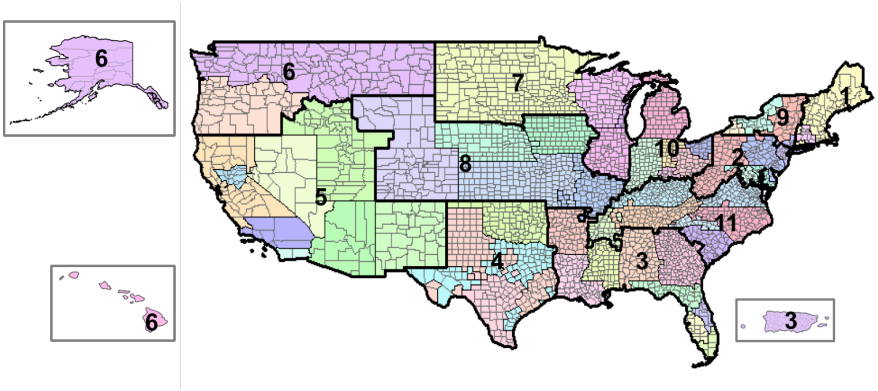


Figure A.1 DSAs and Regions in U.S.

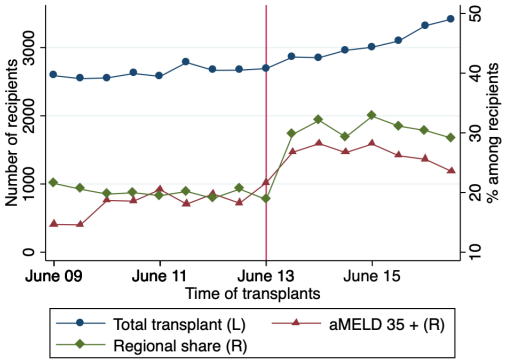
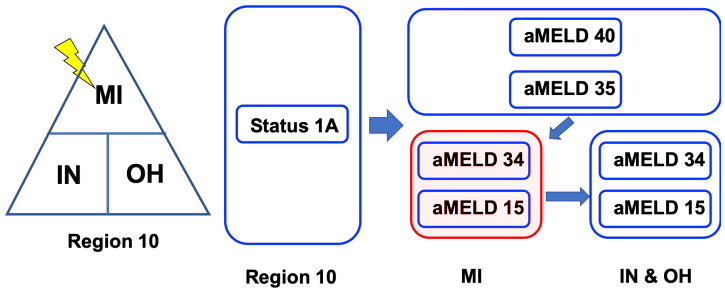
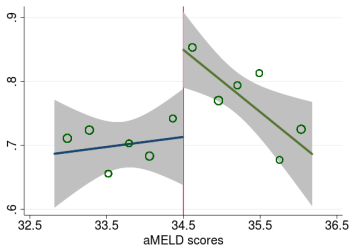


Figure A.2 Effect of the Share 35 policy on the liver transplant market

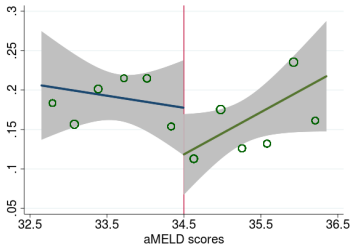


Sources: OPTN Policies (OPTN 2017).
Notes: Allocation for candidates with aMELD scores less than 15 is excluded in the figure. After the match in the figure, the donated liver is matched to candidates with aMELD scores of at least 15 and waitlisted in the U.S. If the liver is not accepted, then candidates with aMELD scores of less than 15 are matched to the liver in order of DSA, Region, and Nation.

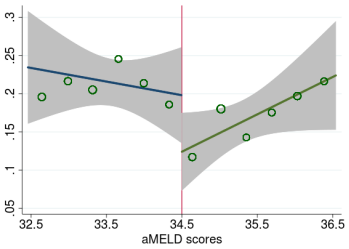
Figure A.3 Deceased donor liver allocation process under the Share 35 policy



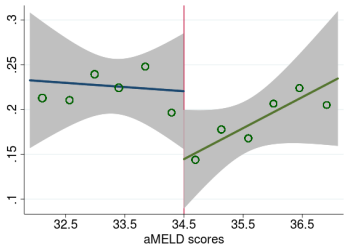
(a) Transplant



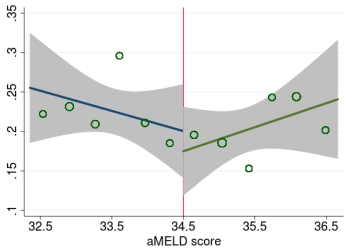
(b) [90d] Waitlist mort



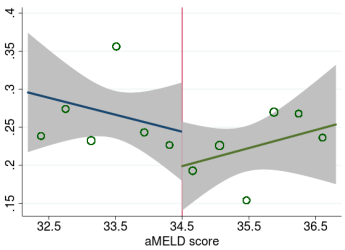
(c) [180d] Waitlist mort



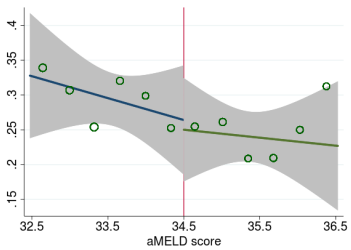
(d) [1yr] Waitlist mort



(e) [90 d] Overall mort



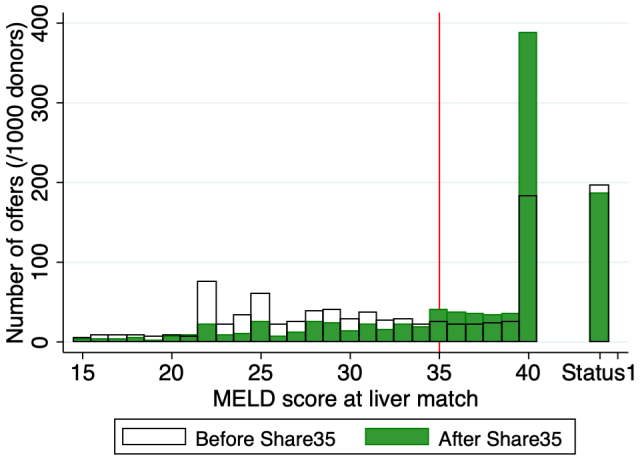
(f) [180d] Overall mort



(g) [1yr] Overall mort

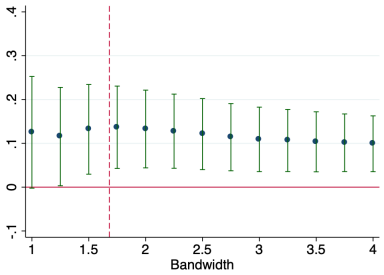
Notes: Panels (a)-(g) plot the mean values of outcome variables along with linear fitted lines (solid lines) and the 95% confidence intervals (shaded area) below and above the aMELD score 35 threshold. Each bin is divided by the same width, and the size of each dot is scaled according to the number of observations in each bin.

Figure A.4 Effect of the Share 35 policy on patient outcomes

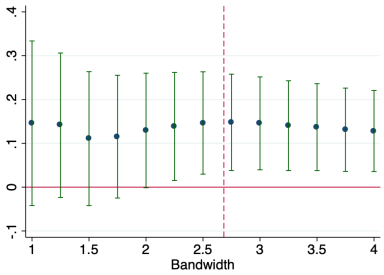


Notes: The figure plots the frequency of liver offers, that were matched to top-ranked transplant candidates, for each aMELD score at the time of offer. As the number of donated livers is different before and after the Share 35 policy implementation, the adjusted number of liver offers per 1000 donors is reported for each aMELD score.

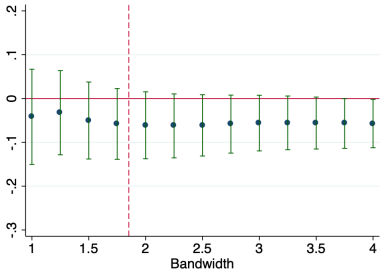
Figure A.5 Change in the access to liver offers



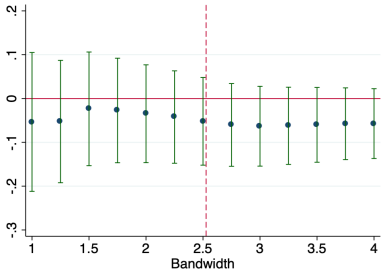
(a) Transplant, lin



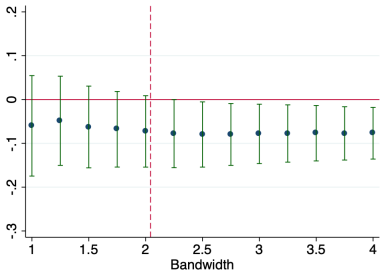
(b) Transplant, quad



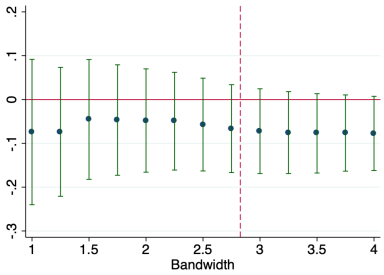
(c) Waitlist mort, 90 days, lin



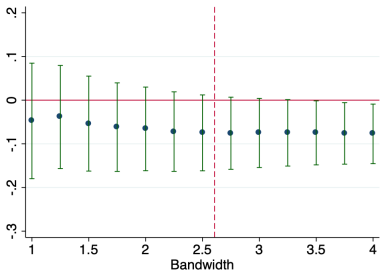
(d) Waitlist mort, 90 days, quad



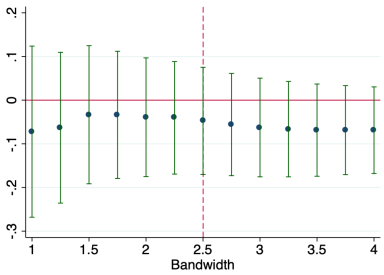
(e) Waitlist mort, 180 days, lin



(f) Waitlist mort, 180 days, quad



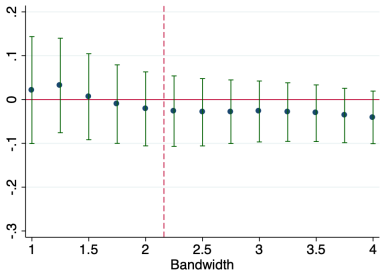
(g) Waitlist mort, 1 year, lin



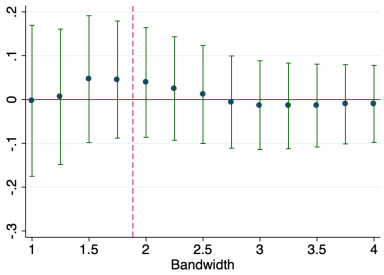
(h) Waitlist mort, 1 year, quad

Notes: I repeated the estimation for each dependent variable for a different choice of bandwidth and polynomial. I test the bandwidth range from 1 to 4 for every 0.25 units. The degrees of polynomials are degree 1 (linear) and degree 2 (quadratic).

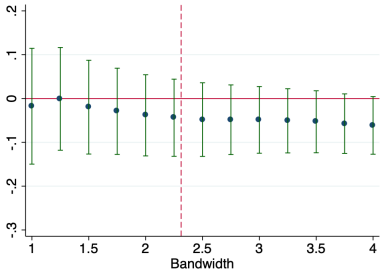
Figure A.6 Sensitivity to bandwidth and polynomial



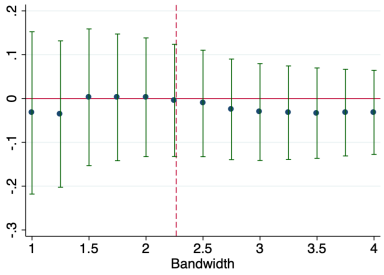
(a) Overall mort, 90 days, lin



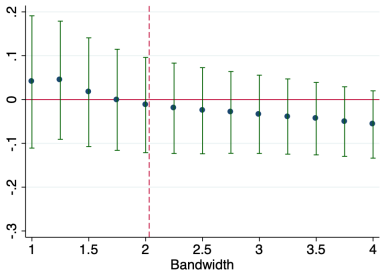
(b) Overall mort, 90 days, quad



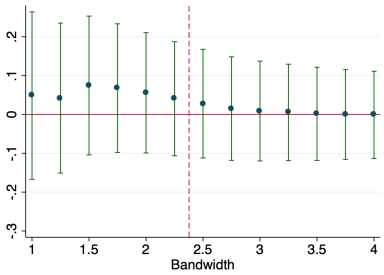
(c) Overall mort, 180 days, lin



(d) Overall mort, 180 days, quad



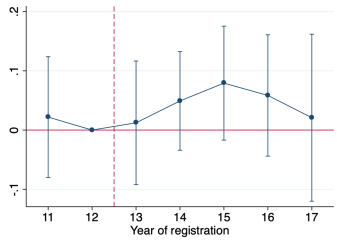
(e) Overall mort, 1 year, lin



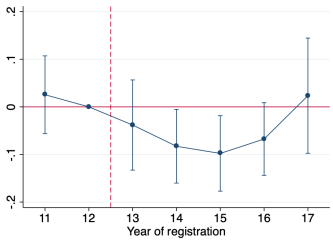
(f) Overall mort, 1 year, quad

Notes: I repeated the estimation for each dependent variable for a different choice of bandwidth and polynomial. I test the bandwidth range from 1 to 4 for every 0.25 units. The degrees of polynomials are degree 1 (linear) and degree 2 (quadratic).

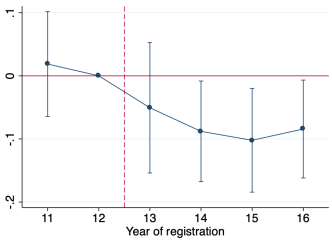
Figure A.7 Sensitivity to bandwidth and polynomial



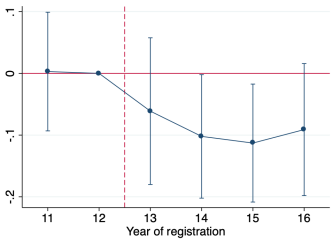
(a) Transplant



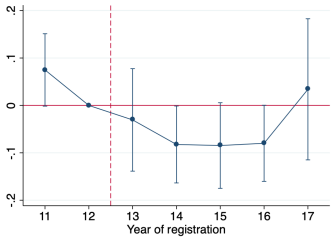
(b) [90 d] Waitlist mort



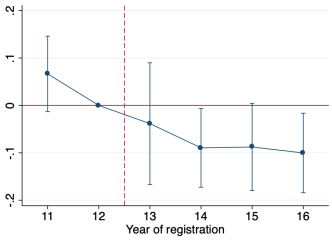
(c) [180 d] Waitlist mort



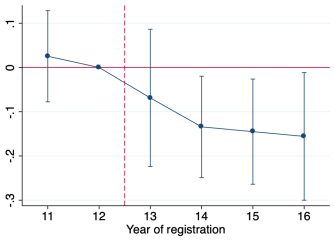
(d) [1 yr] Waitlist mort



(e) [90 d] Overall mort



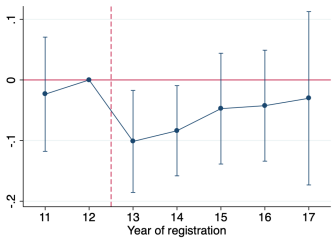
(f) [180 d] Overall mort



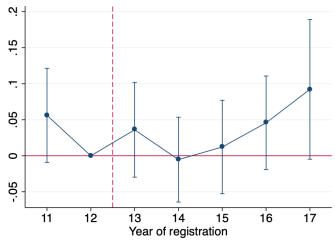
(g) [1 yr] Overall mort

Notes: Panels (a)-(g) plot the estimated coefficients from the event study model for the access to liver transplants and mortality rates for transplant candidates with aMELD scores greater than or equal to 35. The dashed vertical line shows the year when the Share 35 policy was implemented, and the baseline year is one year prior to the year of policy implementation. The estimation includes waitlisted transplant center fixed effects, waitlisted year fixed effects, and covariates of transplant candidates (blood type, gender, age at waitlist registration, race, education level, payment source). Standard errors clustered at the waitlisted transplant center level are used for 95 percent confidence intervals.

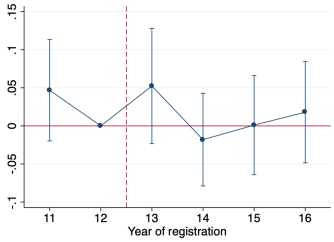
Figure A.8 Event study, transplant and mortality for $aMELD \geq 35$



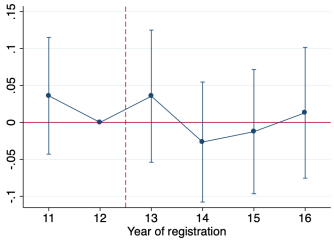
(a) Transplant



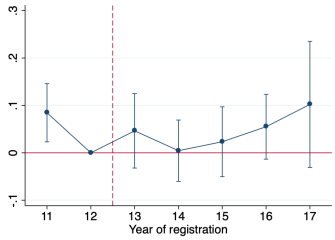
(b) [90 d] Waitlist mort



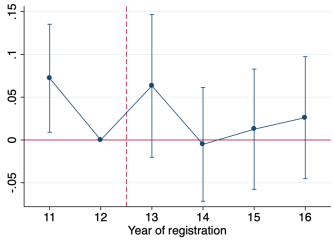
(c) [180 d] Waitlist mort



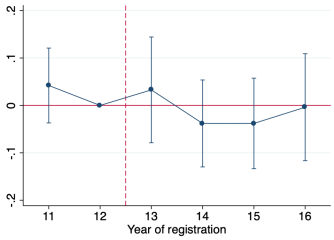
(d) [1 yr] Waitlist mort



(e) [90 d] Overall mort



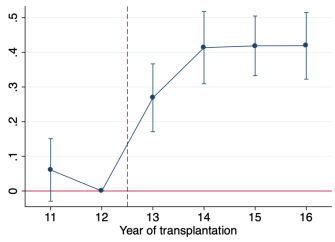
(f) [180 d] Overall mort



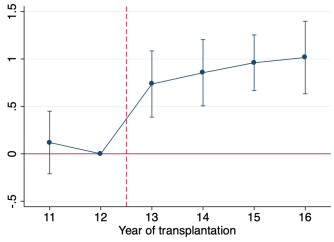
(g) [1 yr] Overall mort

Notes: Panels (a)-(g) plot the estimated coefficients from the event study model for the access to liver transplants and mortality rates for transplant candidates with aMELD scores greater than or equal to 35. The dashed vertical line shows the year when the Share 35 policy was implemented, and the baseline year is one year prior to the year of policy implementation. The estimation includes waitlisted transplant center fixed effects, waitlisted year fixed effects, and covariates of transplant candidates (blood type, gender, age at waitlist registration, race, education level, payment source). Standard errors clustered at the waitlisted transplant center level are used for 95 percent confidence intervals.

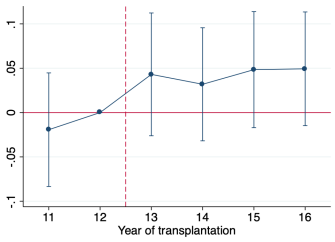
Figure A.9 Event study, transplant and mortality for $aMELD < 35$



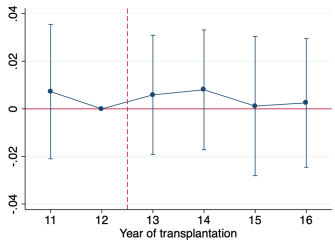
(a) Regional share



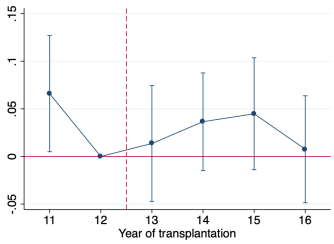
(b) Log (Distance)



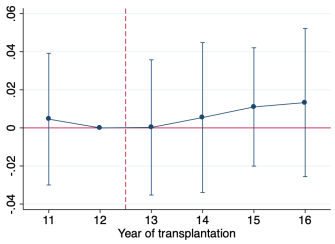
(c) Log (CIT)



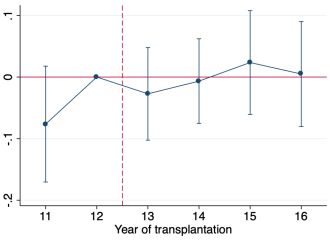
(d) Donor age, over 70



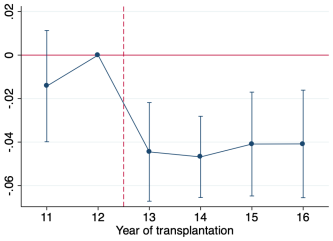
(e) BMI over 35



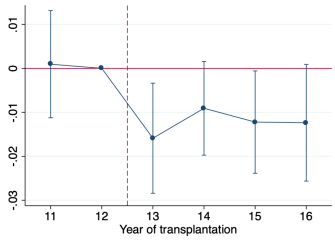
(f) Donation after cardiac death



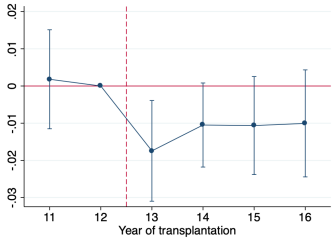
(g) Survival, 1 year



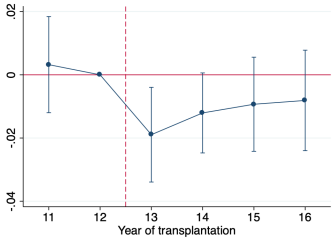
(h) - Log (DRI)



(i) Predicted survival, 1 year



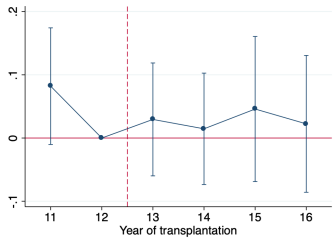
(j) Predicted survival, 3 year



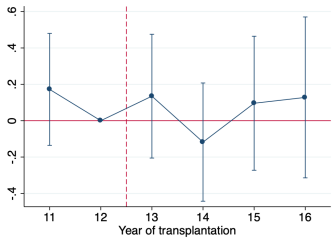
(k) Predicted survival, 5 year

Notes: Panels (a)-(k) plot the estimated coefficients from the event study model for transplanted liver quality for transplant recipients with aMELD scores greater than or equal to 35. The dashed vertical line shows the year when the Share 35 policy was implemented, and the baseline year is one year prior to the year of policy implementation. The estimation includes waitlisted transplant center fixed effects, waitlisted year fixed effects, and covariates of transplant recipients (blood type, gender, age at transplantation, race, education level, payment source). As the posttransplant survival prediction model uses specific recipient and donor covariates, panels (i)-(k) use the set of recipient covariates in Table A.13. Standard errors clustered at the waitlisted transplant center level are used for 95 percent confidence intervals.

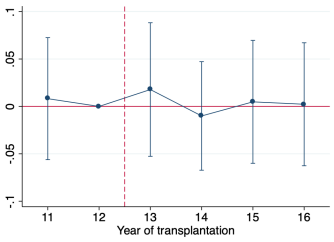
Figure A.10 Event study, transplantation quality for $aMELD \geq 35$



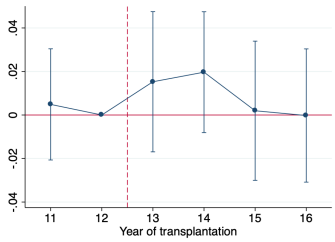
(a) Regional share



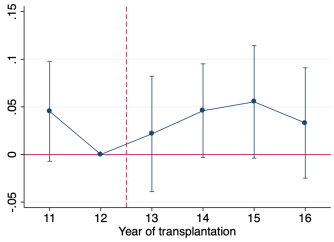
(b) Log (Distance)



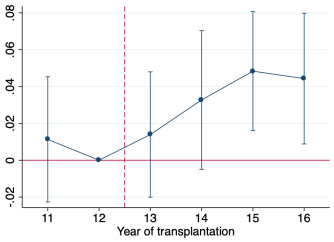
(c) Log (CIT)



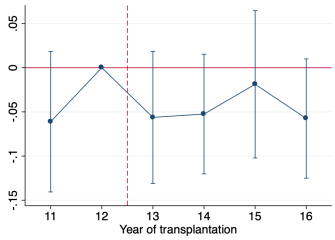
(d) Donor age, over 70



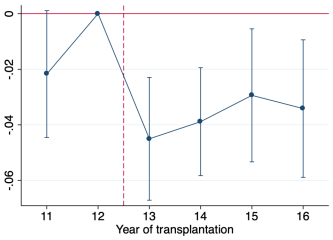
(e) BMI over 35



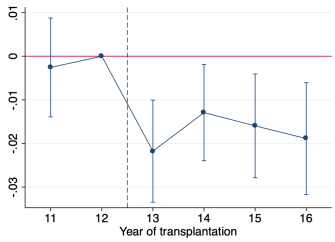
(f) Donation after cardiac death



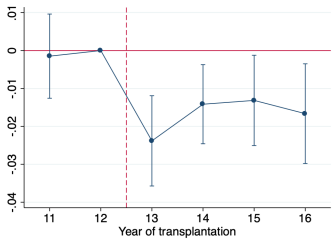
(g) Survival, 1 year



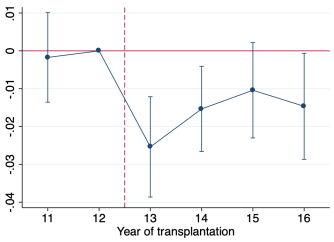
(h) - Log (DRI)



(i) Predicted survival, 1 year



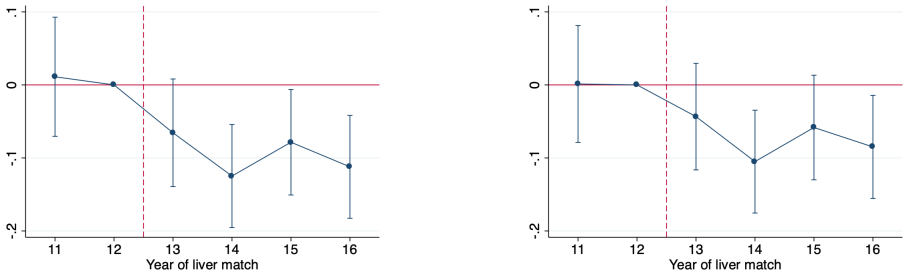
(j) Predicted survival, 3 year



(k) Predicted survival, 5 year

Notes: Panels (a)-(k) plot the estimated coefficients from the event study model for transplanted liver quality for transplant recipients with aMELD scores below 35. The dashed vertical line shows the year when the Share 35 policy was implemented, and the baseline year is one year prior to the year of policy implementation. The estimation includes waitlisted transplant center fixed effects, waitlisted year fixed effects, and covariates of transplant recipients (blood type, gender, age at transplantation, race, education level, payment source). As the posttransplant survival prediction model uses specific recipient and donor covariates, panels (i)-(k) use the set of recipient covariates in Table A.13. Standard errors clustered at the waitlisted transplant center level are used for 95 percent confidence intervals.

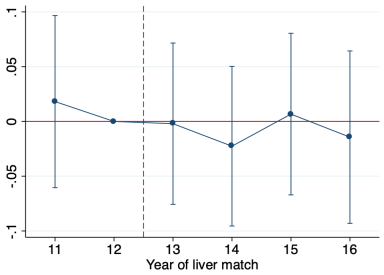
Figure A.11 Event study, transplantation quality for $aMELD < 35$



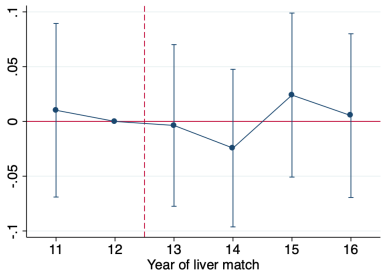
(a) Accept, w/o donor cov. (b) Accept

Notes: Panels (a)-(b) plot the estimated coefficients from the event study model for liver offer-acceptance rates for transplant candidates with aMELD scores greater than or equal to 35. The dashed vertical line shows the year when the Share 35 policy was implemented, and the baseline year is one year prior to the year of policy implementation. Panel (a) includes waitlisted transplant center fixed effects, waitlisted year fixed effects, and covariates of transplant candidates (blood type, gender, age at waitlist registration, race, education level, payment source). Panel (b) additionally includes donor characteristics (age, cause of death, indicator of liver sharing, distance between donor hospital and waitlisted transplant center). Standard errors clustered at the waitlisted transplant center level are used for 95 percent confidence intervals.

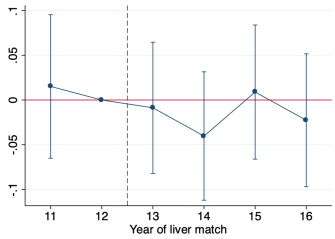
Figure A.12 Event study, liver offer acceptance for $aMELD \geq 35$



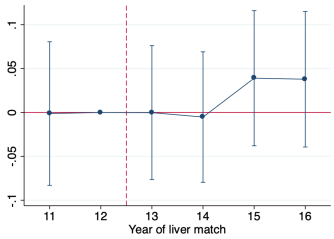
(a) Accept, w/o donor cov.



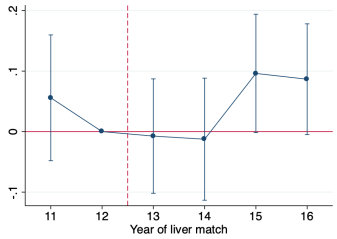
(b) Accept



(c) $25 \leq aMELD < 35$



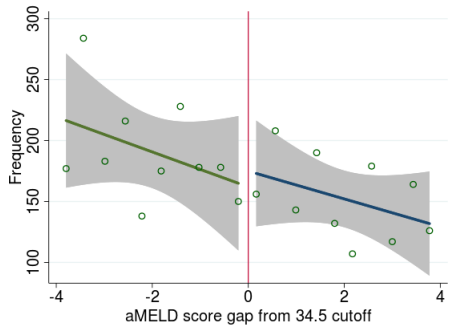
(d) $19 \leq aMELD < 25$



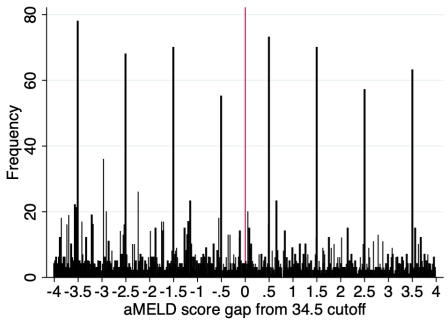
(e) $15 \leq aMELD < 19$

Notes: Panels (a)-(e) plot the estimated coefficients from the event study model for liver offer-acceptance rates for transplant candidates with aMELD scores below 35. The dashed vertical line shows the year when the Share 35 policy was implemented, and the baseline year is one year prior to the year of policy implementation. Panel (a) includes waitlisted transplant center fixed effects, waitlisted year fixed effects, and covariates of transplant candidates (blood type, gender, age at waitlist registration, race, education level, payment source). Panels (b)-(e) additionally include donor characteristics (age, cause of death, indicator of liver sharing, distance between donor hospital and waitlisted transplant center). Standard errors clustered at the waitlisted transplant center level are used for 95 percent confidence intervals.

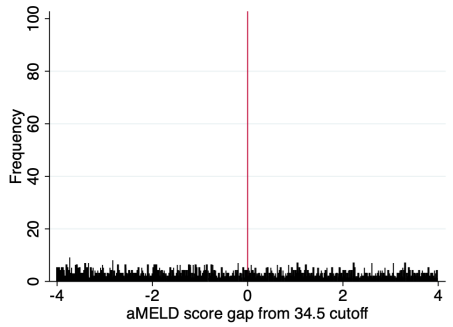
Figure A.13 Event study, liver offer acceptance for $aMELD < 35$



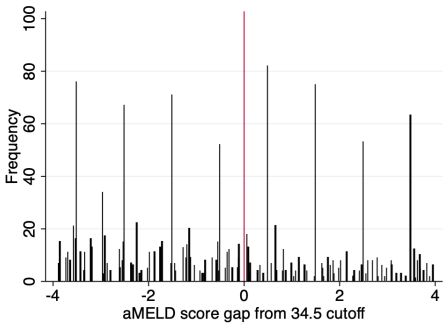
(a) Mean frequency (0.4 binwidth)



(b) Histogram (0.01 binwidth)



(c) Histogram (using previous MELD)



(d) Histogram (using new MELD with sodium)

Notes: Panel (a) plots the mean frequency along with the linear fitted line and the 95% confidence interval above and below the aMELD threshold score of 35. Panel (b) plots the frequency of aMELD scores within the bandwidth 4 units from an aMELD score of 34.5. Panels (c)-(d) plot the frequency of aMELD scores by the applicability of the new aMELD score system, implemented in January 2016, which also considers the level of serum sodium. Only the candidates in panel (d) are affected by the new aMELD score system.

Figure A.14 aMELD distribution

Appendix B Tables and Figures for Chapter 2

Table B.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 B.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 B.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 B.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. * significant at 10%, ** significant at 5%, *** significant at 1%

Table B.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.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table B.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.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table B.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.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table B.8 Heterogeneity of fuzzy RD results by 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.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table B.9 Heterogeneity of fuzzy RD results by 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.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table B.10 Heterogeneity of fuzzy RD results by 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.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table B.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.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table B.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.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table B.13 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.

Table B.14 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.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table B.15 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.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table B.16 Fuzzy RD results by candidates' blood types

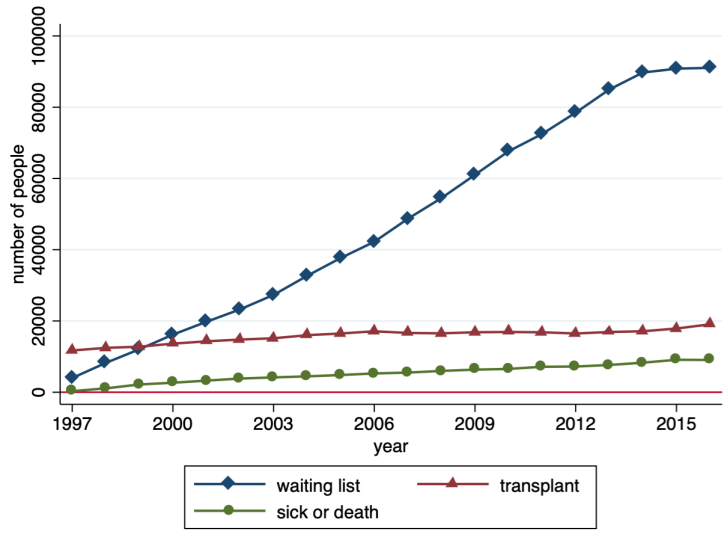
		(1)	(2)	(3)	(4)
		Waitlist mortality		Overall mortality	
		1 year	2 year	1 year	2 year
A type	Pr(deceased)	**0.0163**		**0.0144**	
	{12,226}	**(0.0437)**		**(0.0453)**	
	Pr(deceased)	-0.00867	**0.00367**	-0.0219	**-0.0127**
	{9,069}	(0.0428)	**(0.0644)**	(0.0435)	**(0.0676)**
B type	Pr(deceased)	**-0.0529**		**-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.
* significant at 10%, ** significant at 5%, *** significant at 1%

Table B.17 Fuzzy RD results by candidates' dialysis status

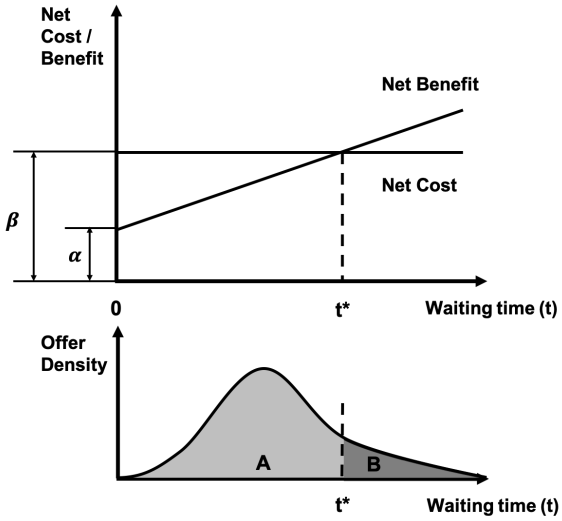
		(1)	(2)	(3)	(4)
		Waitlist mortality		Overall mortality	
		1 year	2 year	1 year	2 year
None	Pr(deceased)	**0.0256**		**0.0298**	
	{7,488}	**(0.0424)**		**(0.0446)**	
	Pr(deceased)	0.00454	**-0.0625**	0.00328	**-0.0522**
	{5,616}	(0.0486)	**(0.0558)**	(0.0489)	**(0.0614)**
Dialysis	Pr(deceased)	**-0.0737****		**-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.
* significant at 10%, ** significant at 5%, *** significant at 1%

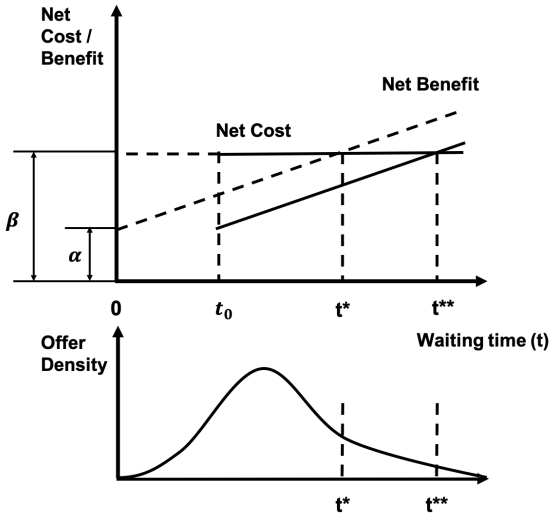


Sources: OPTN database (https://optn.transplant.hrsa.gov/data)
Notes: The OPTN database reports the information on waitlist addition and removal from 1997. The number of waitlisted candidates is calculated by adding the net increase (waitlist addition - removal) to the number of candidates in the previous 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.

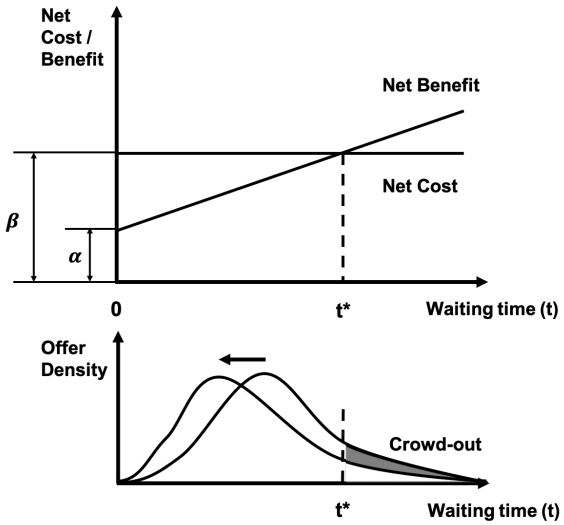
Figure B.1 Trends in the kidney transplant market



(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 B.2 Net costs and benefits of a living kidney transplant

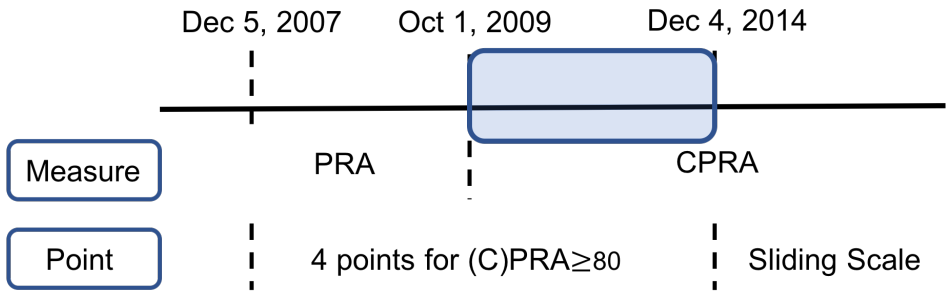
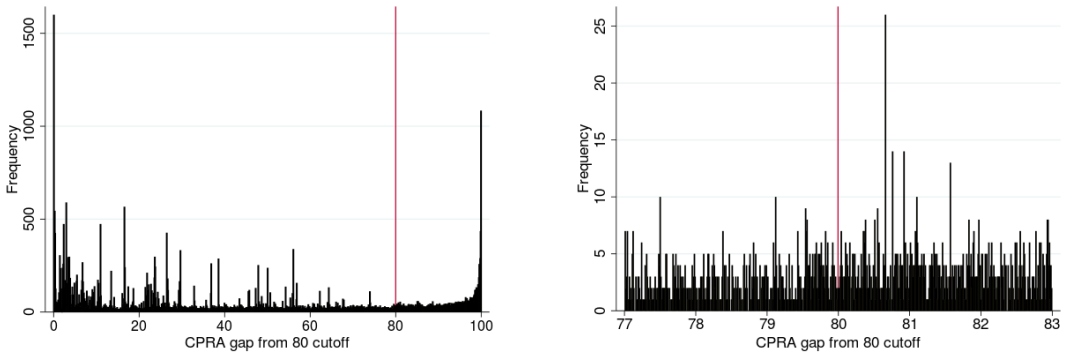


Figure B.3 Kidney sensitization measure and sensitization points

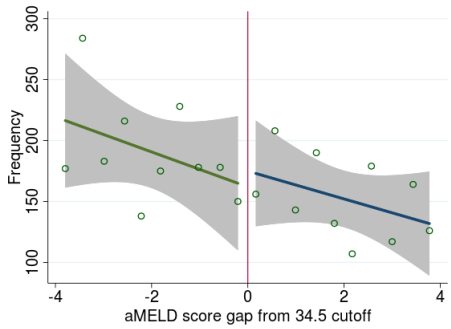


(a) Distribution of CPRA

(b) Distribution of CPRA within bandwidth 3

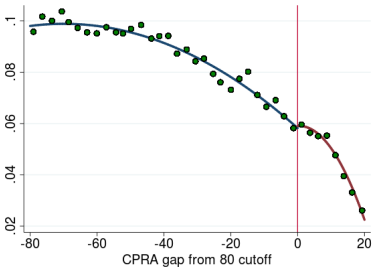
Notes: Panel (a) plots the frequency of CPRA at each 0.1 unit. Candidates with zero CPRA are excluded from the plot. Panel (b) plots the frequency of CPRA at 0.01 units within the bandwidth 3 units from the CPRA 80 threshold.

Figure B.4 CPRA distribution

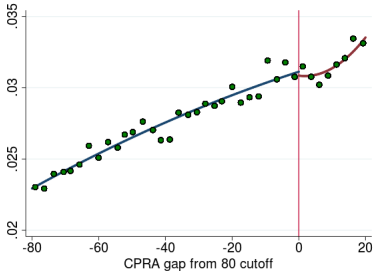


Notes: The figure plots the mean frequency along with quadratic fitted lines (solid lines) and the 95% confidence interval below and above the CPRA 80 threshold.

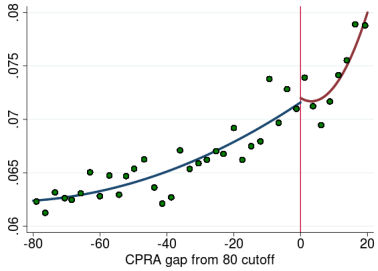
Figure B.5 Mean frequency test



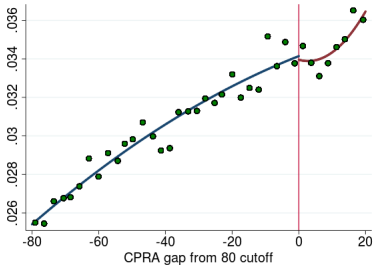
(a) Pr(living tx)



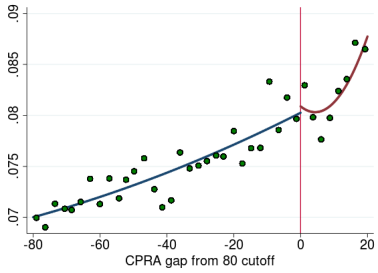
(b) [1 year] Waitlist mortality



(c) [2 year] Waitlist mortality



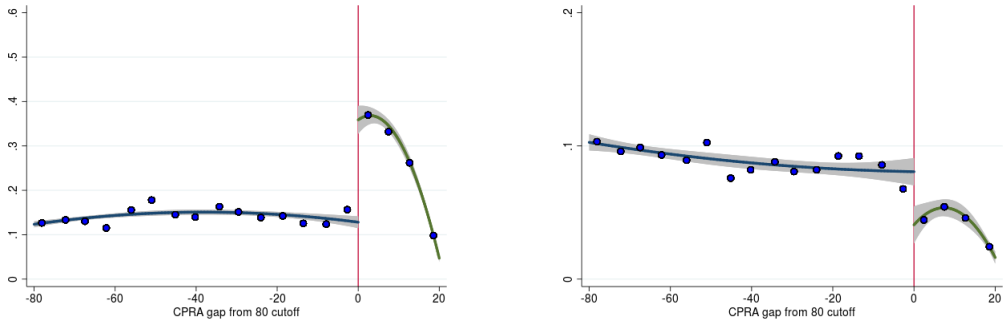
(d) [1 year] Overall mortality



(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.

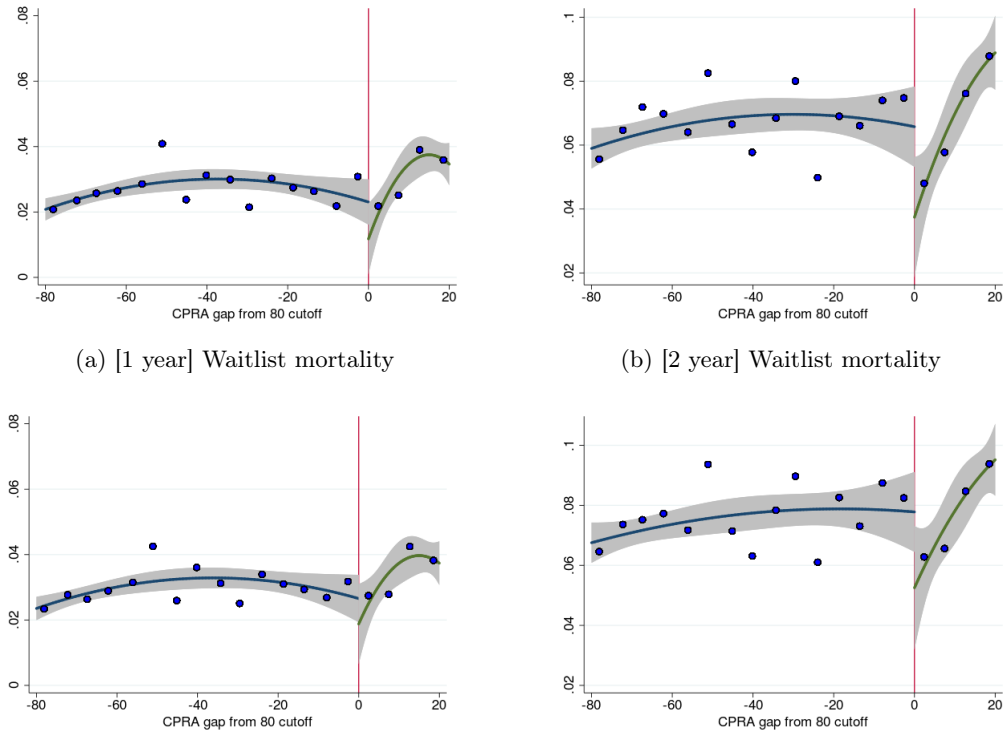
Figure B.6 Discontinuities on predicted outcomes



(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 B.7 Crowd-out effect on the demand of living donor kidneys

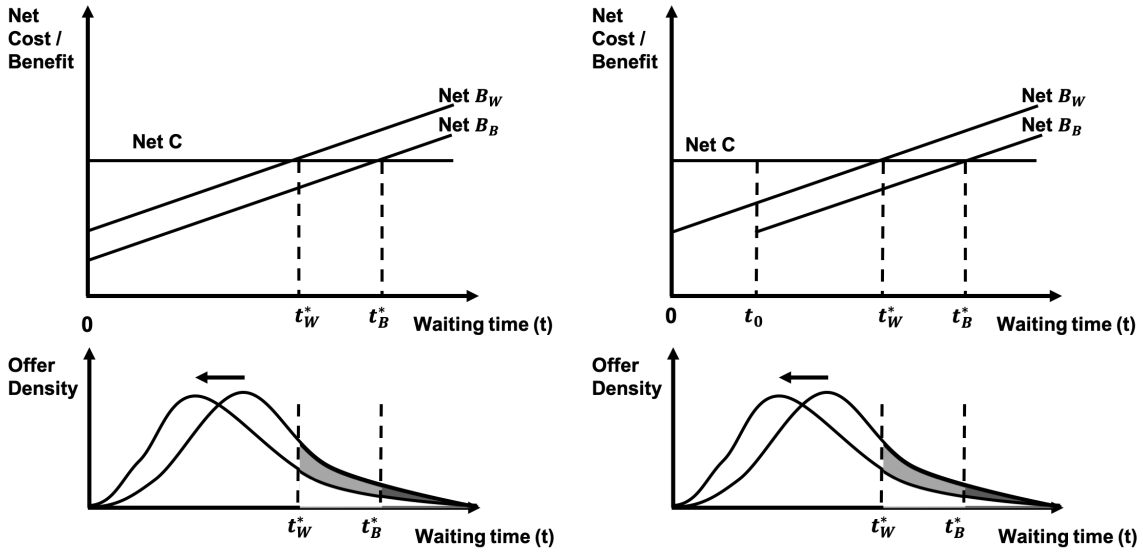


(a) [1 year] Waitlist mortality (b) [2 year] Waitlist mortality

(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.

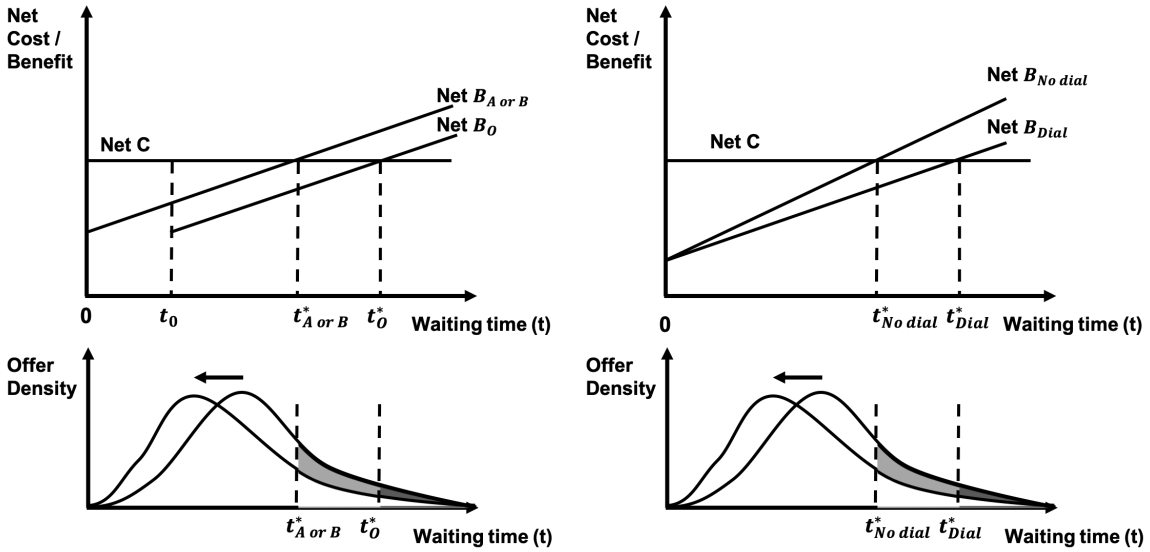
Figure B.8 The effect on patient mortality



(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 B.9 Heterogentiy of the crowd-out effect by candidates' races

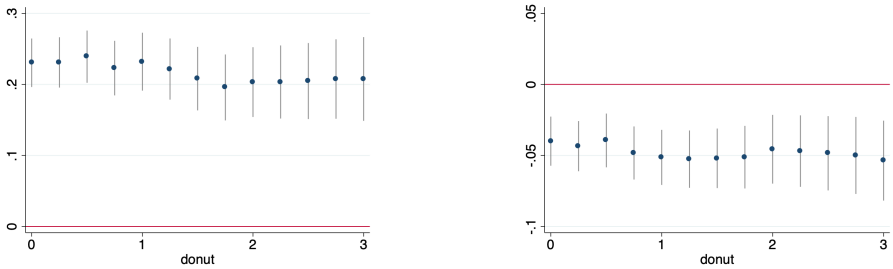


(a) Heterogeneity by blood types

(b) Heterogeneity by dialysis status

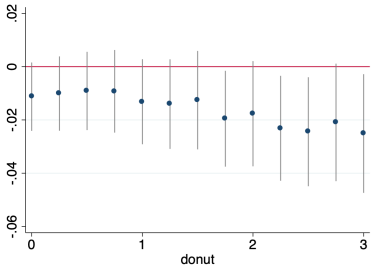
Notes: Net B illustrates the relative benefit of using a living donor kidney compared to waiting for a deceased donor kidney at each waiting time (t) for white and black candidates, respectively. The net cost illustrates the emotional cost of living donor kidney receipients with a closely related donor. 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 B.10 Heterogentiy of the crowd-out effect

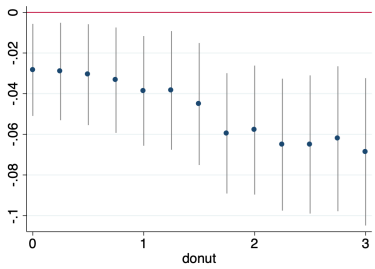


(a) Pr (Deceased)

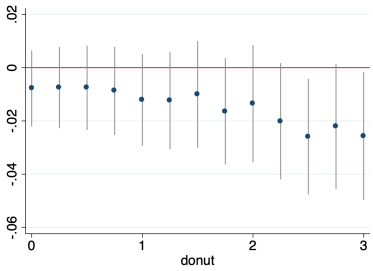
(b) Pr (Living)



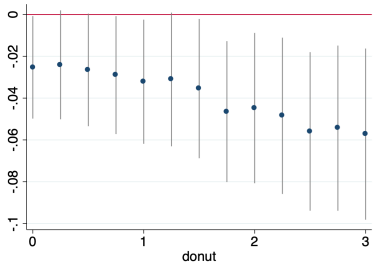
(c) [1 year] Waitlist mortality



(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 B.11 Donut RD estimation

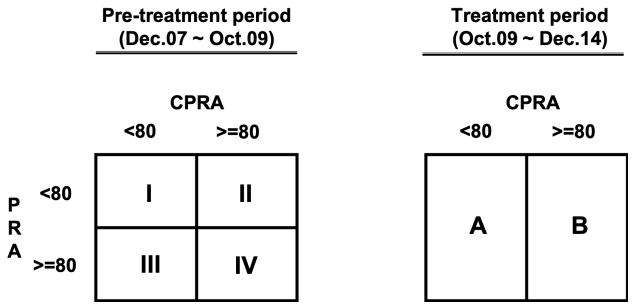


Figure B.12 Sample of a difference-in-difference estimation

Appendix C Tables and Figures for Chapter 3

Table C.1 ESRD patient distance to dialysis facilities

Percentile	(1) All	(2) For-profit	(3) For-profit	(4) Not-for-profit	(5) Not-for-profit
		Freestanding	Hospital	Freestanding	Hospital
10	1.681	1.761	1.386	1.806	0.786
20	2.887	2.928	3.091	2.956	2.500
30	4.134	4.120	4.439	4.227	4.157
40	5.568	5.489	6.044	5.788	5.949
50	7.404	7.236	7.951	7.636	8.269
60	10.109	9.744	10.650	10.227	12.150
70	14.422	13.708	15.231	14.628	18.610
80	22.073	20.658	23.769	21.826	31.272
90	40.846	37.280	46.869	39.932	62.723
Observations	2,183,149	1,639,252	17,759	172,754	353,384

Source: 2016 USRDS data
Notes: The distance between a residence of a patient and the patient's registered dialysis facility is computed by using the GEODIST stata command and coordinates of the two locations. Resident coordinates in ZCTA-level come from United States Census Gazetteer files (https://www.census.gov/geographies/reference-files/time-series/geo/gazetteer-files.html). Dialysis facility coordinates are found based on the facility address available from CMS Dialysis Facility Compare Dataset.

Table C.2 Market characteristics (81 sample markets)

	(1) Mean	(2) Std Dev	(3) Min	(4) Max
Market population	127,484.70	49,771.10	56,548	304,016
Largest market population within 20 miles	10,964.71	7,161.52	-	24,526
Number of census tracts	29.62	12.72	9	70
Number of for-profit dialysis facilities	2.65	1.60	1	7

*Source*s: 2015 U.S. Census ACS, 2016 USRDS data
Notes: The largest market within 20 miles is relative to the market's boundary census tracts. The distance between locations is computed as the distance between the census tract's population-weighted centroids.

Table C.3 Census tract-level characteristics

	(1) Mean	(2) Std Dev	(3) Min	(4) Max
Population				
Total	4,304.40	2,081	0	30,256
Diagnosed with ESRD	7.24	5.15	0	43
65 years and older	591.82	378	0	4,093
Per capita income ($)	24,304.92	9,919.54	0	90,249
Education with high school or under (%)	41.49	16.51	0	88.60
Median gross rent ($)	783.36	230.64	0	2,108

*Source*s: 2015 U.S. Census ACS, 2016 USRDS data
Notes: Median gross rent shows the monthly housing cost expenses for renters. This variable contains the contract rent and the estimated cost of utilities paid by renters. The number of ESRD patients includes the accumulated number of patients whose ESRD status was active in 2015.

Table C.4 Parameter estimates

	(1) Coefficient	(2) Marginal Effect (%)	(3) Coefficient	(4) Marginal Effect (%)
ESRD patients (units: 10 people)	0.3265 (0.0977)	2.01		
Population over 65 years (units: 1,000 people)			0.6810 (0.0209)	3.85
Education with high school or under (units: 1%p)			-0.7484 (0.3709)	-2.70
Per capita income (units: $100,000)			-1.7498 (0.3714)	-3.73
Median gross rent (units: $100)	-0.0193 (0.0278)	-1.17	-0.0434 (0.0164)	-2.97
Competition effect (γ)	-1.8753 (0.9524)		-0.6295 (0.0211)	
Mean of market-level effect distribution (μ)	-2.8078 (1.0166)		-2.0027 (0.2842)	
Standard error of market-level effect distribution (σ)	0.3905 (0.0291)		0.3768 (0.0279)	
Log-likelihood	775.198		769.766	

Notes: Standard errors are reported in parentheses. Parameter estimates are based on 2015 demographic and dialysis facility location data. The marginal effect shows the average change in the probability of location choice conditional on entry for the response to a 10% increase in each demographics.

Table C.5 Robustness to the restrictions on the largest city within 20 miles

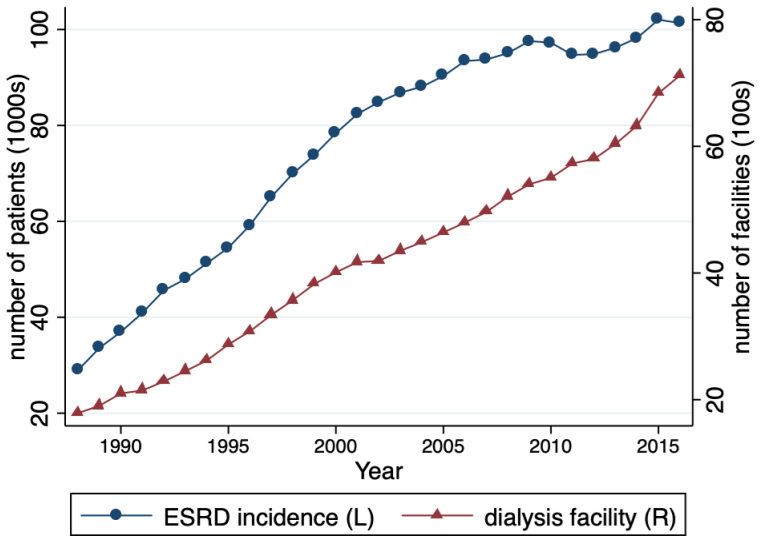
	(1)	(2)	(3)	(4)	(5)	(6)
	Pop $<$ 25,000 (81 markets)		Pop $<$ 40,000 (100 markets)		Pop $<$ 50,000 (108 markets)	
ESRD patients (units: 10 people)	0.3265 (0.0977)		0.3813 (0.0742)		0.3801 (0.0702)	
Population over 65 years (units: 1,000 people)		0.6810 (0.0209)		0.7762 (0.1025)		0.7780 (0.0801)
Education with high school or under (units: 1%p)		-0.7484 (0.3709)		-0.7873 (0.1694)		-0.8190 (0.1087)
Per capita income (units: \$100,000)		-1.7498 (0.3714)		-2.1708 (0.1907)		-2.5712 (0.1144)
Median gross rent (units: \$100)	-0.0193 (0.0278)	-0.0434 (0.0164)	-0.0128 (0.0238)	-0.0328 (0.0240)	-0.0100 (0.0090)	-0.0235 (0.0168)
Competition effect (γ)	-1.8753 (0.9524)	-0.6295 (0.0211)	-1.8353 (0.1366)	-0.8490 (0.1909)	-2.1761 (0.1514)	-0.9450 (0.1143)
Mean of market-level effect distribution (μ)	-2.8078 (1.0166)	-2.0027 (0.2842)	-1.5499 (0.2586)	-1.7927 (0.2967)	-1.2147 (0.2260)	-1.6640 (0.1931)
Standard error of market-level effect distribution (σ)	0.3905 (0.0291)	0.3768 (0.0279)	0.4020 (0.0282)	0.3970 (0.0280)	0.4018 (0.0266)	0.3915 (0.0260)
Log-likelihood	775.198	769.766	903.732	896.320	1,025.564	1,015.205

Notes: The table shows the parameter estimates with different restrictions on the population size of the largest city within 20 miles from each sample market. Standard errors are reported in parentheses. Parameter estimates are based on 2015 demographic and dialysis facility location data.

Table C.6 Robustness to the assumption on the size of potential entrants

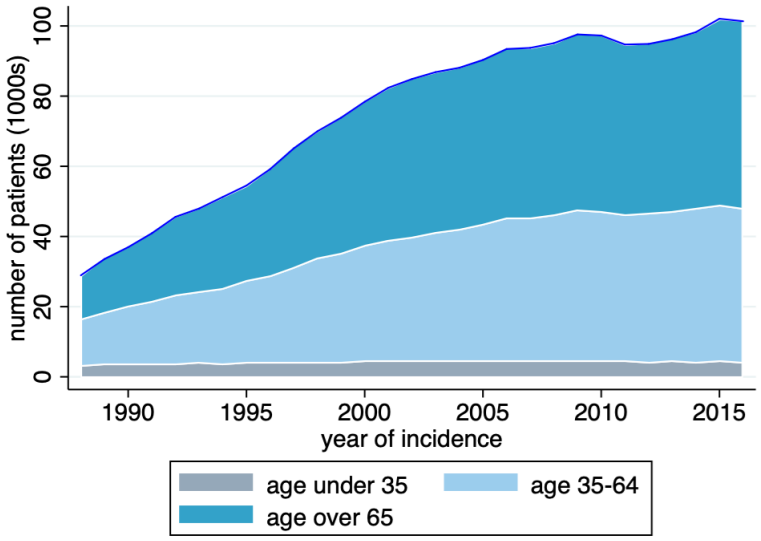
	(1)	(2)	(3)	(4)	(5)	(6)
	2 × entrants		3 × entrants		5 × entrants	
ESRD patients	0.3265		0.3205		0.3817	
(units: 10 people)	(0.0977)		(0.0969)		(0.0968)	
Population over 65 years		0.6810		0.6819		0.6824
(units: 1,000 people)		(0.0209)		(0.1397)		(0.1245)
Education with high school		-0.7484		-0.7495		-0.7504
or under (units: 1%p)		(0.3709)		(0.3858)		(0.2553)
Per capita income		-1.7498		-1.7752		-1.7809
(units: $100,000)		(0.3714)		(0.8694)		(0.3382)
Median gross rent	-0.0193	-0.0434	-0.0189	-0.0425	-0.0191	-0.0426
(units: $100)	(0.0278)	(0.0164)	(0.0276)	(0.0292)	(0.0276)	(0.0275)
Competition effect (γ)	-1.8753	-0.6295	-1.6942	-0.6880	-1.6927	-0.7092
	(0.9524)	(0.0211)	(0.9480)	(0.8354)	(0.9461)	(0.3403)
Mean of market-level effect	-2.8078	-2.0027	-2.3045	-2.6348	-2.9962	-3.3038
distribution (μ)	(1.0166)	(0.2842)	(1.0125)	(1.0142)	(1.0109)	(0.4542)
Standard error of market-level	0.3905	0.3768	0.3903	0.3768	0.3902	0.3768
effect distribution (σ)	(0.0291)	(0.0279)	(0.0291)	(0.0283)	(0.0291)	(0.0281)
Log-likelihood	775.198	769.766	775.171	769.764	775.171	769.764

Notes: The table shows parameter estimates with the different assumptions on the number of potential entrants in each market. Standard errors are reported in parentheses. Parameter estimates are based on 2015 demographic and dialysis facility location data.



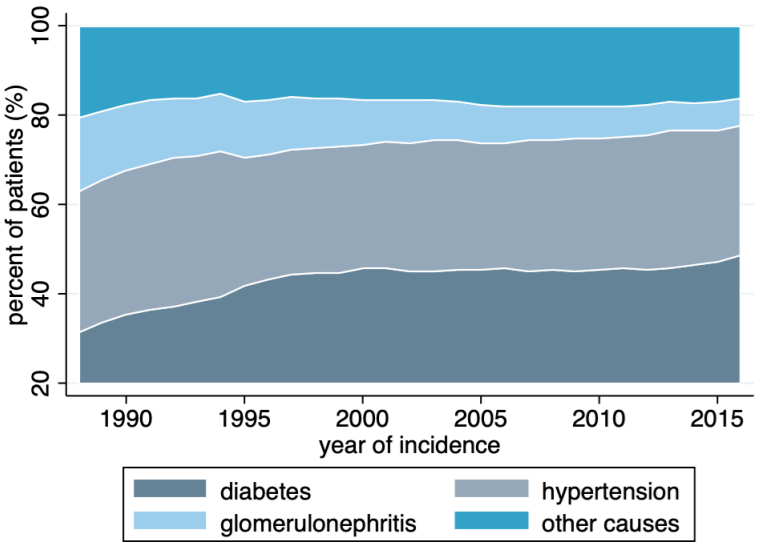
Source: 2016 USRDS data
Notes: The number of ESRD incidences is computed by counting patients who received their first ESRD services in each year. I restrict the sample to ESRD patients who chose in-center hemodialysis as their first treatment modality (73 percent among total ESRD patients). Therefore, the real number of ESRD incidences needs to be scaled up. To calculate the number of dialysis facilities, I count facilities that responded the CMS ESRD Annual Facility Survey in each year.

Figure C.1 Trend of ESRD incidences and dialysis facilities



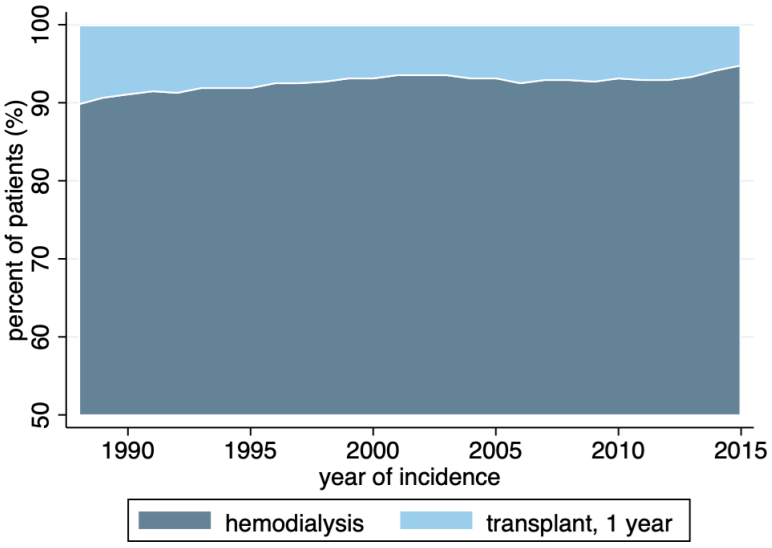
Source: 2016 USRDS data

Figure C.2 Trend of ESRD incidence by age



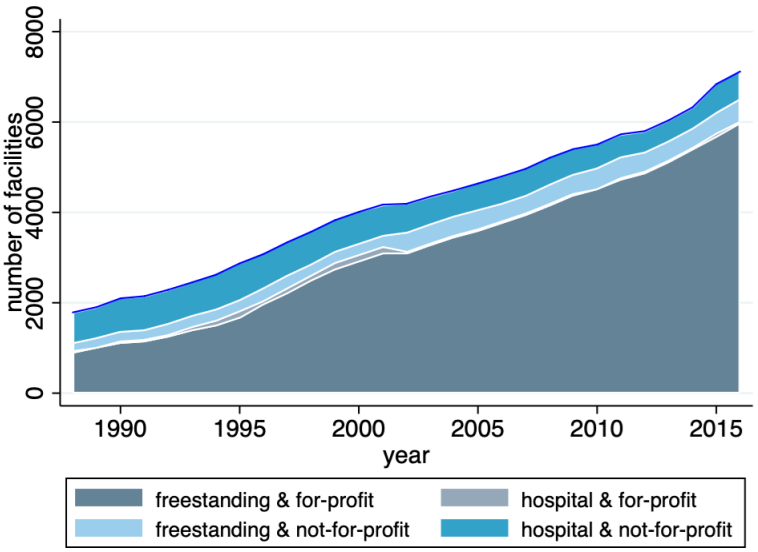
Source: 2016 USRDS data
Notes: Glomerulonephritis is diagnosed for patients with inflammation of the tiny filters in the kidneys.

Figure C.3 Trend of primary causes of ESRD



Source: 2016 USRDS data
Notes: I restrict the sample to ESRD patients who chose in-center hemodialysis as their first treatment modality (73 percent among total ESRD patients). Approximately 6 percent of all ESRD patients receive kidney transplant as their first treatment. Transplant treatment choice in this plot is defined as a broader concept. It counts not only actual transplant, such as decesed or living donor kidney transplants, but also waitlist registration for deceased donor kidneys.

Figure C.4 Treatment choice within 1 year of ESRD incidence



Source: 2016 USRDS data
Notes: Hospital-based facilities are either hospital units or hospital satellites, and freestanding facilities are defined as units not affiliated with a hospital.

Figure C.5 Trend of dialysis facilities

Appendix D Validity Check for RD estimation in Chapter 1

To identify a valid causal relationship by using an RD design, two assumptions are required. First, the liver transplant candidates should be randomly distributed around the 35 threshold. Second, the candidates are not able to perfectly manipulate their aMELD scores to increase the likelihood of receiving liver transplants (Lee 2008; D. S. Lee et al. 2010).

For the first assumption, I test whether the predetermined characteristics of candidates are similar around the 35 threshold. Table A.9 presents the results of the RD estimation for the predetermined characteristics. Using an RD design with a linear polynomial and a triangular kernel, I examine whether the RD estimates of the predetermined characteristics are significantly different from zero. None of the estimates for the predetermined characteristics are significantly discontinuous around the aMELD 35 threshold, which implies that candidates in the analysis sample are as good as randomly distributed around the threshold.

To check the second assumption, I examine whether there is any evidence of aMELD score manipulation near the 35 threshold. Panel (a) of Figure A.14 shows the aMELD score frequency with local linear fitted lines. Each circle shows a mean frequency with 0.4 aMELD score bins within bandwidth 4. Solid lines show local linear regression graphs regressed separately below and above the 35 threshold. The figure shows a smooth mean frequency across the threshold. Panel (b) presents a histogram of the aMELD score with 0.01 aMELD score bins and a bandwidth of 4. I find some large heaps of aMELD scores with whole numbers that could be caused by the new cMELD score system described in Section 1.2.1[53]. Other than those heaps of aMELD scores, I do not observe any irregular heaps around the 35 threshold, which is consistent with patients being unable to perfectly manage their blood factors, namely, creatinine, bilirubin, INR, and sodium.

[53]There would be several other hypotheses for the heaps at whole number units. (1) Rounding in reporting cannot be the reason because the aMELD scores in panel (a) of Figure A.1 are recovered by using blood factors and the MELD equation rather than reported scores. (2) The eMELD score is assigned by whole number units, which would have some effect. However, only 6 candidates have eMELD scores among the 3,557 candidates within bandwidth 4. Furthermore, among the 6 candidates, only 2 have eMELD scores greater than their cMELD score. Hence, the effect of the eMELD score on the observed heaps is almost zero.

Candidates who registered after January 11, 2016, are affected by the new cMELD score system including serum sodium, if their initial cMELD score, which is calculated using the original cMELD score equation, is 11 or higher. The observed heaps are generated as the new cMELD score equation uses the rounded original cMELD score, and the amount of serum sodium is reported as whole numbers. Panels (c) and (d) show the difference in the distribution of aMELD scores between candidates whose aMELD scores do and do not contain serum sodium. Unlike panel (d) which shows no heap for aMELD scores with whole numbers, I find heaps in panel (c) similar to those in the overall sample, panel (b).

If the observed heaps of aMELD scores with whole numbers are irregular, the RD estimates of the liver transplant outcomes may not be valid (Barreca et al. 2016). Hence, I examine whether the RD estimates in Section 1.5.1 are sensitive to heaps of aMELD scores with whole numbers. I compare the RD estimates with donut RD estimates excluding the heaped data in the RD estimation, as proposed by Barreca et al. (2016). If the outcomes at the heaps are outliers and they drive the RD estimates to a large degree, the magnitude of the donut RD estimates would show a large difference from that of the standard RD estimates. Table A.10 shows the standard RD estimates and donut RD estimates regarding the effect of the Share 35 policy on patient outcomes. Overall, the donut RD estimates in Panel B are similar to the standard RD estimates in Panel A in magnitude and significance, suggesting that the heaps with the whole numbers do not drive the RD estimates.

Appendix E Variable Choice for Survival Prediction in Chapter 1

To derive the data-driven liver match quality measure that predicts posttransplant survival, I use the LASSO algorithm. This algorithm selects highly predictive variables by adding a penalization term λ to the OLS objective function (Belloni et al. 2014).

$$\hat{\beta}(\lambda) = \underset{\beta \in \mathbb{R}^k}{argmin} \sum_{i=1}^{k} (y_i - x'\beta)^2 + \lambda \sum_{j=1}^{k} |\beta_j| \tag{23}$$

When predicting a certain outcome using related variables, avoiding over-fitting is important; specifically, a well-fitted model in the sample used for designing the model may not have high prediction power out of the sample. To avoid this concern, I randomly divide the sample into the model sample (80%) and test sample (20%). After selecting highly predictive variables using the LASSO algorithm and the model sample, the predictive power of the model is tested using the test sample. One concern about this approach is that the test sample is not exploited in the prediction model design. If there are outliers in one of the two samples, the model may not show good prediction performance. To address this concern, I randomly split the overall sample into five sets and apply the LASSO algorithm five times using one of the sample sets as the test sample. Among the five different sets of selected variables, I finally select variables chosen at least three times as the predictor of the model. The LASSO algorithm selects 40 variables, and the variables are shown in Table A.13.

When highly predictive variables are selected, I predict the posttransplant survival rates using the logit estimation as the outcome with the binary variable, which is one if the transplant recipient is surviving. In the logit estimation, however, the standard R-squared value cannot be used to check the predictive power of the estimation model. Hence, I use the Brier score, which calculates the mean squared error of the predicted probability, for the predictive power evaluation.

$$Brier\ score = \frac{1}{n}\sum(y_i - \hat{y}_i)^2 = \frac{1}{n}[\sum_{y_i=1}(1 - \hat{y}_i)^2 + \sum_{y_i=0}(\hat{y}_i)^2] \tag{24}$$

where y_i is the actual posttransplant survival outcome and $\hat{y}_i$ is the probability that is predicted in the model. n presents the number of observations used for the predic-

tion. If the prediction model explains the outcome better, the value of the Brier score becomes smaller.

Table A.14 displays the Brier scores of four different prediction models. The first prediction model is DRI which focuses on the liver donor characteristics. The second model expands the approach of the first model by allowing coefficients of DRI factors to be flexible; specifically, I predict the posttransplant survival using the variables of DRI. The third model predicts survival rates with LASSO-selected variables, and the fourth model allows interaction of LASSO-selected variables. To avoid the over-fitting problem, the Brier scores are calculated by comparing the predicted survival rates and the actual survival outcome in the test sample. As I repeat 5 different predictions using one of the five sample sets as the test sample, each prediction model has five different estimates in Columns (1) - (5). Among the four prediction models, the third model, which uses only the LASSO-selected variables without the interaction terms, shows the smallest Brier scores for all 5 results.

Appendix F Selection of Functional Form in Chapter 2

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 (D. S. 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.[54][55] 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 Table B.13 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.

$$AIC \;=\; Nln(\widehat{\sigma^2}) + 2p \tag{25}$$

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.

[54] 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.

[55] 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).

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