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

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Abstract

Liver allocation policies and strategic offer-acceptance decisions determine who ultimately receives liver transplants. For transplant candidates with greater medical need, the Share 35 policy provides priority for livers obtained from areas further away. This paper examines the policy effect on transplant outcomes and the decision to accept or decline a liver offer. First, I find that increasing access to liver transplants effectively reduces mortality risks before receiving transplants, which is the goal of the policy. Second, I find a mixed effect on the quality of transplanted livers for targeted candidates. Although livers travel further that implies lower liver quality, those candidates receive livers with better donor characteristics. This compensation on liver quality can be explained by the change in offer-acceptance incentives. Greater access to liver offers enables targeted candidates to be more selective of offered livers.

Keywords: transplant, organ allocation, organ acceptance, organ quality
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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 mimize 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 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.

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

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

risks before receiving transplants, which is hereafter termed "waitlist mortality". As shown in Figure 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 3 describes the data used for estimation, while Section 4 discusses the identification strategy. Section 5 presents estimates of the access to liver transplants and patient mortality. Section 6 and 7 investigate estimates of transplantation quality, posttransplant survival, and offer-acceptance behaviors. Section 8 provides key robustness and specification checks, and Section 9 concludes.

2 Institutional Detail

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].

2.1.1 Geographical Proximity

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 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 →

[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)

Region → 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.

2.1.2 Medical Need

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

[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.

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.

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

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

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. (Appendix Table D.1).

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.

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 3 shows the mechanism of the Share 35 policy. Let us assume that Region 1

[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)

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.

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 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 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 2.2, 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.

4 Empirical Framework

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 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 esti-

[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 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.

mation 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 Appendix A, and I do not find any evidence of violations for the validity assumptions.

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. 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 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 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 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.

[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.

5 Access to Liver Transplants and Mortality Rates

5.1 Regression Discontinuity Estimates

Panel (a) of Figure 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 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 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 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 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 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 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.

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 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.

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 $aMELD < 35$.

6.1 Transplanted Liver Quality

Table 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 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.

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 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 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

[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.

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 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 Appendix B 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 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 7.

7 Effect on Liver Offer-Acceptance Behavior

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.

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 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 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 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.

8 Robustness and Specification Check

8.1 Placebo Tests

In the analysis of access to liver transplants and patient mortality (Section 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 7. Unlike the positive 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

[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.

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.

8.2 Sensitivity to Bandwidth and Polynomials

As a specification check, I examine whether the RD estimates in Table 2 are sensitive to bandwidths and the degree of the polynomials. Figure 6 and 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 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 7. Overall, the figures suggest that the RD estimates for mortality outcomes are not sensitive to the bandwidth choices and the degree of polynomials.

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 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 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 10 and 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 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 12 and 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.

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

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

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 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).

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10 Figures

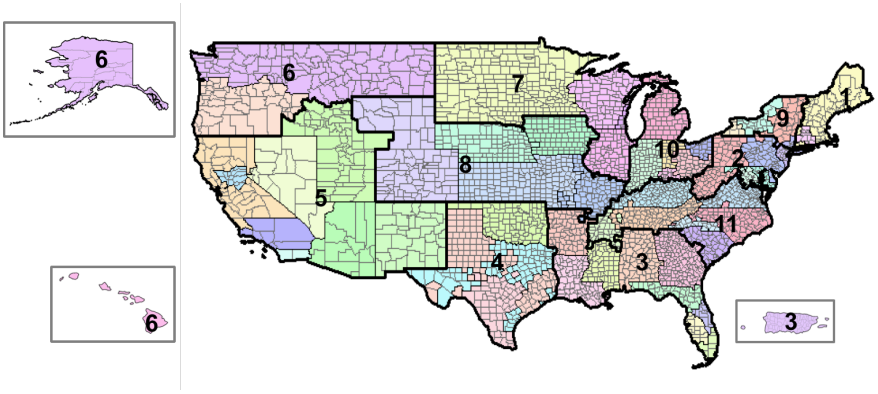


Figure 1: DSAs and Regions in U.S.

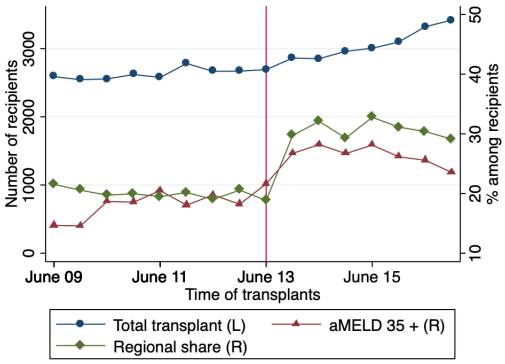
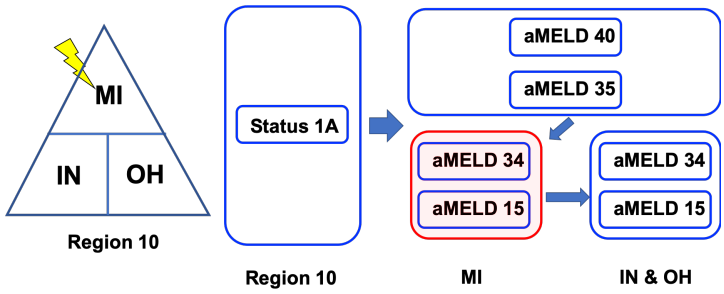
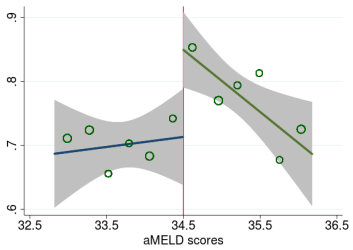


Figure 2: Effect of the Share 35 policy on the liver transplant market

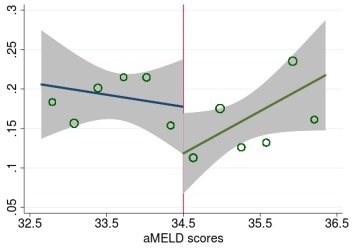


Sources: OPTN Policies (OPTN 2017).
Notes: Allocation for candidates with aMELD scores less than 15 is excluded in the figure. After the match in the figure, the donated liver is matched to candidates with aMELD scores of at least 15 and waitlisted in the U.S. If the liver is not accepted, then candidates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

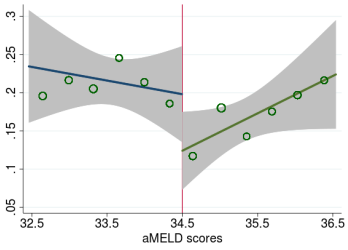
Figure 3: Deceased donor liver allocation process under the Share 35 policy



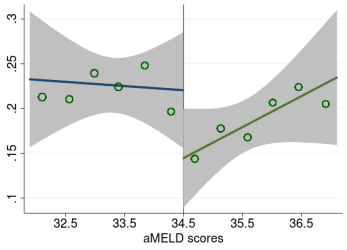
(a) Transplant



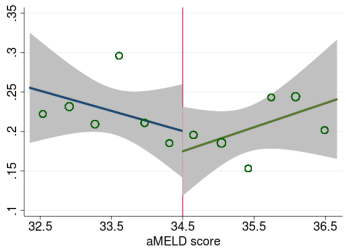
(b) [90 d] Waitlist mort



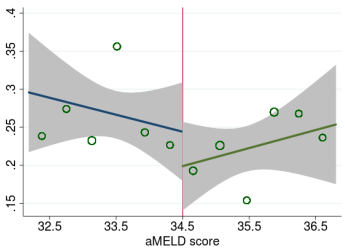
(c) [180 d] Waitlist mort



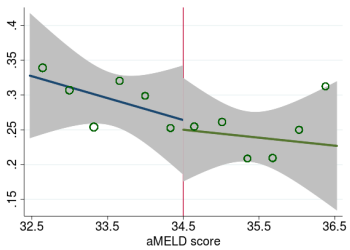
(d) [1 yr] Waitlist mort



(e) [90 d] Overall mort



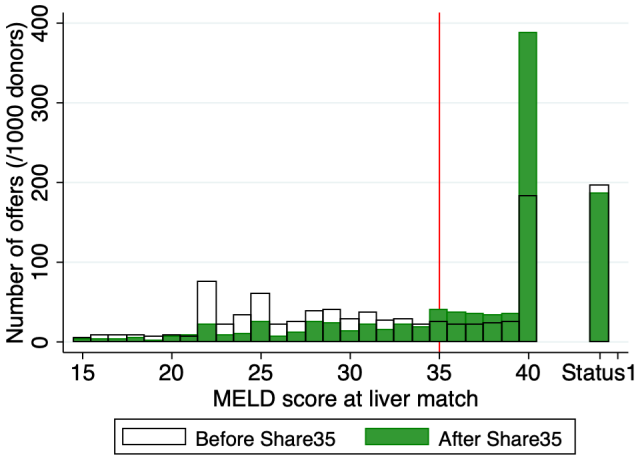
(f) [180 d] Overall mort



(g) [1 yr] Overall mort

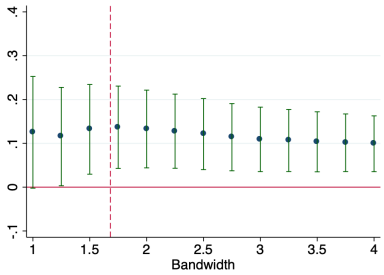
Notes: Panels (a)-(g) plot the mean values of outcome variables along with linear fitted lines (solid lines) and the 95% confidence intervals (shaded area) below and above the aMELD score 35 threshold. Each bin is divided by the same width, and the size of each dot is scaled according to the number of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

Figure 4: Effect of the Share 35 policy on patient outcomes

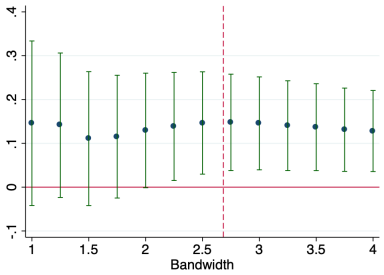


Notes: The figure plots the frequency of liver offers, that were matched to top-ranked transplant candidates, for each aMELD score at the time of offer. As the number of donated livers is different before and after the Share 35 policy implementation, the adjusted number of liver offers per 1000 donors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

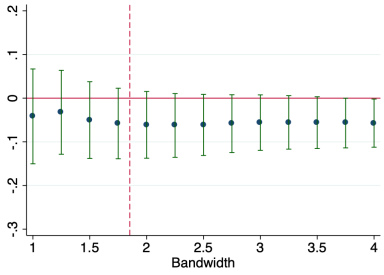
Figure 5: Change in the access to liver offers



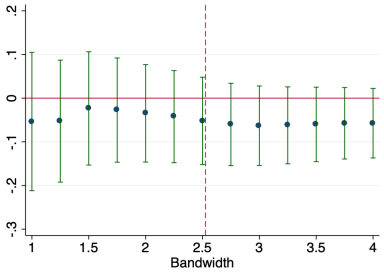
(a) Transplant, lin



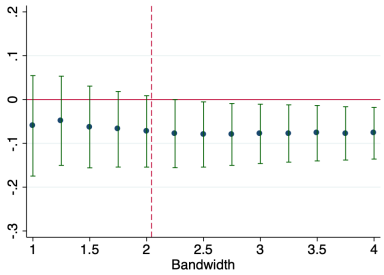
(b) Transplant, quad



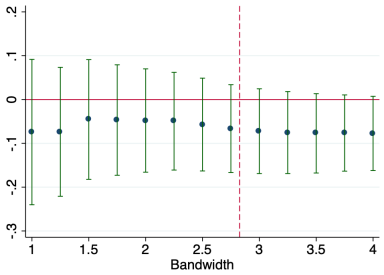
(c) Waitlist mort, 90 days, lin



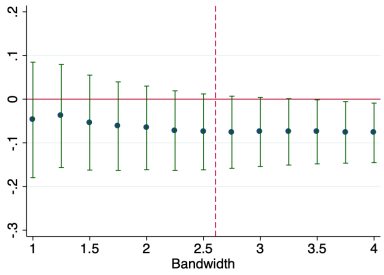
(d) Waitlist mort, 90 days, quad



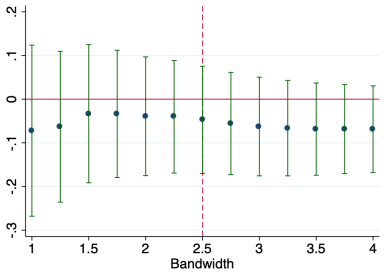
(e) Waitlist mort, 180 days, lin



(f) Waitlist mort, 180 days, quad



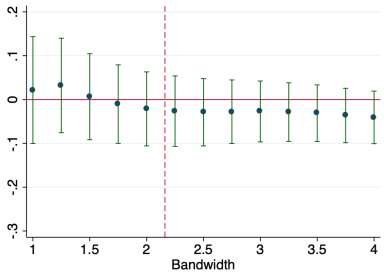
(g) Waitlist mort, 1 year, lin



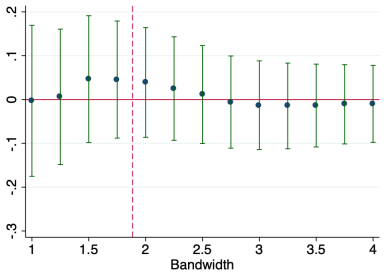
(h) Waitlist mort, 1 year, quad

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).

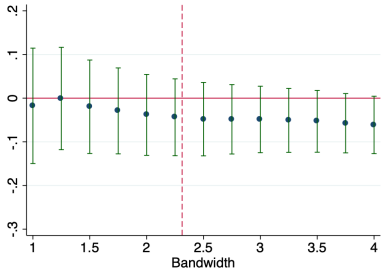
Figure 6: Sensitivity to bandwidth and polynomial



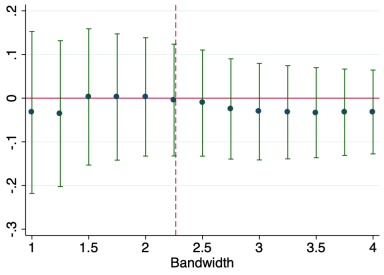
(a) Overall mort, 90 days, lin



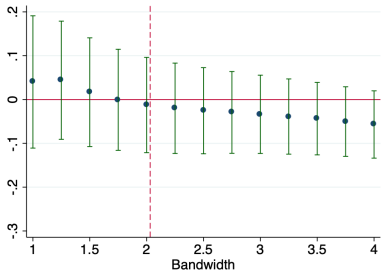
(b) Overall mort, 90 days, quad



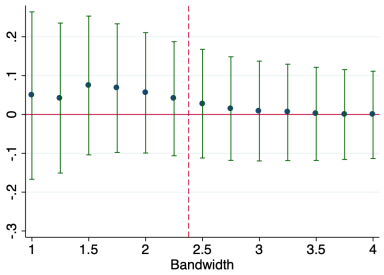
(c) Overall mort, 180 days, lin



(d) Overall mort, 180 days, quad



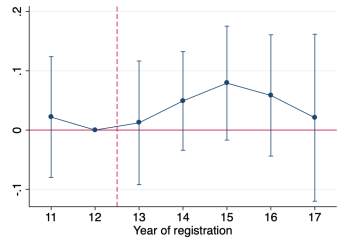
(e) Overall mort, 1 year, lin



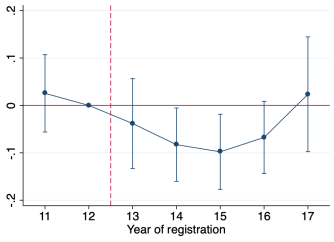
(f) Overall mort, 1 year, quad

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).

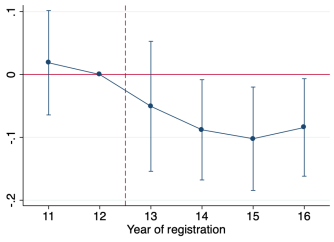
Figure 7: Sensitivity to bandwidth and polynomial



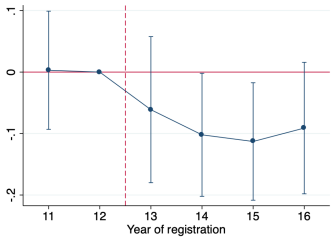
(a) Transplant



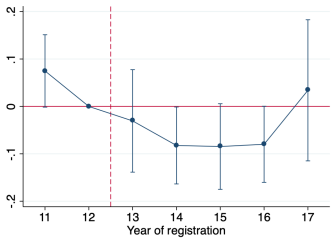
(b) [90 d] Waitlist mort



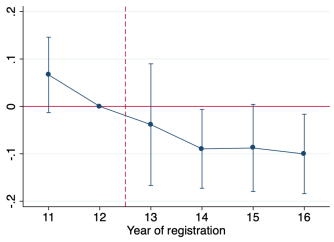
(c) [180 d] Waitlist mort



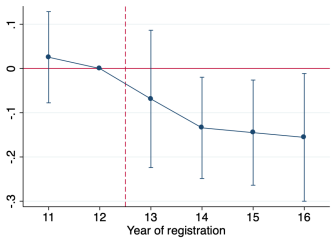
(d) [1 yr] Waitlist mort



(e) [90 d] Overall mort



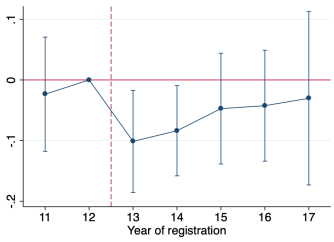
(f) [180 d] Overall mort



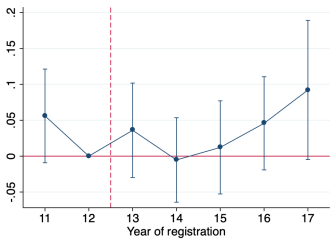
(g) [1 yr] Overall mort

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.

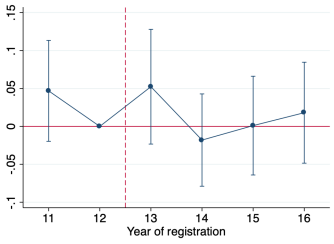
Figure 8: Event study estimates, transplant and mortality for $aMELD \geq 35$



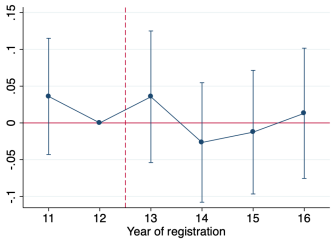
(a) Transplant



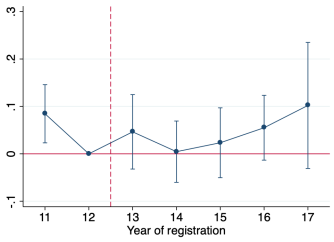
(b) [90 d] Waitlist mort



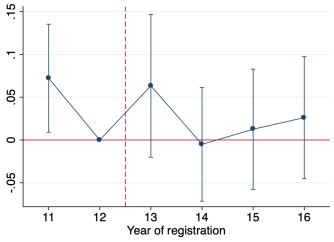
(c) [180 d] Waitlist mort



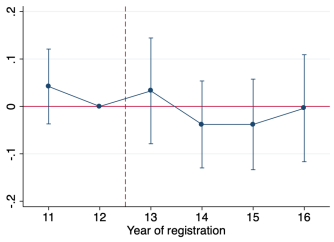
(d) [1 yr] Waitlist mort



(e) [90 d] Overall mort



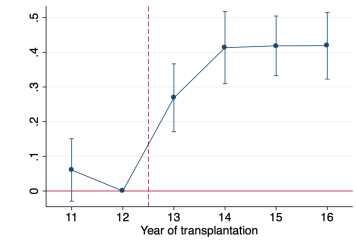
(f) [180 d] Overall mort



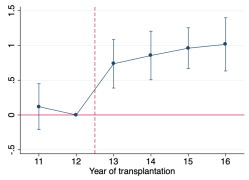
(g) [1 yr] Overall mort

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.

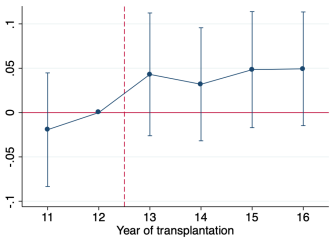
Figure 9: Event study estimates, transplant and mortality for $aMELD < 35$



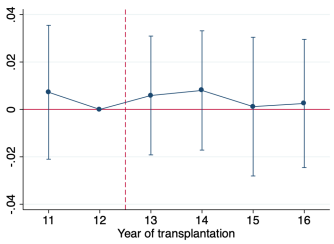
(a) Regional share



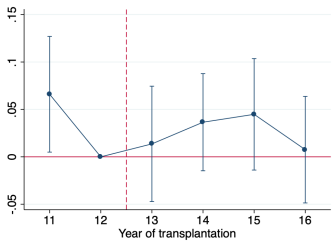
(b) Log (Distance)



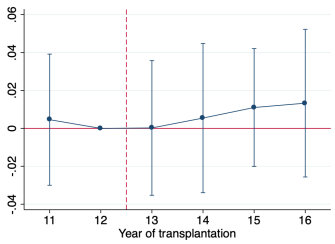
(c) Log (CIT)



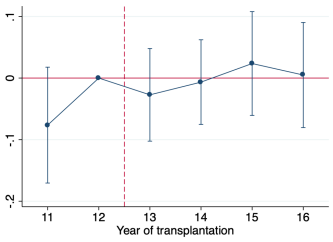
(d) Donor age, over 70



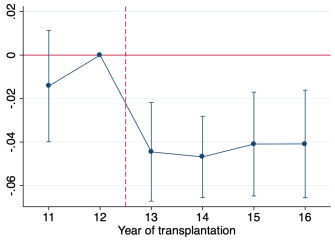
(e) BMI over 35



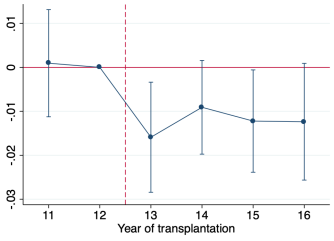
(f) Donation after cardiac death



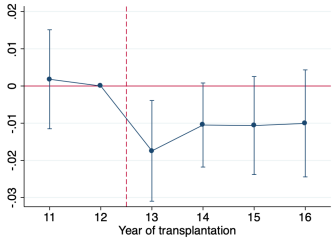
(g) Survival, 1 year



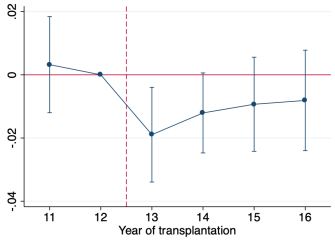
(h) - Log (DRI)



(i) Predicted survival, 1 year



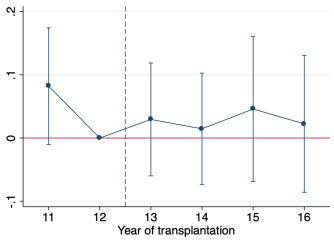
(j) Predicted survival, 3 year



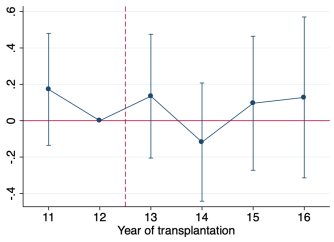
(k) Predicted survival, 5 year

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 Appendix Table D.6. Standard errors clustered at the waitlisted transplant center level are used for 95 percent confidence intervals.

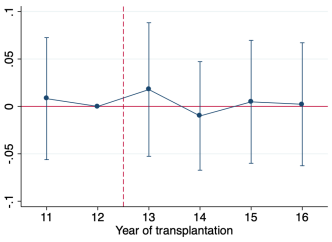
Figure 10: Event study estimates, transplantation quality for $aMELD \geq 35$



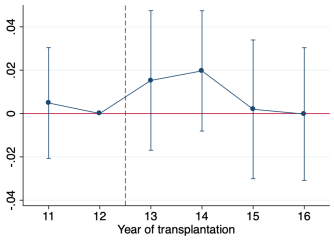
(a) Regional share



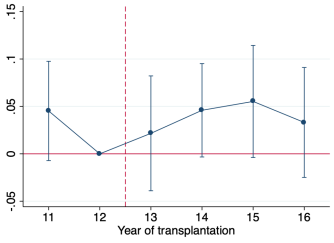
(b) Log (Distance)



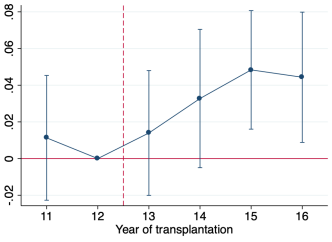
(c) Log (CIT)



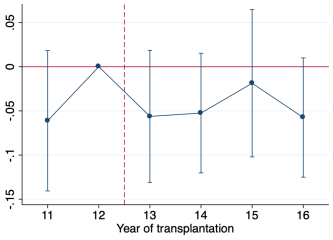
(d) Donor age, over 70



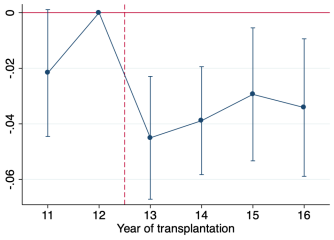
(e) BMI over 35



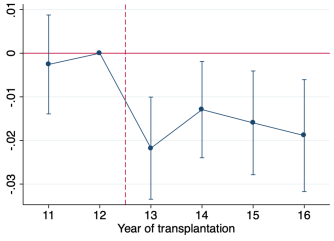
(f) Donation after cardiac death



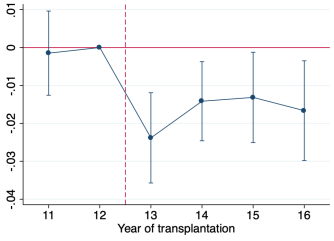
(g) Survival, 1 year



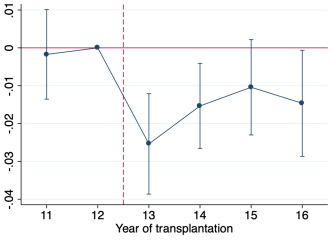
(h) - Log (DRI)



(i) Predicted survival, 1 year



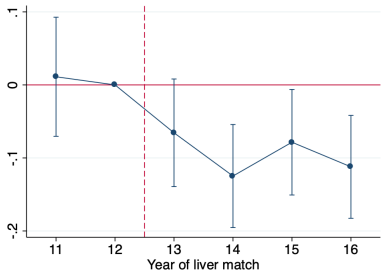
(j) Predicted survival, 3 year



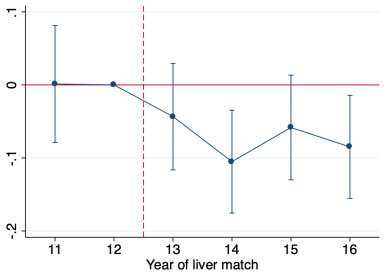
(k) Predicted survival, 5 year

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 Appendix Table D.6. Standard errors clustered at the waitlisted transplant center level are used for 95 percent confidence intervals.

Figure 11: Event study estimates, transplantation quality for $aMELD < 35$



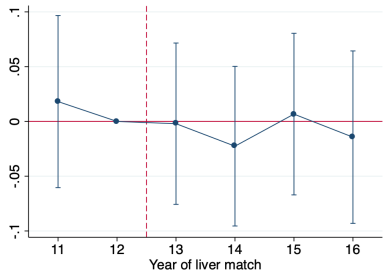
(a) Accept, w/o donor cov.



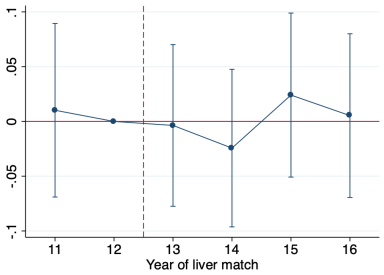
(b) Accept

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.

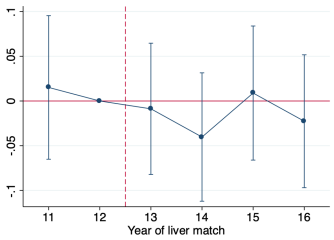
Figure 12: Event study estimates, liver offer acceptance for $aMELD \geq 35$



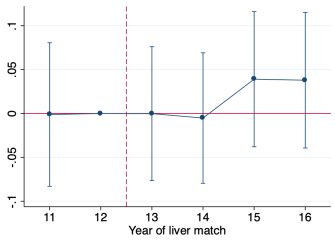
(a) Accept, w/o donor cov.



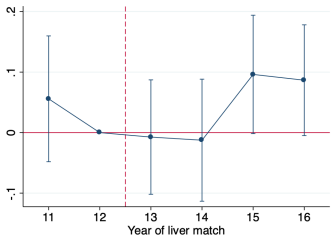
(b) Accept



(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 13: Event study estimates, liver offer acceptance for $aMELD < 35$

11 Tables

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Regional share	Log (Dist)	Log (CIT)	Donor age over 70	BMI over 35	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 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 Appendix Table D.6 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 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 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%

Appendix A Validity Check for RD estimation

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; Lee et al. 2010).

For the first assumption, I test whether the predetermined characteristics of candidates are similar around the 35 threshold. Table D.2 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 C.1 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 2.1.2[15]. 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.

[15]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 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 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 D.3 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 B Variable Choice for Survival Prediction

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).

$$\hat{\beta}(\lambda) = \underset{\beta \in \mathbb{R}^k}{argmin} \sum_{i=1}^{k} (y_i - x'\beta)^2 + \lambda \sum_{j=1}^{k} |\beta_j| \tag{13}$$

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 Appendix Table D.6.

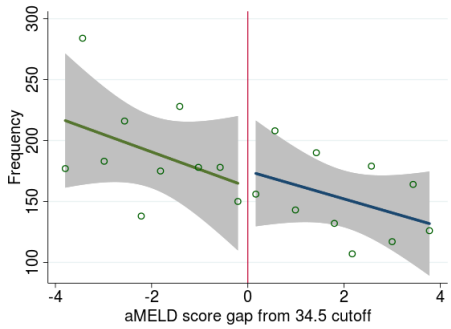
When highly predictive variables are selected, I predict the posttransplant survival rates using the logit estimation as the outcome with the binary variable, which is one if the transplant recipient is surviving. In the logit estimation, however, the standard R-squared value cannot be used to check 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.

$$Brier\ score = \frac{1}{n}\sum(y_i - \hat{y}_i)^2 = \frac{1}{n}[\sum_{y_i=1}(1 - \hat{y}_i)^2 + \sum_{y_i=0}(\hat{y}_i)^2] \tag{14}$$

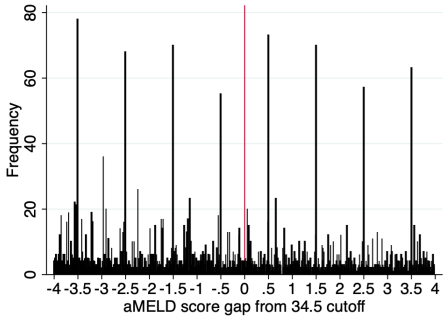
where y_i is the actual posttransplant survival outcome and $\hat{y}_i$ is the probability that is predicted in the model. n presents the number of observations used for the prediction. If the prediction model explains the outcome better, the value of the Brier score becomes smaller.

Table D.7 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.

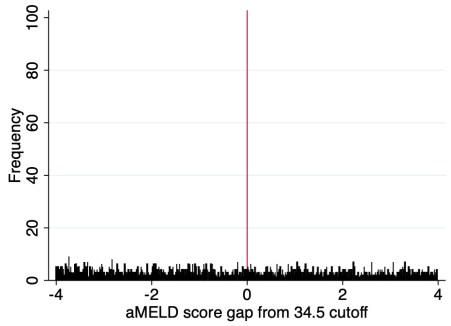
Appendix C Figures



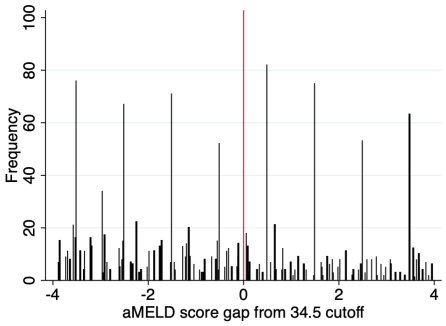
(a) Mean frequency (0.4 binwidth)



(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 C.1: aMELD distribution

Appendix D Tables

Table D.1: 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 D.2: 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 D.3: 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 D.4: 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 D.5: Descriptive statistics for liver transplant 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 D.6: 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 D.7: 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.