Endogenous Priority in Centralized Matching Markets: The Design of the Heart Transplant Waitlist

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Abstract

Centralized matching markets that prioritize specific participants to achieve certain policy goals are common in practice, but priority is often assigned using endogenous characteristics of participants. In the heart transplant waitlist in the United States, the treatment that a patient receives is used to assign waitlist priority. Policymakers recently changed the prioritization in an attempt to reduce waitlist mortality by assigning higher priority to patients receiving specific treatments previously associated with high waitlist mortality. First, I document a significant response to waitlist incentives in treatments given and transplants that take place. Then, I develop and estimate a structural model of treatment and transplant choices to evaluate the effect of the policy change on patients' outcomes and doctors' decisions. I find three main results from my model. First, there is little change in aggregate survival, and the effect of the change has been mainly redistributive. Second, the change has effectively targeted patients with lower untransplanted survival, with these patients receiving higher expected survival under the current design. Third, the effect on survival is largely driven by changes in the decision to accept/decline offers for transplants rather than directly due to a change in treatment decisions. The policy implications suggest that future designs of the waitlist should disincentivize declining offers for transplants.

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1 Introduction

Centralized matching markets are used to allocate goods when it is not feasible to do so solely through prices. Examples include deceased donor organ transplants, public housing allocation, and school admissions. Policymakers often design these markets to prioritize participants who are perceived to benefit more, such as patients expected to die sooner in organ transplantation or poorer households in public housing and school admissions. Priority often depends on decisions made by market participants, such as the medical treatments a patient receives in organ transplant waitlists, household income in public housing, or neighborhood choice in school admissions.[1] But participants who respond to endogenous priority and receive goods are potentially not those intended, resulting in outcomes contrary to policy goals.

This paper studies endogenous priority in the heart transplant waitlist in the United States, specifically a change to the design intended to target patients at a higher risk of waitlist mortality. There are two facts that motivate targeting patients with a high risk of waitlist mortality. First, post-transplant survival typically exceeds ten years while waitlist survival is typically less than a year, so a patient's survival drastically improves after receiving a transplant.[2] Second, donor hearts do not remain viable long enough to be offered to all patients on the waitlist, so if a donor heart is declined by too many higher priority patients, then it will likely go to waste.[3] Absent any response to waitlist incentives, assigning higher priority to patients on specific treatments would result in these patients receiving more frequent offers under the current design. This could improve the aggregate survival due to a

[1]To elaborate on the two examples that are not the focus of this paper: household income in public housing and neighborhood choice in school assignment. Households choose income by deciding where to work or whether to engage in informal labor that is not reported to the housing authority. Households influence neighborhood choice when they decide which neighborhood to live in or whether to fraudulently report an address belonging to a friend or relative (Bjerre-Nielsen et al., 2023; Park and Hahm, 2023).

[2]The median post-transplant survival is 13 years while patients that die before receiving a transplant have a median survival of 6 months. For end-stage heart failure patients, median survival without a transplant is around 1 year (Friedrich and Böhm, 2007).

[3]Around 40% of donor hearts that are offered, go untransplanted each year. Each donor heart is offered to an average of 75 patients before it is no longer offered, despite the fact that there are hundreds of compatible patients on the waitlist that could feasibly receive a transplant from any given donor.

reduction in discards and consequent increase in transplants. However, if more patients are put on high priority treatments and offers are more frequently declined, the waitlist design change could be redistributive and result in similar aggregate outcomes.

Priority is endogenous because it depends on the treatment that a patient receives for end-stage heart failure. Patients on the waitlist either receive temporary, more intensive, treatments that they remain on for days or weeks, or durable treatments that they remain on for months or years.[4] From 1999-2018, the waitlist design assigned similar priority to both treatments, although temporary treatments had higher waitlist mortality. In 2018, policy-makers changed the design to assign higher priority to patients on temporary treatments to address differences in waitlist mortality.[5] However, doctors responded to this change by using more temporary treatments, potentially offsetting the intended benefits of the change. I estimate the effect that the change has had on the distribution of health outcomes and study how two channels related to selection into treatments and transplants separately affect this change.

The first channel is the effect of receiving different treatments due to the design change on a patient's waitlist survival. If a particular patient receives a temporary treatment, then their expected overall survival might improve under the current design because they receive a transplant sooner. However, the treatment could decrease their expected survival while on the waitlist. For example, remaining on an intensive temporary treatment potentially increases the likelihood that the patient experiences a life-threatening complication. The effect of this mechanism on outcomes depends on the doctor's preferences for the treatment that includes the effects on waitlist survival and on the arrival rate of offers for deceased donor hearts.

[4]The typical temporary treatment is an intra-aortic balloon pump that is inserted into the patient through an artery and requires large external hardware to control the device. The typical durable treatment is a durable left-ventricular assist device that is implanted by opening the patient's chest (sternotomy) and is controlled through small external hardware contained in a bag that the patient wears. Further details are provided in Section 2 and Appendix A.1 of this paper.

[5]Policy makers stated that the goal was to "better stratify the most medically urgent patients" (Schnellinger et al., 2022).

The second channel is the effect of the transplant that a patient receives on their health and their doctor's selectivity over these offers. Doctors frequently decline compatible donor heart offers for their patient, resulting in donor heart wastage. Giving their patient a high priority treatment leads to more frequent future offers, but the possibility of a better offer in the future could also make doctors more selective over accepting a particular offer today. More frequent declines due to selectivity could reduce the number of transplants and potentially worsen aggregate survival. Doctors' forward-looking preferences over treatments and transplants determine whether there is an increase, decrease, or constant expected number of transplants when changing from the previous design to the current design.

I estimate a structural model of doctor's preferences and patient's health outcomes to disentangle these mechanisms. The model yields the distribution of treatments, transplants, and outcomes for each patient under both waitlist designs. Furthermore, the model allows me to separately vary treatments according to one waitlist design and transplants according to another to determine how treatments and transplants separately affect outcomes.

Before providing model-based evidence, I establish several descriptive facts. First, I find that patients on temporary treatments have higher average waitlist survival under the current design. Next, I find that a higher share of patients receive temporary treatments under the current design, consistent with a response to waitlist incentives. Finally, I demonstrate that doctors decline more offers for patients on temporary treatments under the current waitlist design. This evidence suggests that treatment and transplant behavior has meaningfully changed under the current design. However, while the descriptive evidence demonstrates changes in aggregate outcomes and decisions, it does not clarify how the changes in treatment and transplant behavior separately affect outcomes or how they relate to untransplanted outcomes.

Next, I use a structural model to evaluate the effect of the design change on patients' treatments and health outcomes and disentangle these channels. I estimate a dynamic discrete choice model of the doctors' treatment and transplant decisions with three major com-

ponents: (i) preferences over remaining on the waitlist with a specific treatment or receiving a transplant; (ii) deceased donor offer arrival to each patient given the waitlist design; and (iii) patient survival given treatment and transplant decisions. To estimate counterfactual distributions of outcomes and treatments under both waitlist designs, I use the estimated flow utility parameters and adjust the deceased donor offer arrival process depending on the waitlist design. I also estimate distributions of untransplanted treatment decisions and health outcomes to obtain each patient's underlying health status.

The results from the model demonstrate that the design change did not improve aggregate expected life-years. About 48% of patients have improved expected survival from the day they enter the waitlist under the current design and the remaining 52% have lower expected survival. Aggregate health outcomes are similar under both designs with average expected life-years declining from 14.7 years to 14.2 years, and 80% of patients experience little change in expected treatment durations or expected life-years. However, there is substantial redistribution in outcomes among the remaining 20%.

There are 8% of patients who receive temporary treatments under the previous design with bad survival outcomes who have improved survival under the current waitlist design. The median expected life-years for this group of patients increased from 7 years to 14 years, largely through reduced waitlist mortality. Meanwhile, 12% of patients who receive temporary treatments under the current design but not under the previous design experience worse survival outcomes. This group's median expected survival declines from 16 years to 8 years. Throughout, I will refer to these groups as the beneficiaries and the disadvantaged, respectively. Overall, the beneficiaries are the intended targets of the change and experience improved survival under the current design, but these gains are offset by reduced survival for the disadvantaged patients.

Then, I use the model to estimate the counterfactual distribution of untransplanted survival to determine whether the beneficiaries would die sooner without a transplant. Beneficiaries have a lower median untransplanted survival of 7.6 months compared to 9.9 months

for disadvantaged patients. The median untransplanted survival across the remaining 80% of patients is 9.2 months. Thus, sicker patients, as measured by expected untransplanted survival, benefit from the change while the change worsens outcomes for healthier patients.

Finally, I use the model to disentangle the effect of receiving different treatments versus the effect of receiving different transplants on each patient's survival. To do so, I estimate the distribution of each patient's survival based on their transplant distribution under the current waitlist design and their treatment distribution under the previous waitlist design. I find that while disadvantaged patients experience an increase in waitlist mortality, this is mainly due to selectivity over offers lengthening time spent on the waitlist rather than due to receiving treatments that negatively affect their health. That is, the current design results in doctors frequently declining offers for healthy patients on temporary treatments, resulting in these patients dying more frequently on the waitlist. This provides a clear policy implication that the design should disincentivize declining offers in order to improve outcomes for disadvantaged patients and further reduce waste of donor hearts.[6]

This paper is organized as follows. The remainder of this section presents the related literature. Section 2 presents additional background on the setting and data. Section 3 presents the descriptive evidence. Section 4 gives an overview of the structural model. Section 5 presents the empirical specification of the model, discusses estimation of parameters, and discusses computation of counterfactuals. Section 6 presents the model-based evidence. Section 7 summarizes policy implications and concludes.

1.1 Related literature

This paper primarily contributes to the market design literature on centralized matching markets (Roth, 1984; Roth et al., 2004; Agarwal and Somaini, 2018; Sönmez et al., 2020; Çelebi and Flynn, 2021; Agarwal et al., 2021; Waldinger, 2021; Bjerre-Nielsen et al., 2023;

[6]In addition, transplant center performance metrics are currently based on post-transplant outcomes rather than waitlist outcomes. Chan and Roth (2023) find that these performance metrics provide a possible explanation for the preferences of doctors that I estimate.

Perez-Richet and Skreta, 2023; Park and Hahm, 2023). Much of this literature focuses on paired kidney donation, e.g. Roth et al. (2004), rather than on deceased donor waitlists. This paper is most closely related to Agarwal et al. (2021). They study the effect of equilibrium responses to the waitlist design on outcomes for the kidney transplant waitlist. Patients with end-stage kidney disease can manage their ailment by remaining on dialysis for years, while patients with end-stage heart failure have multiple less reliable treatment options. As a result, the kidney transplant waitlist does not employ endogenous priority. Agarwal et al. only model the decision to accept or decline an offer for a transplant which simplifies the estimation of counterfactual waitlist designs. In my paper, strategic behavior while on the waitlist is a key component of the model, but outcomes are evaluated under two waitlist designs where the offer processes are observed in the data. Estimating equilibrium outcomes, as done by Agarwal et al., is left for future work.

This paper is also related to the theoretical literature on dynamic matching and queuing (Kingman, 1962; Naor, 1969; Hassin, 1985; Su and Zenios, 2004, 2005, 2006; Ünver, 2010; Ata et al., 2017; Bloch and Cantala, 2017; Doval and Szentes, 2019; Akbarpour et al., 2020; Baccara et al., 2020; Ashlagi et al., 2021; Che and Tercieux, 2021; Schummer, 2021; Castro et al., 2022; Ashlagi et al., 2022; Leshno, 2022; Nikzad and Strack, 2023). My paper is most closely related to the theoretical research stemming from Su and Zenios (2004). They find that first-come-first-served transplant waitlists generate excessive wastage of organs compared to last-come-first-served waitlists that incentivize doctors to accept offers sooner. My paper empirically demonstrates the importance of this tradeoff in the context of heart transplantation. My econometric model allows for rich heterogeneity in preferences over remaining on the waitlist with each treatment. This results in healthy patients remaining on the waitlist longer after receiving temporary treatments. My results along with the results of Su and Zenios (2004) suggest that a design in which patients lose priority when they decline offers could ameliorate these issues.

There is also a connection to the literature on physicians' decisions and how these de-

cisions impact health outcomes (Kessler and McClellan, 1996; Dranove et al., 2003; Cutler et al., 2004; Crawford and Shum, 2005; Dafny, 2005; Chandra and Staiger, 2007; Jacobson et al., 2010; Song et al., 2012; Kolstad, 2013; McWilliams et al., 2013; Ho and Pakes, 2014; Dickstein, 2017; Einav et al., 2018; Cutler et al., 2019; Currie and MacLeod, 2020; Gaynor et al., 2023; Gowrisankaran et al., 2023). The extant research has focused on a wide range of incentives that impact physicians' decisions including payment schemes, the risk of malpractice lawsuits, and learning-by-doing. My paper studies healthcare providers' trade-off between patients' short-run and long-run survival. This is reflected in doctors choosing waitlist treatments, impacting short-run health, to potentially extend their patient's lifespan in the long-run, after receiving a transplant. Motivated by previous research demonstrate many other factors that affect physicians' decisions, e.g. financial incentives, I use a revealed-preference approach to estimate preferences over treatments that parsimoniously captures many of these features.

2 Background

2.1 Overview of heart transplantation in the United States

About 3,500-4,500 adults with end-stage heart failure join the waitlist for a heart transplant in the United States each year. The waitlist is designed, maintained, and administered by the United Network for Organ Sharing (UNOS) which oversees the Organ Procurement and Transplantation Network (OPTN) comprising 147 heart transplant centers. When a suitable organ donor dies, the heart is offered to blood type compatible patients based on policies set forth by UNOS, and doctors at the transplant center then decide whether to decline or accept the offer for the specific patient.[7,8] In addition to transplanting hearts, the care team

[7]The hospital at which the donor died is required to contact the local Organ Procurement Organization which is then responsible for coordinating procurement and making offers based on the policy set forth by UNOS/OPTN.

[8]Donor hearts are frequently offered to many patients at once to help speed the procurement process and keep organs from deteriorating before they can be transplanted. This allows offers to be tentatively accepted

at the patient's transplant center is responsible for providing other treatments for the patient as well, discussed further in Section 2.2.

Heart transplantation is often considered the best treatment for a patient with end-stage heart failure with a median post-transplant survival of around 13 years, which far exceeds the median untransplanted survival rate of one year for patients that have been diagnosed with end-stage heart failure (Friedrich and Böhm, 2007).[9] Despite the large benefits of heart transplantation, there is likely underutilization of donor hearts due to doctors' selectivity over offers. There are around 4,000-5,500 donor hearts offered each year but only 2,500-3,500 transplants performed each year, resulting in roughly 40% of donor hearts that are offered going untransplanted. Offer declines are common, even among hearts that are transplanted, with transplanted hearts being offered to an average of 10 patients before being accepted for transplantation. Decisions to decline offers also depend on the likelihood of receiving offers in the future so that heart wastage is also likely affected by the waitlist design as discussed in Section 3.1 and Appendix **??**.

The heart transplant waitlist has the stated policy aim of prioritizing patients that are most "medically urgent" (42 CFR §121.8). To do so, patients are placed into one of several priority groups at a specific point in time. Priority is typically determined by the treatments that the patient receives as these are associated with mortality. Offers are made first-come-first-served within each priority group to ensure that patients receive higher priority if they have been on the waitlist longer. Furthermore, offers are made to patients nearer to the donor's hospital first as longer travel times likely result in worse post-transplant outcomes, so that patient priority varies across donors.[10] The waitlist design components relevant for

in the event that those with higher priority decline the offer. After a tentative acceptance, the doctor is able to consider whether to actually accept or decline the heart once higher priority patients are not going to receive the offer. Doctors most frequently decide to decline the offer despite making a tentative acceptance, limiting time-savings in making simultaneous offers.

[9]For patients that enter the waitlist, the median untransplanted survival rate is even lower, at 90 days. Drawing conclusions from this number is difficult as there is selection into the waitlist and into remaining on the waitlist. However, the estimated median untransplanted survival based on my model estimates is close to the 1-year estimate for patients with end-stage heart failure.

[10]Offers are exclusively made to blood type compatible adult patients. Priority is also given based on patient and donor blood type. For example, blood type O and B patients receive higher priority for blood

the present paper are the qualifying criteria for the priority groups, discussed in greater detail in Section 2.3.

2.2 Treatments for patients on the heart transplant waitlist

While on the waitlist for a heart transplant, most patients receive a treatment for end-stage heart failure to help their heart function prior to receiving a transplant. The treatments relevant for the waitlist design are mechanical circulatory support devices that can be categorized as durable devices or temporary devices. Treatments in these categories differ in their duration of use, in their resource intensiveness for the hospital, and in their intrusiveness in the patient's life. Durable devices are designed to be implanted in the patient for months or years and allow the patient to leave the hospital. In contrast, temporary treatments are designed to be implanted for days or weeks and require the patient to remain in the hospital under close supervision of healthcare providers.

Although both types of treatment improve patient survival by helping the heart pump blood, the mechanism used to help the heart results in differences between the two that are relevant in modeling the decision to use them. Durable treatments are surgically attached to the patient's heart to help the heart pump blood directly, which results in an invasive implantation procedure but allows the patient to leave the hospital after recovering from surgery. Temporary treatments are instead inserted through the patient's blood vessels, resulting in a less invasive implantation at the cost of relying on large external equipment to pump blood. Both treatments employ mechanical pumps to aid the heart, but these pumps carry the risk of malfunctioning or forming blood clots, resulting in premature device removal. The categorization of treatments as durable or temporary suffices for this paper, but additional details of the treatments included in each category are given in Appendix A.1.

type O donors in order to account for the scarce supply of compatible donors for these blood types.

2.3 Treatment-based priority and the current policy debate

As discussed at the beginning of this section, the waitlist design aims to prioritize patients with lower expected waitlist survival to ensure that they receive a heart transplant rather than dying on the waitlist. In practice, this is achieved by designing priority groups with specific qualifying criteria submitted and updated for each patient on the waitlist by their transplant center. Since 1999, the treatments that a patient receives have been one of the main qualifying criteria used to define priority groups. Patients requiring treatment to help their heart function generally have worse expected short-run survival. As a result, the waitlist design has always prioritized patients receiving treatments relative to those not receiving treatments.

Eventually, it became apparent that patients on temporary treatments were less likely to survive than patients that received durable treatments. Figure 1 demonstrates survival curves for patients that entered the waitlist from 2007-2017 from the day they entered the waitlist, broken down by whether they received a durable treatment or a temporary treatment. The figure demonstrates that the six month survival rate for patients that received durable treatments is 0.95 compared to 0.92 for patients on temporary treatments. This suggested that patients on temporary treatments had higher urgency that was not accounted for in the existing priority scheme. To address this difference in survival, UNOS/OPTN announced a change to the waitlist design in 2016 that would take effect on October 18, 2018 wherein patients on temporary treatments would receive higher priority than patients on durable treatments.

The newly increased priority for temporary treatments relative to durable treatments has resulted in a policy debate around the usage of treatments in heart transplant waitlist priority (Hanff et al., 2020; Shah and Stevenson, 2020). The concern is that the increased priority will result in over-utilization of temporary treatments for patients on the waitlist. Increased usage of temporary treatments relative to durable treatments at heart transplant centers is documented in Section 3.1 and in the medical literature, e.g. Parker et al. (2020);

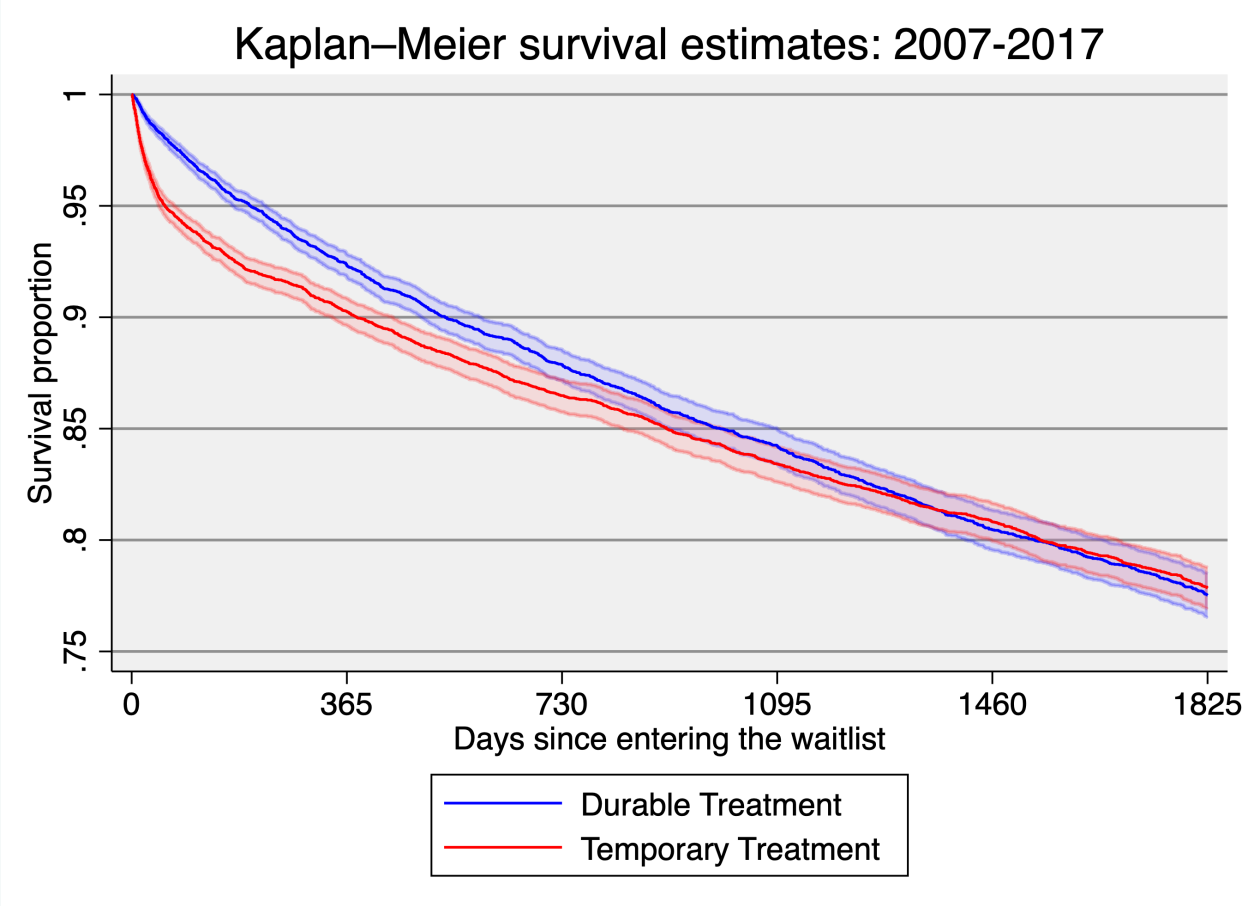


Figure 1: Kaplan-Meier survival curves estimated based on all patients that entered the waitlist from 2007 to 2017 broken down by whether they were on a durable treatment or a temporary treatment at some point while on the waitlist. The figure demonstrates that patients on temporary treatments had worse short-run survival outcomes suggesting higher waitlist mortality for this subgroup relative to those on durable treatments. Meanwhile, the long-run survival is similar, suggesting similar post-transplant survival. For patients that ever received a temporary treatment about 46% also received a durable treatment at some point in time, but these patients are only included in the survival curve for the temporary treatment. Shaded regions denote the 95% confidence intervals.

Varshney et al. (2020); Kilic et al. (2021). However, the extent to which this has resulted in patients receiving temporary treatments in a manner detrimental to their short-run survival cannot be estimated without estimating the counterfactual survival in the absence of these incentives. This is done using a structural model in Section 6.

2.4 Data

This paper uses two administrative datasets provided by the United Network for Organ Sharing as the contractor for the Organ Procurement and Transplantation Network that maintains the waitlist. These are the Standard Transplant Analysis Research (STAR) data and the Potential Transplant Recipient (PTR) data. The STAR data includes information on every patient that entered the waitlist to receive a heart transplant through June 2023. The PTR data contains information on the deceased donor offers made including the order of these offers and whether each was declined. These two datasets allow me to construct decision and survival data at the level of a patient-day, which includes the treatments the patient received, the deceased donors that the patient was offered, whether the patient's doctor accepted/declined each offer, and the characteristics of patients and donors.

I focus on the subpopulation of adult patients that entered the waitlist from January 1, 2015 to December 31, 2019 for estimating the structural model. For estimating the post-transplant survival model, I restrict attention to adult patients that entered from January 1, 2000 to December 31, 2010 to ensure sufficient post-transplant followup time.[11] The final sample for estimating the structural model contains 2.5 million patient-days arising from 14,658 patients. Further information on data construction is available in Appendix A.

STAR data This dataset includes patient characteristics at the date that they enter the waitlist and the date that they are removed from the waitlist, including weight, gender, diagnosis categories, blood type, measures of kidney function, and other clinically relevant

[11] Appendix Figure B.9 demonstrates that the predicted post-transplant survival fits the patients in the main sample (2015-2019) despite being estimated on patients from 2000-2010.

pieces of information. The data also includes the reason the patient was removed from the waitlist, e.g. due to death or due to receiving a transplant. Patients that receive a transplant are also included in follow-up data that records the death date for patients that died after receiving the transplant. For patients that receive a treatment while on the waitlist, the data includes implant and removal dates for each treatment that the patient received including the treatment type and brand, allowing for these to be categorized as durable or temporary treatments as described in Appendix A.1. This allows me to determine whether each patient received a durable or temporary treatment on each day that they were on the waitlist. The STAR data also includes characteristics of all deceased donors at the time of donation including the cause of death, measures of the heart function, whether they have Hepatitis C, and other characteristics that impact post-transplant survival. Patient and donor characteristics are used in the flow utility, offer process, and survival process with the specific characteristics used described in Appendix Table B.1.

PTR data This dataset consists of offers made for deceased donor hearts including the sequence of patients offered each deceased donor heart. This includes the date that the offer was made, whether the offer was declined, and the distance between the patient's transplant center and the donor's hospital. Offers are linked to patients and donors in the STAR data allowing me to track the characteristics of donor offers received for each day a patient is on the waitlist. However, the PTR data only includes offers made up until the offer was accepted, so the full ranking of patients cannot be constructed from this dataset. In cases where the donor heart was not transplanted, offers are given through the final offer made before the heart was decided to be no longer transplantable and other organs began to be recovered.

3 Descriptive evidence

This section presents descriptive evidence regarding the change to the waitlist design to provide motivation for the structural model. First, the treatment and transplant decisions are different under the current waitlist design. Temporary treatment utilization has increased while durable treatment utilization has decreased, consistent with doctors responding to waitlist incentives to utilize temporary treatments. As expected, transplant offers have increased for patients on temporary treatments, but the number of offers declined has also increased, consistent with a response to the dynamic incentives of a first-come-first-served waitlist design. Finally, a higher fraction of patients receive transplants under the current design, but this could be driven by underlying trends in the arrival rate of donors. The section concludes with a description of heterogeneity in treatments and transplants by observable characteristics.

3.1 Waitlist design change, treatments, and outcomes

Panel A of Table 1 describes the relationship between the waitlist design, treatment decisions, and patient outcomes. The first two rows demonstrate that temporary treatment utilization increased dramatically following the change to the waitlist design with only 18% of patients receiving temporary treatments under the previous design compared to 48% of patients under the current design. Appendix Figure B.4 demonstrates that trends are stable prior to the waitlist change going into effect, suggesting that this is a response to the waitlist design.[12]

The next set of numbers depict the offers and declines that each patient received per day based on whether they ever received a durable or temporary treatment, respectively, under each waitlist design. This suggests that there was an increase in offers made over time with an especially dramatic increase for patients on the temporary treatment, as expected given that these patients receive higher priority under the current design. However, these offers are also frequently declined, suggesting a response to dynamic incentives expected in a first-come-

[12]This was previously documented in the medical literature by Hanff et al. (2020) and Kilic et al. (2021).

first-served queue. The panel concludes by demonstrating that there is a general increase in the percentage of patients receiving a transplant, especially among patients on temporary treatments. However, there is a decline in 3-year post-transplant survival for patients on durable treatments, suggesting that they are now receiving lower quality transplants.

3.2 Choices and observed characteristics

Panel B of Table 1 demonstrates heterogeneity in choices by observable patient characteristics. The first row demonstrates that the majority of patients on the waitlist are diagnosed with cardiomyopathy, a diagnosis that is typically less severe than adult congenital heart disease or re-transplantation. The remaining rows break down whether the patient has kidney disease. Taken together, they demonstrate that many of the patients that receive temporary treatments under the current design are relatively healthier.

Panel C of Table 1 demonstrates heterogeneity in donor and patient-donor characteristics. This panel demonstrates that patients who receive temporary treatments under the current design receive offers for relatively younger donors, who are closer and a better size match. The final four rows demonstrate that the transplants that actually take place have resulted in substantially improved transplant matches for patients on temporary treatments.

4 Model of waitlist design, doctor's decisions, and patient's outcomes

4.1 Setting and economic primitives

The waitlist is composed of patients, indexed by i, who remain on the waitlist until they die or receive a heart transplant. Each day that a patient is on the waitlist, indexed by t, their doctor selects a treatment for the patient where t has large finite horizon T.[13] Each day,

[13]For estimation, T is set to 10,000 days which far exceeds the expected life-years spent on the waitlist for all patients.

Panel A: Relationship between waitlist design, treatments, and outcomes

	Previous design		Current design	
	Durable	Temporary	Durable	Temporary
Treatment usage				
Within first week	35%	11%	22%	34%
Any time on waitlist	43%	18%	25%	48%
Priority and declines				
Offers per day (s.d.)	0.21 (0.20)	0.30 (0.26)	0.45 (0.41)	0.81 (0.52)
Declines per day	0.20 (0.18)	0.26 (0.24)	0.41 (0.38)	0.71 (0.47)
Position in offer sequence	92 (150)	85 (153)	108 (172)	59 (144)
Patient outcomes				
Received transplant	81%	70%	87%	92%
Survived 3 years post-transplant	86%	86%	81%	86%

Panel B: Relationship between patient characteristics and treatments

	Previous design		Current design	
	Durable	Temporary	Durable	Temporary
Cardiomyopathy diagnosis	41%	15%	23%	43%
No/mild kidney disease	27%	10%	15%	28%
Moderate kidney disease	14%	6%	8%	16%
Severe/end-stage kidney disease	2%	2%	1%	4%

Panel C: Donor and patient-donor characteristics

	Previous design		Current design	
	Durable	Temporary	Durable	Temporary
Offered donor				
Donor age	36 (13)	36 (13)	37 (13)	34 (12)
Donor left-ventricular ejection fraction	0.60 (0.08)	0.60 (0.08)	0.60 (0.08)	0.61 (0.08)
Patient-donor distance	337 (300)	348 (302)	506 (387)	487 (349)
Patient-donor weight ratio	1.09 (0.31)	1.08 (0.32)	1.13 (0.32)	1.05 (0.30)
Accepted donor				
Donor age	34 (12)	34 (12)	37 (12)	35 (12)
Donor left-ventricular ejection fraction	0.61 (0.07)	0.61 (0.07)	0.61 (0.08)	0.61 (0.08)
Patient-donor distance	182 (226)	211 (248)	358 (335)	379 (283)
Patient-donor weight ratio	1.05 (0.24)	1.04 (0.26)	1.09 (0.28)	1.01 (0.26)

Table 1: Panel A demonstrates that the change in the waitlist design is associated with an increase in temporary treatment utilization, a decline in durable treatment utilization, patients receiving more offers that are also more frequently declined, and more transplants occurring. Panel B demonstrates that patients who receive temporary treatments under the current waitlist design are frequently healthier, i.e. have a less severe diagnosis of cardiomyopathy and better renal function. Panel C demonstrates that there is substantial heterogeneity in offers made across treatments under the current waitlist design and that patients on temporary treatments frequently receive hearts that are a better match and higher quality. This excludes patients who are on the waitlist under both designs (10% of patients in the sample). Patients below the second row of Panel A are included in columns according to whether they receive that treatment at any point in time on the waitlist. Percentages are taken over all patients in that time period. Means and standard deviations are reported otherwise.

the doctor can choose to put the patient on no treatment, a durable treatment, a temporary treatment, or both treatments. The treatment decision for patient i in period t is denoted by the vector $y_{it} \in \{0,1\} \times \{0,1\}$ where a specific component of y_{it} is 1 if the patient receives the corresponding treatment.

The state variables that enter the doctor's preferences over treatments are patient characteristics, time spent on the waitlist, time spent on each treatment, the treatments that the patient received in the previous period, whether the period is under the previous or current waitlist design, and whether the patient is alive. The patient characteristics at the time of listing are denoted x_i and include the patient's diagnosis, weight, age, and other characteristics described in Table B.1. The number of days spent on each treatment, denoted $\tilde{y}_{i,t-1} \in \mathbb{N} \times \mathbb{N}$, and the treatments received in the previous period, $y_{i,t-1}$, are also state variables for the doctor. This allows treatment duration and treatment lags to impact the state transition process, both through an effect on survival and on donor heart offer arrival.[14]

When a deceased donor, indexed by j, arrives, their heart is offered to a subset of compatible patients based on the waitlist design. The doctor of each patient can choose to accept the offer if a higher ranked patient declines, allowing subsequent offers to lower ranked patients.[15] Donors have observable characteristics z_j that include the donor's cause of death, age, weight, and other characteristics described in Table B.1. When patient i receives a heart transplant from donor j in period t, it implies a post-transplant survival function, denoted $S_{ijt} : \mathbb{R}_+ \to [0,1]$. When a donor heart is offered to a patient, the doctor chooses to accept or decline the offer based on the donor characteristics z_j and post-transplant survival S_{ijt}. If the doctor accepts the heart then the patient is removed from the waitlist with an implied post-transplant survival, and no further decisions made for them within the model. If the doctor declines the offer, then the patient remains on the waitlist and the donor is offered

[14]The complete path history could instead appear as a state variable. However, this would greatly increase the complexity of the state space, so this is instead simplified to treatment durations and treatments in the previous period.

[15]The ranking is donor specific, allowing for the waitlist to prioritize differently based on the donor. This is due to the prioritization of patients closer to the donor before offering to patients further away.

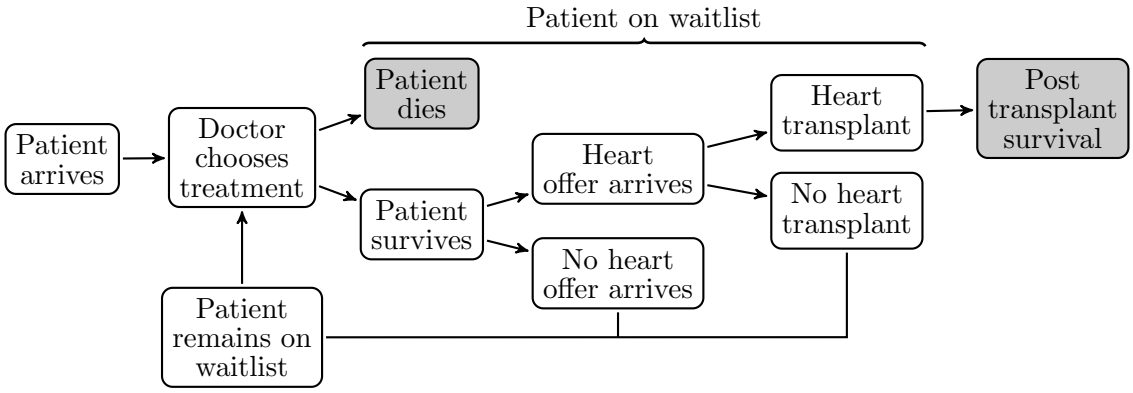


Figure 2: Overview of the choices and state transitions in the doctor's dynamic discrete choice model. Conditional on the state variables after the initial treatment is chosen, the patient survives into the second period with some probability determined by the survival state transition process. If the patient survives, they receive an offer for a deceased donor heart determined by the associated state transition process that also depends on the waitlist design. If the patient receives an offer for a deceased donor heart transplant, they may choose to accept the offer and enter a terminal node with a post-transplant survival implied by the transplant that they received. Or, the patient's doctor can decline the offer and choose to continue or change the patient's treatment. This decision problem repeats each period until the patient reaches a terminal node, either by dying on the waitlist or receiving a heart transplant, as highlighted in gray.

to the next patient on the waitlist.

The treatment and transplant decision process is described in Figure 2. In the initial period, the doctor makes a treatment decision and the patient receives either no treatment, a durable treatment, a temporary treatment, or both.[16] Then, the patient survives into the next period with some probability according to a waitlist survival process, known to the doctor, that depends on treatments the patient received (y_{i0}) and patient characteristics (x_i). If the patient survives, they might be offered a donor heart with given characteristics and post-transplant survival according to the donor heart offer process, which depends on the waitlist design and is also known to the doctor. Upon receiving offers, the doctor can choose to accept a particular offer, leading to the patient's removal from the waitlist.[17]

[16]Some patients have already received treatments prior to entering the waitlist and continue those treatments in the initial period. For these patients, the doctor's choice is whether to continue the treatment rather than to implant the treatment where implantation, as described later, results in additional disutility.

[17]There are patients on the waitlist who are in need of a second heart transplant as their transplanted heart begins failing or being rejected by their immune system. But very few need a new heart transplant within the first year after receiving a transplant. As a result, it is reasonable to assume that doctors do

Alternatively, the doctor can choose to continue or change the patient's treatment. In this case, the patient survives in the next period, remaining on the waitlist to repeat the process, or dies in the next period, again based on the waitlist survival process.

The doctor's preferences over treatments and transplants are determined by the solution to the corresponding finite horizon nonstationary dynamic program in which doctors know the state transition processes but are uncertain about the future realizations of these processes.[18] Doctors' preferences over treatments and transplants depend on the flow utility of receiving a specific treatment in the current period along with the continuation value that reflects the flow utility of future treatments, the patient's waitlist survival, offers the patient receives for transplants, and the value of receiving a transplant in a future period. These components can be classified as preference parameters or state transition parameters and constitute the economic primitives that I estimate to evaluate endogenous priority in the waitlist design. The remaining subsections describe each of these components in detail. Estimation and functional form specification are discussed in Section 5.

4.2 Waitlist design, offer arrival, and post-transplant survival

The waitlist design is given by a function $\mu(\cdot)$ that maps each patient i on their t-th day on the waitlist when donor j arrives to a priority score $\mu(x_i, z_j, y_{i,t-1}, \tilde{y}_{i,t-1}, t)$ based on observable patient and donor characteristics.[19] Offers are made to compatible patients on the waitlist on the date when donor j arrives in descending order of their priority score until

not anticipate continuing to care for the patient if they need a new heart transplant and enter the waitlist again. The alternative would be to not assume that receiving a transplant results in a terminal node, but that patients re-enter the waitlist with some probability in the future. However, this would greatly increase the complexity of solving the doctor's dynamic program without capturing additional insights for evaluating the waitlist design.

[18]The model does not include the decision to list a patient on the waitlist. In practice, doctors frequently choose to put patients on the waitlist as soon as a heart transplant has been decided as the best treatment route so that the patient can begin accruing days as soon as possible. The data used also do not include patients that never enter the waitlist, so the entry decision has been left for future work.

[19]The time period, denoted t, refers here to the patient's time spent on the waitlist, rather than the calendar date at which the donor arrived. As a result, the time period will be generally be different across patients for the same donor.

one of them accepts the offer.[20] The waitlist assignment is determined by the set of patients on the waitlist, the set of donors that arrived, the waitlist design that assigns priority, and the accept/decline decisions of patients that received offers.

Each doctor only has beliefs over the arrival of offers for their patient conditional on their patient's characteristics, rather than having beliefs over the characteristics of other patients on the waitlist and decisions made by the doctors of these patients. The dependence only on the patient's characteristics and not on the characteristics of other patients on the waitlist drastically reduces the state space and simplifies the estimation of the model. This is summarized by the assumption below:

Assumption 1 (Offer arrival depends only on patient characteristics and waitlist design)**.** *Patient i with observed characteristics x_i on their t-th day on the waitlist (with design μ) with current treatment combination y_{it} and treatment history vector $\tilde{y}_{i,t-1}$ is offered deceased donor hearts with probability*

$$\Pr_\mu(N_{it} = n | x_i, t, y_{it}, \tilde{y}_{i,t-1})$$

where $n \in \mathbb{N}$.[21]

Once a patient has received an offer (or multiple offers), the value of receiving a transplant depends on the characteristics of the deceased donor heart and the post-transplant survival of the patient. For patients with relatively higher priority, i.e. higher probabilities of receiving

[20] In practice, donor hearts are not offered to all possible patients because there is a time past which the heart is no longer transplantable. Offers should then be made until the priority score reaches some threshold at which point the donor heart is never transplanted, but modeling this feature will not be necessary as discussed throughout this subsection.

[21] Each patient only receives an offer for a deceased donor heart if all patients with higher priority have declined the offer, resulting in a strategic interaction between patients on the waitlist wherein selectivity over transplants impacts offer arrivals for other patients. As a result, the environment could be modeled by a dynamic game that explicitly incorporates these strategic interactions between patients. Then, the offers made to patients are the result of players employing Markov perfect equilibrium strategies on each day that they are on the waitlist. However, since there are many patients on the waitlist and each doctor has little control over which patients are eventually offered a deceased donor, the value function associated with the dynamic game is approximated by a dynamic discrete choice model in which doctors have beliefs over receiving an offer for a deceased donor and the characteristics of the donor offered. This is similar to applying the oblivious equilibrium concept of Weintraub et al. (2008).

an offer, the offers that they receive have been declined by fewer patients than for those patients with relatively lower priority. To reflect this, the distribution of donor characteristics is indexed by the probability of receiving an offer to ensure that patients with higher priority receive a greater variety of offers as well. Indexing only by the probability of receiving an offer simplifies the state space, similar to the simplifying assumptions made for the offer probabilities while still capturing the effect that priority has on the variety of offers. This is summarized by the following assumption:

Assumption 2 (Donor characteristics indexed by offer probability)**.** *For each patient blood type compatibility group, there exists a family of compatible deceased donor heart characteristic distributions indexed by the probability of receiving an offer:* $\left\{G(z|\text{blood type}, \Pr_\mu(N > 0) = P)\right\}_{P\in[0,1]}$*. Distributions in this family satisfy the following condition in their support:* $\text{support}\left[G(z|\text{blood type}, \Pr_\mu(N > 0) = P)\right] \subseteq \text{support}\left[G(z|\text{blood type}, \Pr_\mu(N > 0) = P')\right]$ *whenever* $P < P'$*.*

Finally, if the patient receives a heart transplant from donor j, then they have a post-transplant survival curve based on patient and donor characteristics. The post-transplant survival is important for evaluating treatment-based priority as it allows for the calculation of the expected life-years for a particular patient under both waitlist designs. It also enters the doctor's preferences over accepting an offer for a transplant, as described in Section 4.4. Post-transplant survival is given by a parametric survival function as summarized in the assumption below:

Assumption 3 (Post-transplant survival)**.** *The post-transplant survival function of patient* i *on period* $\hat{t}$ *after receiving a transplant from donor* j *on their* t*-th day on the waitlist is given by* $S(\hat{t}|x_i, z_j, t, y_{it}, \tilde{y}_{i,t-1})$*, often denoted* $S_{ijt}(\hat{t})$ *for brevity.*

4.3 Patient waitlist survival process

The waitlist survival is both a state transition process and used to estimate expected life-years under each waitlist design. The probability that a patient is alive in a particular day, conditional on the state variables for the previous day, is dependent on a function of state variables and an idiosyncratic shock.[22] This is summarized below:

Assumption 4 (Waitlist survival)**.** *The probability that a patient dies on their t-th day on the waitlist is given by*

$$\Pr\left(h\left(x_i, y_{i,t-1}, t, \tilde{y}_{i,t-1}\right) + \eta_{it} > 0 \middle| x_i, y_{i,t-1}, t, \tilde{y}_{i,t-1}\right)$$

where $h(\cdot)$ is a known function of the state variables in the previous period and η_{it} is drawn iid from distribution H.

4.4 Doctor's payoffs

Each period that the patient is on the waitlist, the doctor receives a flow payoff associated with giving the patient a specific combination of treatments y_{it}. The payoff depends on observed state variables, treatments the patient received in the previous period, and an idiosyncratic preference shock. This allows for a flow utility that is specific to each treatment combination, as well as a switching cost when the patient receives a new treatment or is taken off of a treatment. This is summarized below:

Assumption 5 (Flow payoff of treatments)**.** *The doctor's flow payoff of giving patient i treatment y_{it} is given by*

$$U_{it}(y_{it}) = u(x_i, y_{i,t-1}, y_{it}) + \epsilon_{it}(y_{it})$$

[22] This contrasts with specifying survival directly, as done for the post-transplant survival process. This simplifies estimation of the model while allowing for a flexible survival process that easily enters the decision problem as a state transition process.

where $\epsilon_{it}(y_{it})$ is an idiosyncratic preference shock drawn from known distribution F.

The assumption that doctors receive a flow payoff and are not maximizing the patient's long-run survival is reflective of the non-survival incentives to put patients on treatments. That is, there are differences in costs and resource-intensiveness of different treatments that are not reflected in the survival of the patient and depend on observed characteristics. For example, financial incentives that make it more desirable to provide a treatment to a patient on private insurance rather than public insurance. However, a model in which doctors simply want their patient to survive longer is nested within a model in which they maximize revealed preference value functions as this corresponds to constant flow utilities across treatments. Finally, the revealed preference approach also allows me to capture medical complications that might result in device removal but are not reflected in survival data. For example, some devices run the risk of blood clots forming that result in device removal without death of the patient with a higher likelihood of removal for patients that weigh less. The revealed preference approach parsimoniously captures all of these features.

There is also a terminal value associated with giving the patient a transplant from donor j with characteristics z_j in period t.

Assumption 6 (Value of a transplant)**.** *The terminal value of receiving a transplant is given by*

$$V_{ijt} = v(x_i, \tilde{y}_{i,t-1}, z_j, S_{ijt}) + \epsilon_{ijt}$$

where ϵ_{ijt} is an idiosyncratic preference shock drawn from F.

The specification of the terminal value is general enough to allow for it to depend on patient-donor characteristics and the post-transplant survival function. This allows for doctors to make decisions based on the expected post-transplant survival along with other features. For example, the distance between the patient's center and donor's hospital often

impacts the decision to accept an offer due to logistical factors that are not reflected in post-transplant survival.

Finally, since a patient dying on the waitlist in a future period is a terminal state, it should be associated with some terminal value. The value of dying in a future period is normalized to 0, so that the value of receiving a treatment or transplant are relative to the value of dying on the waitlist. This normalization also assumes that the disutility of dying on the waitlist does not depend on which treatments a patient received prior to dying, which is reasonable to assume as doctors likely do not have meaningful preferences over a patient dying while on a specific treatment relative to other treatments.

4.5 Rational expectations and conditional independence of shocks

Doctors frequently engage with patients on the waitlist and are knowledgeable about the waitlist and its changes, so I assume that they know the state transition processes.[23] To simplify estimation, I also assume that the state-transition and preference shocks are conditionally independent, as is common in dynamic discrete choice models (Rust, 1987; Hotz and Miller, 1993). This is summarized in the assumption below:

Assumption 7 (Rational expectations and conditional independence)**.** *Doctors have rational expectations over the uncertainty of future states. Specifically, the doctor assumes that offers arrive with donor characteristics according to Assumption 1; that patients have waitlist survival given by Assumption 4 and post-transplant survival given by Assumption 3; and that the preference shocks are iid draws from* $F(\epsilon)$.

4.6 Summary of doctor's decision problem

To summarize, the doctor's decision problem is a nonstationary finite horizon dynamic program in which they choose treatments or transplants to maximize the value of being on the

[23] In general, doctors could have biased beliefs that do not reflect the offers that they will receive based on decline decisions of other patients on the waitlist which could be estimated as in Aguirregabiria and Magesan (2019).

treatment or the terminal value associated with receiving the transplant. The subscript i associated with the patient is ignored below for notational simplicity since all decisions are for patient i. This subsection summarizes their state variables and value function.

4.6.1 State variables and choices

The state variables of the dynamic program are:

(i) $x \in \mathbb{R}^J$: J-dimensional vector of observed patient characteristics;

(ii) $C_t = \{0,1\} \times \{0,1\} \bigcup \left\{(z_j)_{j=1}^{N_t}\right\}$: the choice set, including possible treatments and characteristics of any donors offered (where $\left\{(z_j)_{j=1}^{N_t}\right\} = \emptyset$ when $N_t = 0$);

(iii) $y_{t-1} \in \{0,1\} \times \{0,1\}$: vector of treatments given in the previous period;

(iv) $\tilde{y}_{t-1} \in \mathbb{N} \times \mathbb{N}$: number of days spent on each treatment in periods 1 to $t-1$;

(v) $a_t \in \{0,1\}$: indicator that is 1 if the patient is alive in period t and 0 if they are dead.

4.6.2 Treatment-specific value function

It is simpler to state the decision problem in terms of the utility that a doctor receives for putting their patient on a specific treatment y. This is called the treatment-conditional value function, and is given by

$$\begin{aligned} v(y; x, y_{t-1}, \tilde{y}_{t-1}) + \epsilon_t(y) = u(x, y_{t-1}, y) + \epsilon_t(y) \\ + \beta \Pr\left(a_{t+1} = 1 | x, y, t, \tilde{y}_{t-1}\right) \\ \times \sum_{n \in \mathbb{N}} \Pr_{\mu_{t+1}}\left(N_{t+1} = n | x, y, \tilde{y}_{t-1}\right) \mathbb{E}V(x, y, \tilde{y}_{t-1}, \hat{C}_{t+1}, \hat{\epsilon}) \end{aligned}$$

The first line gives the flow payoff associated with providing treatment y with a switching cost through the dependence on y_{t-1}. The second line gives the discount factor and the likelihood of survival into the next period dependent on the treatment given in period t.

The third line gives the expected continuation value given the number of donor offers they receive in the next period where $V(\cdot)$ denotes the solution of the dynamic program as a function of the state variables, described below. The expectation in the third line is taken over the characteristics of deceased donors via $\hat{C}_{t+1}$ and the preference shocks through $\hat{\epsilon}$.

4.6.3 Value function of treatment and transplant decision problem

The value function for a patient in period t when the patient has received N_t offers from donors with characteristics $\{z_j\}_{j=1}^{N_t}$ resulting in choice set $C_t = \{0,1\} \times \{0,1\} \cup \{z_j\}_{j=1}^{N_t}$. This gives the value function:

$$V(x, y_{t-1}, \tilde{y}_{t-1}, C_t, \epsilon) = \max_{y \in \{0,1\}^2 \text{ or } z \in \{z_j\}_{j=1}^{N_t}} \Big\{ v(y; x, y_{t-1}, \tilde{y}_{t-1}) + \epsilon_t(y), \\ v(z; x, y_{t-1}, \tilde{y}_{t-1}) + \epsilon_t(z) \Big\}$$

5 Empirical specification and estimation

There are five sets of economic primitives to be estimated. The first three correspond to the state-transition processes: the probability of receiving an offer for a transplant, the post-transplant survival process, and the waitlist survival probability. The latter two correspond to the revealed preference value of the doctors decisions: the flow utility of each treatment decision and the terminal value of performing a transplant, both of which are normalized relative to the value of the doctor's patient dying on the waitlist. The covariates included in the model are summarized in Appendix B.6. The parameterization is described in further detail in the two subsections that follow. This section concludes with a description of estimation.

5.1 Specification of state-transition processes

Deceased donor arrival and characteristics The probability of receiving an offer for a deceased donor heart is assumed to follow a multinomial logit with no more than 2 deceased donor hearts arriving on a given day.[24] The probability that n offers will arrive for patient i in period t is given as follows

$$\Pr(N_{it} = n|x_i, \tilde{y}_{i,t-1}, y_{i,t-1}, d_{it}, t; \gamma_N) = \begin{cases} \frac{\exp(R(x_i, \tilde{y}_{i,t-1}, y_{i,t-1}, t, d_{it}; \gamma_{Nn}))}{1+\sum_{\hat{n}=1}^{2} \exp(R(x_i, \tilde{y}_{i,t-1}, y_{i,t-1}, t, d_{it}; \gamma_{N\hat{n}}))} & n \in \{1, 2\} \\ \frac{1}{1+\sum_{\hat{n}=1}^{2} \exp(R(x_i, \tilde{y}_{i,t-1}, y_{i,t-1}, t, d_{it}; \gamma_{N\hat{n}}))} & n = 0 \end{cases} \quad (1)$$

where $R(x_i, \tilde{y}_{i,t-1}, y_{i,t-1}, t, d_{it}; \gamma_{Nn})$ is a linear-in-parameters (γ_{Nn}) function of patient characteristics (x_i), the time patient i has spent on each treatment while on the waitlist ($\tilde{y}_{i,t-1}$), the treatments that the patient was most recently on ($y_{i,t-1}$), the time spent on the waitlist (t), and an indicator variable for whether period t is under the current waitlist design (d_{it}).

When the doctor considers the continuation value of remaining on the waitlist, they must incorporate both the probability that an offer arrives and the characteristics of the deceased donor heart conditional on arrival. Conditional on the number of hearts that arrive being positive, I use the empirical distribution of deceased donor characteristics to determine the likelihood of each heart type arriving.

Specifically, if n offers arrived, I first condition on the deceased donors j that are observed as being offered to at least one patient ι on the waitlist with an estimated $\Pr(N_{\iota t} = n|x_\iota, \tilde{y}_{\iota,t-1}, y_{i,t-1}, d_{it}, t) \leq \Pr(N_{it} = n|x_i, \tilde{y}_{i,t-1}, y_{i,t-1}, d_{it}, t)$. This prompts the offered deceased donor types to not be more desirable than would have been offered to patient i. Next, I condition on patient characteristics to ensure that the conditional distribution includes only offers that would be appropriate given blood type compatibility. This gives a set of donor types $\tilde{J}|_{x_i, \Pr(N_{it}=n|x_i, \tilde{y}_{i,t-1}, d_{it}, t)}$ that are offered with equal probability.

[24] This is reasonable since more than 2 offers arrived on fewer than 1% of observed patient-days in my sample. Details on how choice sets were handled on these days is discussed in Appendix A.

Post-transplant survival Post-transplant survival is modeled using a Gompertz survival model. This specifies baseline survival for patient i receiving transplant from donor j in period t as

$$S_{ijt}(\hat{t}) = \exp\left\{-\lambda^{-1}\exp\left(\gamma'_{\text{post}} w_{ijt}^{\text{post}}\right)\left[e^{\lambda\hat{t}} - 1\right]\right\} \tag{2}$$

where w_{ijt}^{post} denotes patient and donor characteristics and their interactions, γ_{post} is a vector of parameters, and λ is a parameter to be estimated.

Waitlist survival The waitlist survival process is specified as a probit model that depends on state variables and their interactions. Specifically, the waitlist survival process is dictated by the latent variable A_{it} where

$$A_{it} = \gamma'_A w_{it}^A + \eta_{it} \tag{3}$$

where γ_a is a vector of parameters to be estimated; w_{it}^A is a vector of observed characteristics (x_i), days spent on each treatment $(\tilde{y}_{i,t-1})$, treatments $(y_{i,t-1})$, days spent on the waitlist (t), and their interactions; and η_{it} is a standard normal survival shock.

5.2 Specification of doctors payoffs for treatments and transplants

Flow utility of receiving treatments The flow utility when the patient is given combination of treatments y_{it} is given by

$$u(x_i, y_{i,t-1}, y_{it}, \epsilon) = \gamma'_{y_{it}} x_i + \underbrace{\iota' \mathbb{I}\left[y_{it} - y_{i,t-1} = \mathbb{1}\right]}_{\text{Implant flow}} + \underbrace{\rho' \mathbb{I}\left[y_{i,t-1} - y_{it} = \mathbb{1}\right]}_{\text{Explant flow}} + \epsilon(y_{it})$$

where $\gamma_{y_{it}}$ is a treatment combination-specific parameter vector, $\mathbb{I}$ denotes a vector of indicator functions, $\mathbb{1}$ denotes the unit vector, and $\varepsilon(y_{it})$ represents an idiosyncratic flow utility shock associated with treatment y_{it}. The first term of the flow utility determines the pref-

erences over each combination of treatments. The next two terms, with parameters ι and ρ, determine the flow utility associated with device implantation and explantation, respectively.

Value of receiving a heart transplant The decision to accept a heart for transplantation results in a terminal value for the transplant that depends on the patient's predict post-transplant survival and the distance between the donor's hospital and the patient's transplant center. The value that patient i receives from a transplant from donor j is

$$V_{ijt} = \frac{1}{1-\beta}\left[\gamma_{\text{tx,0}} + \sum_{a=0}^{4} \gamma_{\text{tx,a}} S_{ijt}^{-1}(0.1 + 0.2a) + \gamma_{\text{tx,d}} \log\left(1 + m_{ij}\right)\right] + \varepsilon_{ijt} \tag{4}$$

where m_{ij} is the distance from donor j to the transplant center of patient i and $S_{ijt}^{-1}(0.1+0.2a)$ for $a = 0, \ldots, 4$ denotes the 10th, 30th, 50th, 70th, and 90th percentiles of the post-transplant survival curve of patient i given a transplant from donor j as given above.

5.3 Estimation

The model is estimated on adult patients who entered the waitlist from 2015-2019 who were either alive at the end of the sample period, removed from the waitlist due to death, or removed from the waitlist due to receiving a transplant. Because most patients are expected to survive for more than a decade after receiving a transplant, the post-transplant survival model is estimated separately on patients listed from 2000-2010 as estimating this model on patients listed from 2015-2019 results in the majority of observations being censored. The post-transplant survival process is straightforward to estimate using maximum likelihood.

5.3.1 Log-likelihood function

The log-likelihood for the dynamic discrete choice and waitlist survival model is given by

$$\log \mathcal{L}_{NAC} = \underbrace{\sum_{i=1}^{I}\sum_{t=1}^{T_i} \log \Pr(N_{it}|x_i, \tilde{y}_{i,t-1}, w_{it}, t; \gamma_N)}_{\text{Heart offer process}} + \underbrace{\sum_{i=1}^{I}\sum_{t=1}^{T_i} \log \Pr(a_{it}|x_i, \tilde{y}_{i,t-1}; \gamma_A)}_{\text{Waitlist survival process}} + \underbrace{\sum_{i=1}^{I}\sum_{t=1}^{T_i} \log \Pr(c_{it}|x_i, \tilde{y}_{i,t-1}; \gamma_N, \gamma_A, \gamma_C)}_{\text{Dynamic discrete choice process}} \tag{5}$$

where the parameters to be estimated are the offer parameters $\gamma_N = (\gamma_{N1}, \gamma_{N2})$, the survival parameters γ_A, and the choice parameters $\gamma_C = (\{\gamma_y\}_{y\in\mathcal{Y}}, \gamma_{\text{tx},0}, \ldots, \gamma_{\text{tx,d}})$. As is typical in dynamic discrete choice models, the state-transition parameters γ_N and γ_A can be estimated separately and consistent estimates can be inserted into the choice likelihood to obtain consistent estimates of γ_C.

5.3.2 Estimation procedure

The model parameters are first estimated by estimating the partial log-likelihoods associated with the heart offer and waitlist survival processes. As is common since Rust (1987), these estimates are then inserted into the partial log-likelihood associated with the choice process which is then maximized. Estimating the choice parameters also requires solving the doctor's dynamic choice problem which is difficult to do using a nested fixed point procedure as in Rust (1987) because the problem is nonstationary. Instead, a procedure similar to Aguirregabiria and Mira (2002) that iteratively estimates conditional choice probabilities is used. This reduces the variance of the estimated choice parameters relative to a two-step procedure as in Hotz and Miller (1993) while allowing for the dynamic program to be approximately solved via forward simulation. A brief overview of the estimation procedure is given below with a more detailed description in Appendix D.

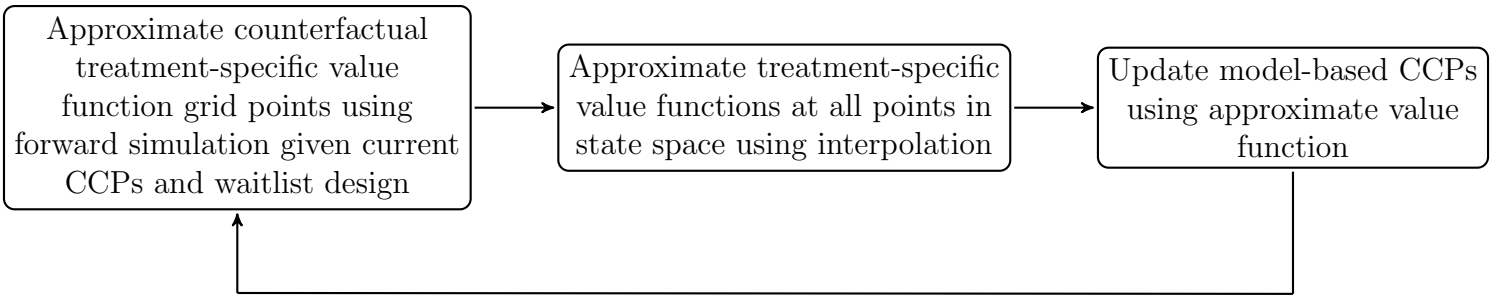


Figure 3: Demonstration of iterative estimation of counterfactual conditional choice probabilities under (1) untransplanted counterfactual, (2) the previous waitlist design, or (3) the current waitlist design.

Estimation algorithm steps The algorithm initializes by estimating the post-transplant survival and the state transition parameters γ_N and γ_A. Initial conditional-choice probabilities are estimated using choices observed in the data. The estimation procedure then iterates over the following steps:

1. The choice-conditional value function is approximated using forward simulation based on the conditional-choice probabilities on a grid of the state variables observed in the data for arbitrary γ_C.

2. Interpolation is used to approximate the choice-conditional value function at all points in the data for arbitrary γ_C.

3. Preference parameters, γ_C, are estimated by maximizing the associated partial likelihood given the approximate choice-conditional value functions.

4. Given estimated preference parameters, the conditional-choice probabilities are updated based on the values implied by the model.

5.4 Computing counterfactual outcomes

The counterfactuals estimated in this paper require varying the deceased donor offer arrival process and the treatment and transplant decisions of doctors as follows:

1. **Previous design**: This corresponds with each doctor choosing optimal treatments for their patient under the previous waitlist design in which durable and temporary treatments received similar priority. The patient receives offers for transplants as they would under the previous waitlist design.

2. **Current design**: This corresponds with each doctor choosing optimal treatments for their patient under the current waitlist design in which temporary treatments give higher priority than durable treatments. The patient receives offers for transplants as they would under the current waitlist design.

3. **No transplant**: This corresponds with a scenario in which each doctor chooses optimal treatments for their patient, given that the patient does not receive offers for a transplant (i.e. $\Pr(N_{it} > 0) = 0$). This ensures that doctors are not influenced by waitlist incentives at all while making treatment decisions.

4. **Previous treatment and current transplant**: This counterfactual does not require recomputing optimal decisions. Instead, patients receive treatments while on the waitlist according to the optimal decisions under the previous waitlist design but receive offers and a transplant according to the optimal decisions under the current design. As a result, the distribution of exit times from the waitlist due to transplant coincides with the distribution estimated under the current design.

There are two sources of uncertainty from the perspective of the econometrician computing counterfactuals stemming from preference shocks and state transitions. Taking the expectation of patient life-years under each scenario with respect to state transitions, given a decision path is straightforward. Furthermore, given an estimate of the conditional choice probabilities for the particular counterfactual for the patient, it is also straightforward to take the expectation with respect to preference shocks. However, these CCPs are not observed in the data since each patient is only observed under one specific design (or both for

those that overlap). Thus, the distribution of counterfactual treatment decisions must be computed by computing the CCPs associated with each scenario.

This is done using an iterative approach akin to reinforcement learning depicted in Figure 3. The procedure is initialized with a function that returns approximate CCPs at all points in the state space. Then, it iterates over the following steps:

1. Compute approximate treatment-specific value functions for each patient on a grid of state variables (time spent on waitlist, time spent on treatments, and treatment lags) using forward simulation given CCPs.

2. Approximate treatment-specific value functions elsewhere in the state space using values obtained via forward simulation.

3. Obtain updated model-based CCPs using the approximate treatment-specific value functions obtained in step 2.

This continues until convergence in value functions or expected life-years. Once model-based CCPs have been obtained, additional forward simulations are performed to better estimate the expected survival under each scenario.

6 Effect of the new waitlist design and channels

In this section, I use the model to estimate the effect of the waitlist design change on doctors' treatment and transplant decisions and patients' waitlist mortality and expected survival. Specifically, I study the expected years a patient is expected to live after entering the waitlist. I also compute the expected number of days that each patient spends on a temporary treatment to evaluate incentives to use this treatment under the current design. I compute both of these expectations for each patient under the four counterfactual scenarios described in Section 5.4.

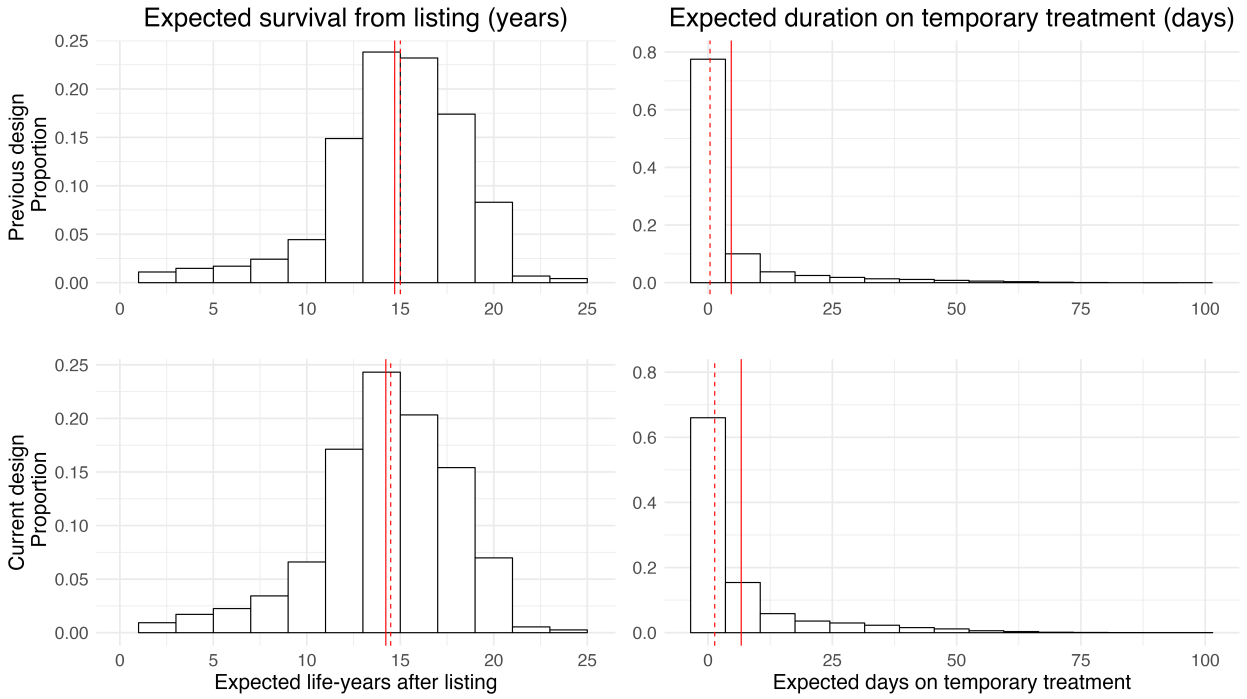


Figure 4: This figure depicts the histogram of the distribution of estimates of expected survival in years from the day the patient entered the waitlist and the expected days spent on temporary treatments under each waitlist design. Dashed lines denote the median of each distribution and solid lines denote the means. The mean and median expected life-years are lower under the current design while the expected temporary treatment duration is longer.

In Section 6.1, I evaluate the previous and current designs by computing counterfactual scenarios 1 and 2 described in 5.4. In Section 6.2, I evaluate whether the current design targets patients who have a lower expected survival if they do not receive a transplant by computing the 'no transplant' counterfactual. In Section 6.3, I compute the final counterfactual to disentangle the effect of different selectivity over offers vs. changing treatments under the current design.

6.1 Effect of the waitlist design change on expected survival and expected treatment durations

I am first interested in estimating the effect of the waitlist design change on survival outcomes and temporary treatment decisions. Figure 4 contains histograms for the distribution

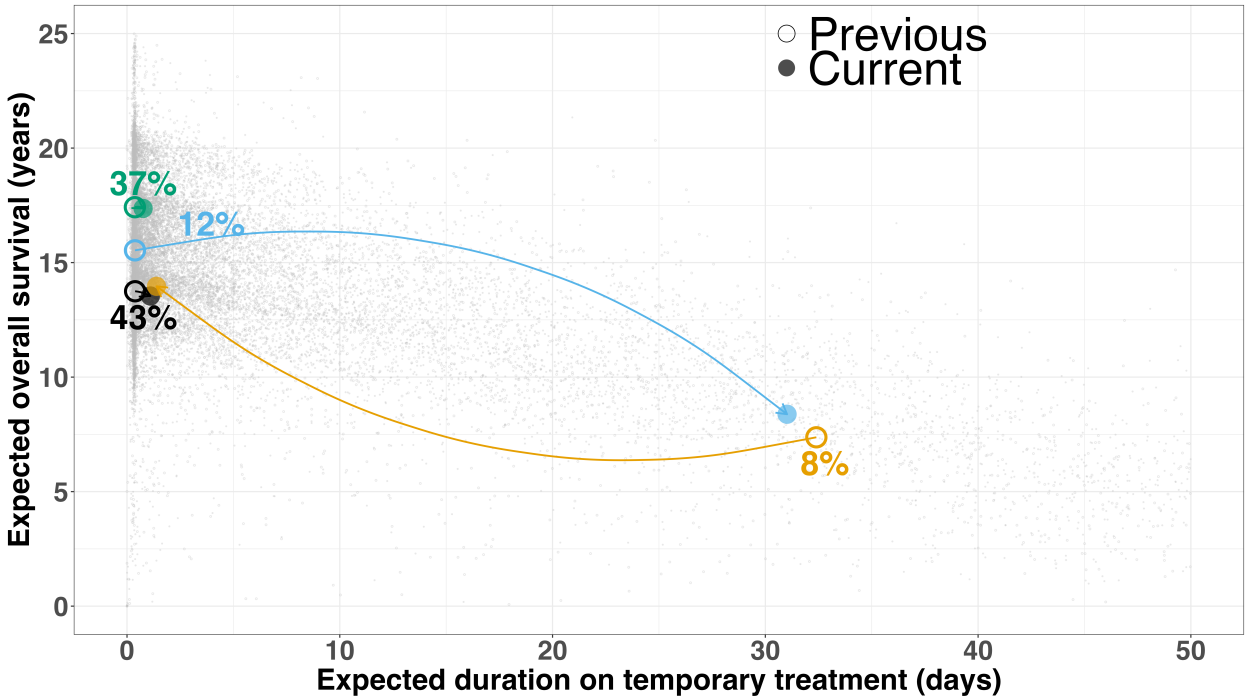


Figure 5: Comparison of median expected temporary treatment duration (in days) and median expected survival after entering the waitlist (in years) for each cluster of patients. Open circles denote previous waitlist design while filled circles denote current waitlist design. The percentage of patients in each cluster are given as a percent near corresponding open circles. This figure demonstrates that the bulk of patients, shown in the black (37%) and green (43%) circles, experience little change in treatment and survival following the change. Two groups experienced meaningful changes, seeming to come from a redistribution from one group to another.

of estimated expected life-years and expected temporary treatment duration under both designs. They exhibit heterogeneity in expected outcomes and choices that the model is able to capture. The figures demonstrate that the expected survival declined on average across all patients by about six months and that the expected time on temporary treatments increased on average by about 2 days.

I am primarily interested in how these quantities change for each patient when the waitlist design changes. Because there are many patients in the sample, I cluster patients by the four estimated quantities of interest: expected life-years and expected temporary treatment duration under the previous and current waitlist design. I use the median quantities of four clusters constructed using k-medians clustering. Further details on the unclustered changes

and the clusters are provided in Appendix C.

The results from the clustering exercise are provided in Figure 5. The figure demonstrates that 80% of patients fall into one of two clusters that have little median change in temporary treatment duration or survival. However, there was substantial redistribution among the remaining patients with 8% of patients being beneficiaries of the current design and experiencing an increase in median survival and 12% of patients being disadvantaged. Furthermore, the disadvantaged patients spend more time on temporary treatments as a result of the policy change. The medians are also reported in Panel A of Table 2.

These results suggest that the disadvantaged patients received temporary treatments more frequently (in expectation) in response to stronger incentives under the current waitlist design. Meanwhile, the beneficiaries are simply the intended targets of the policy change and are able to exit the waitlist more quickly under the current design. Therefore, they spend less time on temporary treatments.

6.2 Evaluating targeting using survival without a transplant

To better understand which patients are beneficiaries or disadvantaged from the current design, I estimate the expected no transplant survival for each patient on the waitlist. Figure 6 depicts the histogram of the distributions of expected survival without a transplant for patients who are beneficiaries or disadvantaged by the change as clustered above. There is heterogeneity in the expected survival for both groups of patients. However, patients that are disadvantaged tend to be healthier, with a higher average and median survival than beneficiaries. This is consistent with doctors responding to the policy change primarily for patients that are healthier, resulting in these patients being made worse off. Results for no transplant survival are summarized in Panel B of Table 2.

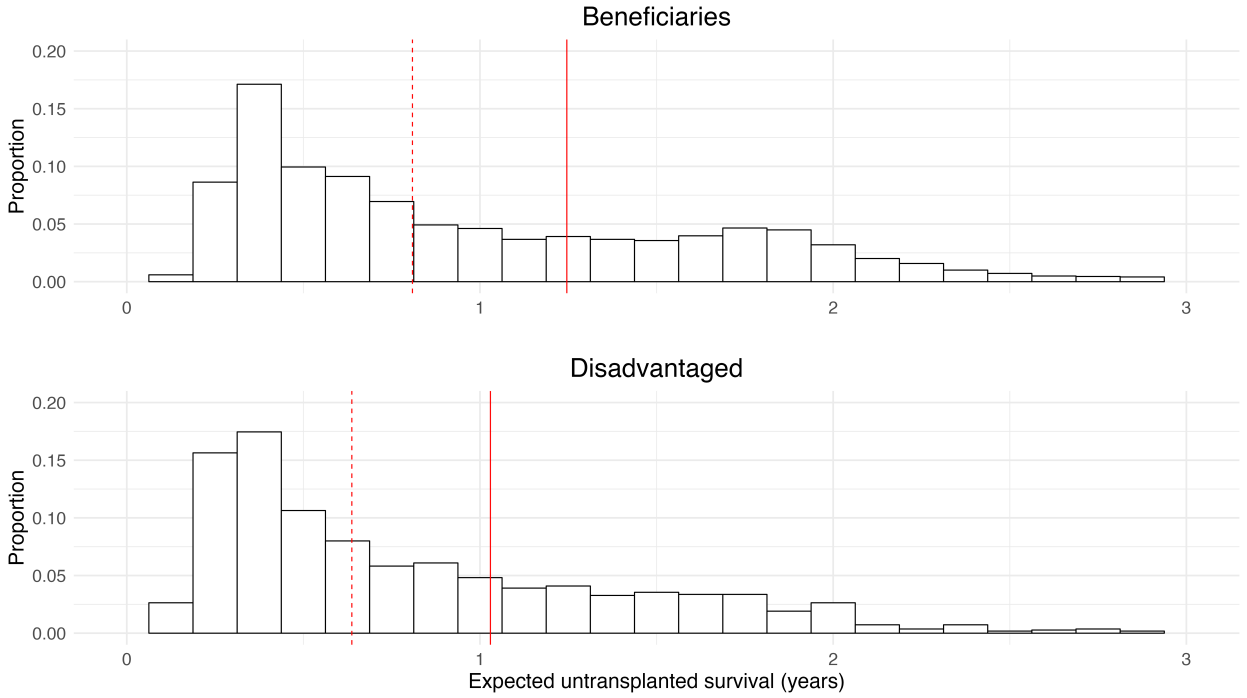


Figure 6: This figure depicts the histogram of the distribution of estimates of expected survival no transplant, in years measured from the patients first day on the waitlist. The figure depicts these outcomes based on whether a patient is in the group of beneficiaries (8% of patients) or disadvantaged (12% of patients) as discussed in Section 6.1 and Figure 5. The figure demonstrates heterogeneity in untransplanted survival within both groups but a higher average and median in the group of disadvantaged patients.

6.3 Effect of receiving different treatments vs. different transplants

Last, I study the effect of selection into different treatments vs. selection into different transplants using the 'previous treatment and current transplant' counterfactual described in Section 5.4. The results are given in Panel C of Table 2. Comparing the survival for disadvantaged patients in Panel C against Panel A demonstrates that the median survival of 9.6 years is similar to their median survival under the current design. This suggests that the reduction in life-years is primarily due to additional time spent on the waitlist and the coincident rise in waitlist mortality for these patients. Furthermore, their median durable treatment duration is 122.8 days while it is only 13.3 days for temporary treatments. This corroborates that these patients receive temporary treatments more and durable treatments less in response to the current waitlist design.

For the beneficiaries, the results are in the opposite direction. These patients have median survival under this counterfactual of 13.3 years which is similar to 14.0 years under the current waitlist design.

Taken together, the reduction in expected survival for disadvantaged patients is mainly due to these patients spending additional time on the waitlist rather than because they spend additional time on temporary treatments. Meanwhile, the improvements for beneficiaries are largely because they exit the waitlist sooner.

6.4 Patient characteristics within clusters

7 Conclusion

This paper evaluates the usage of endogenous priority in the waitlist for deceased donor heart transplants by studying a recent change to priority. The results from my model suggest that the change to the waitlist design largely results in a redistribution in the patients that receive

	Beneficiaries		Disadvantaged		Other patients	
	Panel A: Waitlist outcomes					
	Previous	Current	Previous	Current	Previous	Current
Median expected life-years	7.4	14.0	15.5	8.4	15.3	15.1
Median expected temporary treatment (days)	32.4	1.4	0.4	31.0	0.4	0.9
Median expected durable treatment (days)	32.3	4.0	8.5	33.8	6.7	2.8
	Panel B: No transplant outcomes					
Median expected life-years	0.64		0.82		0.77	
Median expected temporary treatment (days)	45.3		45.4		44.6	
Median expected durable treatment (days)	167.0		219.1		202.2	
	Panel C: Waitlist outcomes with previous treatments and priority and transplant from current design					
Median expected life-years	13.3		9.6		15.1	
Median expected temporary treatment (days)	8.0		13.3		0.7	
Median expected durable treatment (days)	6.0		122.8		8.1	
Percent of patients	8%		12%		80%	

Table 2: This table demonstrates median expected survival in years from entering the waitlist and median expected duration spent on temporary and durable treatments for patients in each cluster under the four counterfactuals that I estimate. Panel A includes these quantities for the estimates under the previous and current waitlist design. This panel demonstrates that beneficiaries frequently spend less time on temporary treatments under the current waitlist design while disadvantaged patients spend a longer duration on temporary treatments. Panel B includes them when the patients are not on the waitlist. This panel demonstrates that beneficiaries are typically less healthy than disadvantaged patients. Panel C includes the estimates when the treatment decisions are determined under the previous waitlist design while the transplant offers and acceptance decisions are decided under the current design as if the doctor responded to waitlist incentives. By comparing the median expected life-years in this panel to those in Panel A, it is clear that the reduction in survival is not due to patients receiving different treatments but due to them remaining on the waitlist longer.

	Beneficiaries	Disadvantaged	Other patients
Physical characteristics			
Age (years)	52.4	52.6	53.6
Weight (kg)	83.5	73.3	84.6
Female	33%	34%	27%
Blood type O	51%	54%	39%
Blood type B	18%	14%	16%
Blood type A	27%	28%	39%
Blood type AB	4%	4%	5%
Health characteristics			
Severe or end-stage kidney disease	18%	3%	7%
Congenital heart disease	9%	8%	2%
Limitations in physical activity	66%	47%	50%

Table 3: This table . . .

a transplant. That is, the change in response to priority incentives is met with a change in accepting offers for transplants. As a result, healthier patients frequently remain on the waitlist longer and have reduced life expectancies. Meanwhile, the usage of temporary treatments to assign priority has effectively targeted sicker patients and increased their life expectancy. Taken together, this suggests that the waitlist design could be further improved by taking action to disincentivize declining offers for heart transplants rather than necessarily prohibiting the usage of treatments in assigning priority.

This paper focuses on the previous and current waitlist design as the equilibrium offer rates can be estimated from the data under these designs. In future work, the framework can be extended to simulate waitlist designs that are not observed in data and compute equilibrium offer rates for waitlist designs that have not been implemented. Doing so would provide the benefit of allowing waitlist designs to be evaluated before being implemented.

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A Data

A.1 Summary of Mechanical Circulatory Support Devices

There are five types of MCSDs that are used to construct the durable/temporary treatment decision in this paper. Two are durable devices:

1. Durable left-ventricular assist device (dLVAD)
2. Durable right-ventricular assist device (dRVAD)

Three are temporary devices:

1. Temporary ventricular assist device (tVAD)
2. Intra-aortic balloon pump (IABP)
3. Extracorporeal membrane oxygenation (ECMO)

Each device serves a different purpose in extending the patients life and certain treatments might be more or less suitable for certain patients based on the severity of their condition as well as the specific nature of their condition. Figure A.1 depicts the Kaplan-Meier survival curves associated with each of these treatments for patients listed from 2007-2017. The nature of the devices is discussed below followed by a discussion of the manner in which they are used.

Ventricular assist devices The ventricular assist devices (VADs) can be either durable or temporary and are implanted to help the patients heart pump blood throughout the body. The durable devices are typically implanted on the left ventricle of the heart and aid the heart in pumping blood to the rest of the patient's body. Sometimes they are implanted on the right ventricle to help pump blood to the lungs. Patients on an RVAD are also oftentimes on an LVAD so that these patients can be used in conjunction with one another.

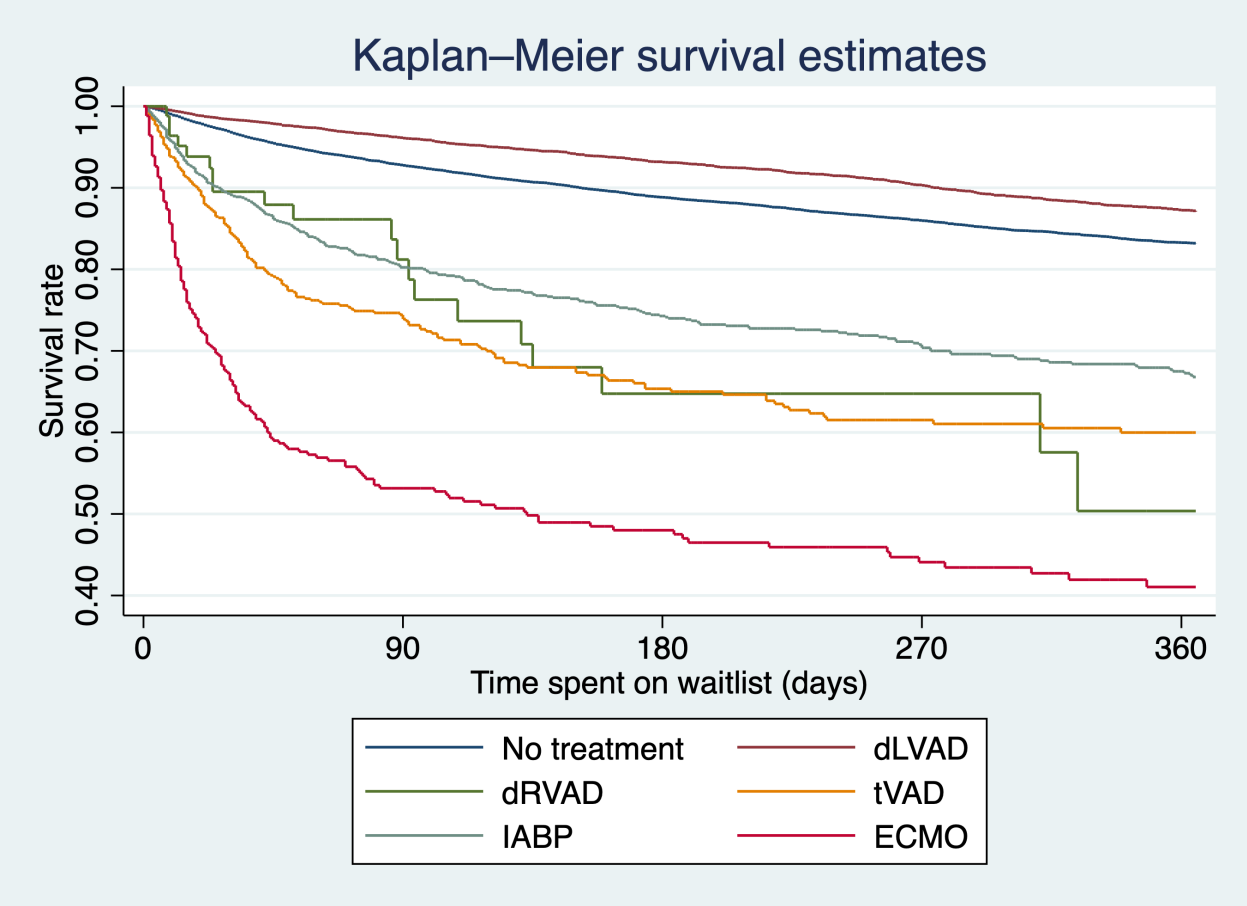


Figure A.1: Kaplan-Meier survival estimates for patients listed from 2007-2017 broken down by which of the five MCSDs the patient was on at listing. There were 1.7% of patients that received multiple treatments upon joining the waitlist, in which case they are included in the survival curve of the treatment associated with the lowest survival (e.g. patients on dLVAD and ECMO are included in ECMO).

The typical modern durable VAD is surgically implanted by cutting through the patient's sternum to place the device inside the patient's chest attaching one end at the bottom of the ventricular and the other at the relevant blood vessel exiting the heart. The procedure itself is invasive, but once the device has been implanted, the only external sign of the device is the driveline that powers the pump and the batteries and system controller that the patient wears using a small vest. Durable VADs allow for patients to leave the hospital after healing from the surgery and patients can safely remain on the device for years. Once implanted, the patient is typically on the VAD until they receive a transplant.

Temporary VADs are instead inserted through a blood vessel in a much less invasive

procedure. This often consists of inserting the device in an artery in the leg and snaking it up to the patient's heart. The device then sits partially in the patients heart and partially in the blood vessel exiting the heart in order to pump blood. These devices can only remain implanted for a matter of weeks and are much more short-term treatments than durable VADs. Temporary VADs are also sometimes used in conjunction with durable VADs. Patients are also unable to leave the hospital while on temporary VADs. The less invasive procedure thus comes at the cost of durability and the ability to leave the hospital after implantation.

Intra-aortic balloon pump The intra-aortic balloon pump (IABP) is a temporary device that helps the heart pump blood. Similar to the temporary VAD, it is implanted by insertion into an artery and then snaked through the artery to the large artery exiting the heart that pushes blood pumped from the heart to the rest of the body (the aorta). It works by inflating and deflating a balloon to create a pressure differential that helps pump the blood out of the heart. Patients can remain on this treatment for a period of weeks and sometimes receive this treatment while already being on some form of VAD. They are taken off of the device after their condition stabilizes or they receive a transplant.

Extracorporeal membrane oxygenation Extracorporeal membrane oxygenation (ECMO) consists of cardiopulmonary bypass to support the function of the heart and the lungs. Tubes are inserted into the patients veins and arteries allowing blood to flow through an external machine that oxygenates the blood and then returns it to the body to be circulated without necessarily relying on the heart to pump the blood or the lungs to oxygenate it. It is the most severe treatment that a patient can receive and requires constant monitoring of their condition. Patients typically remain on this treatment for a period of days or weeks until their condition stabilizes or they receive a transplant.

A.1.1 Suitability of MCSDs

The most common causes of heart failure for patients on the waitlist are cardiomyopathy and coronary artery disease, though patients with adult congenital heart disease have been growing and are expected to grow further over time. Patients are more or less suitable for receiving certain MCSDs based on a number of factors including diagnosis, age, weight, etc. Historically, waitlisted patients in worse condition have been put on short-term MCSDs (temporary VAD, IABP, ECMO) to improve or stabilize their condition before receiving a long-term MCSD (durable VAD) or a transplant. This resulted in sicker patients receiving temporary devices so that higher waitlist mortality rates were associated with temporary MCSDs.

There are still a number of factors other than likelihood of death in the short-term that are relevant for these treatment decisions. For example, older patients are less suitable for durable VADs because of the strain put on their body during the implantation, and patients with congenital heart disease and certain other diagnoses are unsuitable for durable VADs (Han et al., 2018). Meanwhile, for IABPs, insertion is done through an artery in the patients leg so that a significant buildup of plaque in these arteries increases the likelihood of complications and makes these options much less desirable. There are many other examples that highlight the ways in which each treatment is more or less suitable for a patient depending on the specific nature of their condition.

A.1.2 Summary of Ventricular Assist Devices

The most common form of mechanical circulatory support on the waitlist are ventricular assist devices (VADs). These devices can be broken down into left and right-ventricular assist devices depending on which ventricle they are supporting. They can also be broken down by durable and temporary VADs depending on the specific device. This classification is independent of whether the device is used for left- or right-ventricular support. The end result is four types of VADs broken down by durable/temporary and left/right. The

distinction for durable vs. temporary by brand of the VAD is given below where the asterisk denotes that a particular brand only appears in the sample used in the descriptive evidence.

Type	Brand
Durable	HeartMate IP, HeartMate XVE, HeartMate II, HeartMate III, HeartWare HVAD, Evaheart, Heartsaver, Jarvik 2000, Terumo DuraHeart, Thoratec IVAD, WorldHeart Levacor, Heart Assist 5, NuPulse iVAS, DeBakey*, Novacor*, Toyobo*, Berlin Heart EXCOR*, Medtronic HVAD*, VentraCor VentrAssist*
Temporary	Abiomed AB5000, Abiomed BVS 5000, Biomedicus, Cardiac Assist Protek Duo, Cardiac Assist Tandem Heart, CentriMag, Impella, Rotaflow, Thoratec PVAD, TandemHeart

A.2 Treatment bundles

The treatments that can be given to patients can be put in two main categories: durable and temporary. The durable devices are either left- or right-ventricular assist devices as described in the previous subsection. The temporary devices are temporary ventricular assist devices (not delineated by ventricle), intra-aortic balloon pumps, and extracorporeal membrane oxygenation (ECMO). The choice set is simplified into four possible choices based on whether the patient receives a device in one of these two categories:

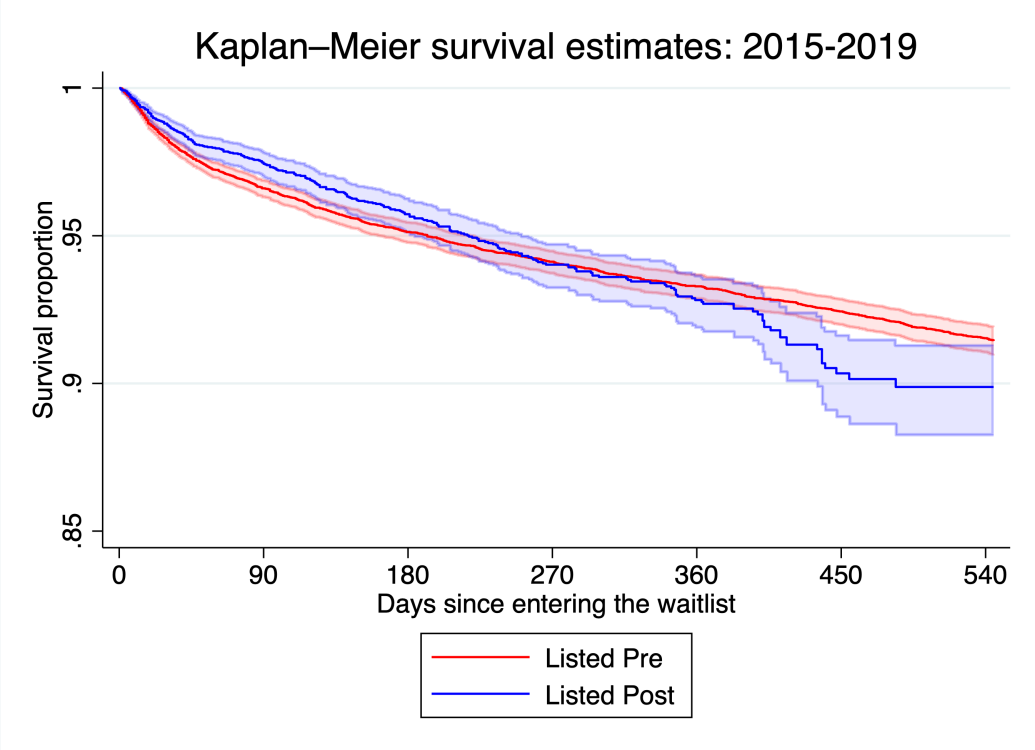
1. No treatment
2. Durable LVAD/Durable RVAD
3. Temporary VAD/IABP/ECMO
4. Durable and Temporary device

The treatment bundle can be represented as a vector $y = (y^1, y^2) \in \{0,1\}^2$ where the components correspond to whether the patient received a durable device or temporary device, respectively. This gives the choice set of treatment bundles:

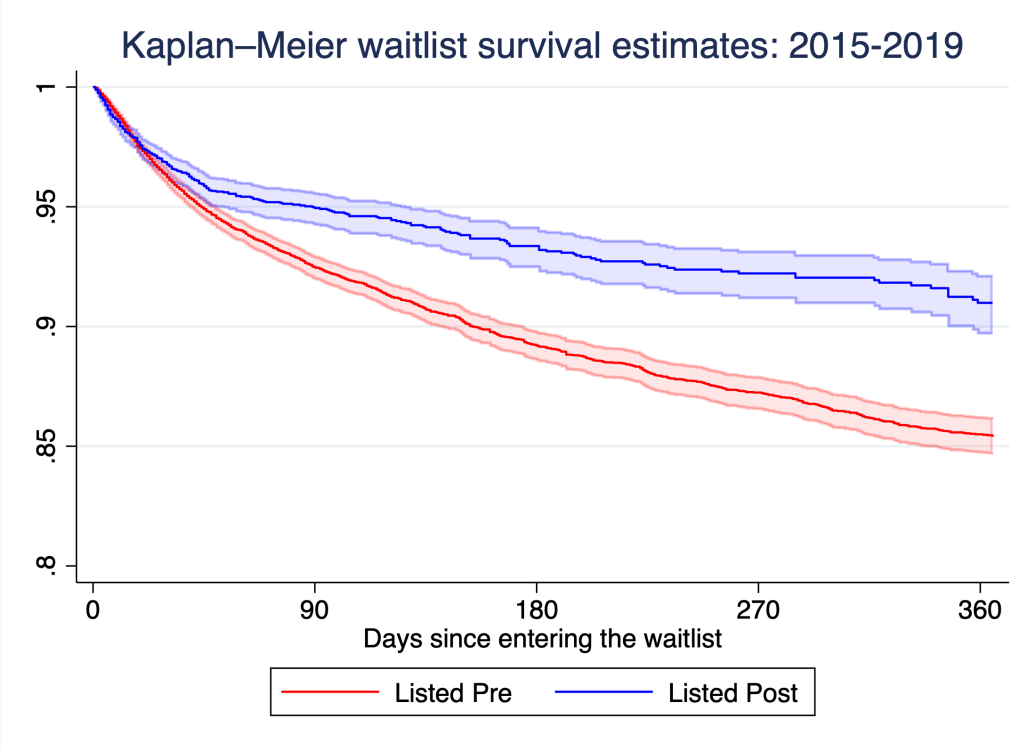
$$\mathcal{Y} = \{(0,0),(1,0),(0,1),(1,1)\}.$$

B Additional descriptive evidence

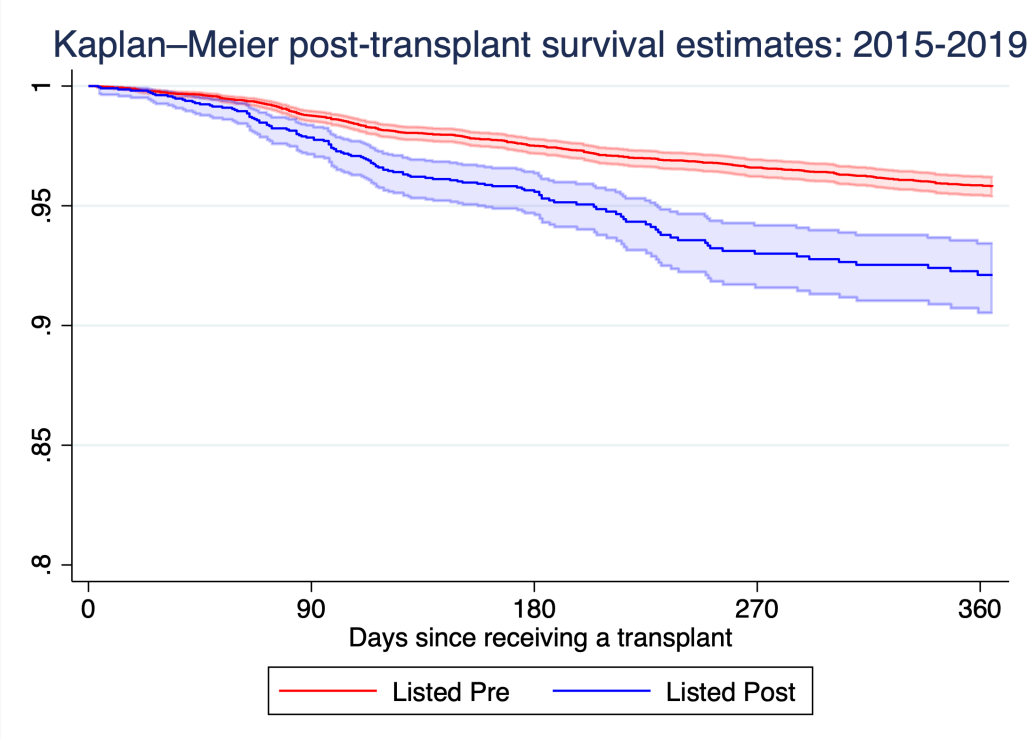
B.1 Waitlist survival is improved while post-transplant survival is reduced following the waitlist design change



(a) Survival curve of patients from the day they entered the waitlist broken down by whether they entered before or after the change. Shaded regions denote the 95% confidence intervals.



(a) Survival curve of patients on the waitlist broken down by whether they entered before or after the change. Shaded regions denote the 95% confidence intervals.



(b) Survival curve of patients on the waitlist broken down by whether they entered before or after the change and by the treatment that they received at listing. Shaded regions denote the 95% confidence intervals.

Figure B.3

B.2 Shares of treatments over time

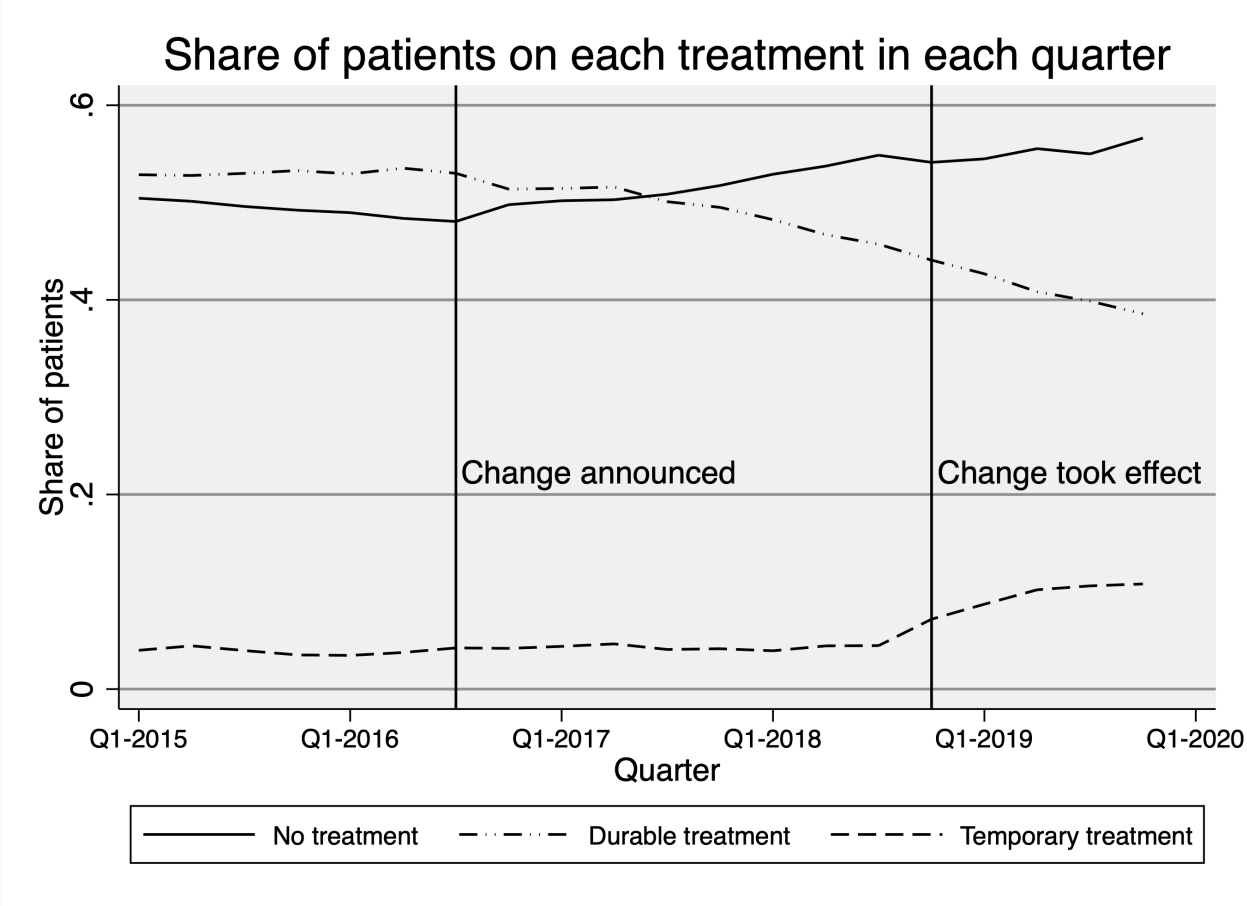


Figure B.4: Share of patients in each treatment group in each quarter where a patient is defined as being in the durable or temporary treatment group if they received the treatment at some point in the quarter. Patients are able to be counted in both the durable and temporary treatment group if they received both treatments in a particular quarter.

B.3 Number of patients and donors each year

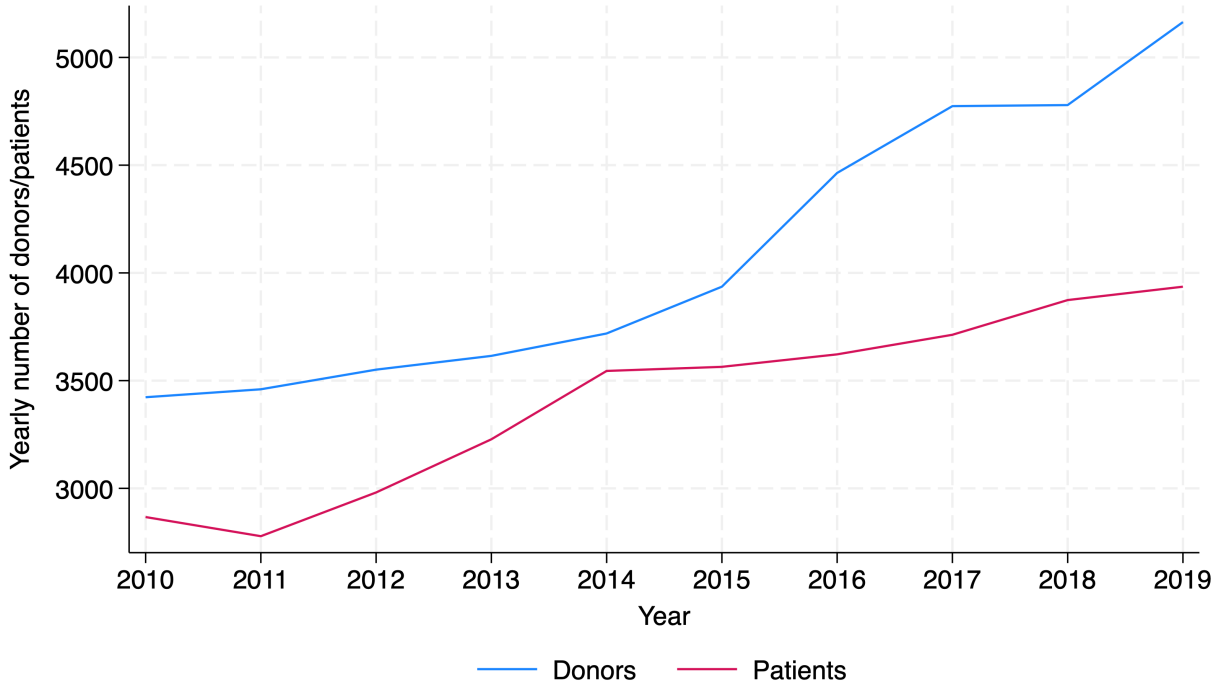


Figure B.5: This figure shows the number of donors and patients that arrive each year from 2010-2019. The figure demonstrates that the number of donors increases quicker than the number of patients.

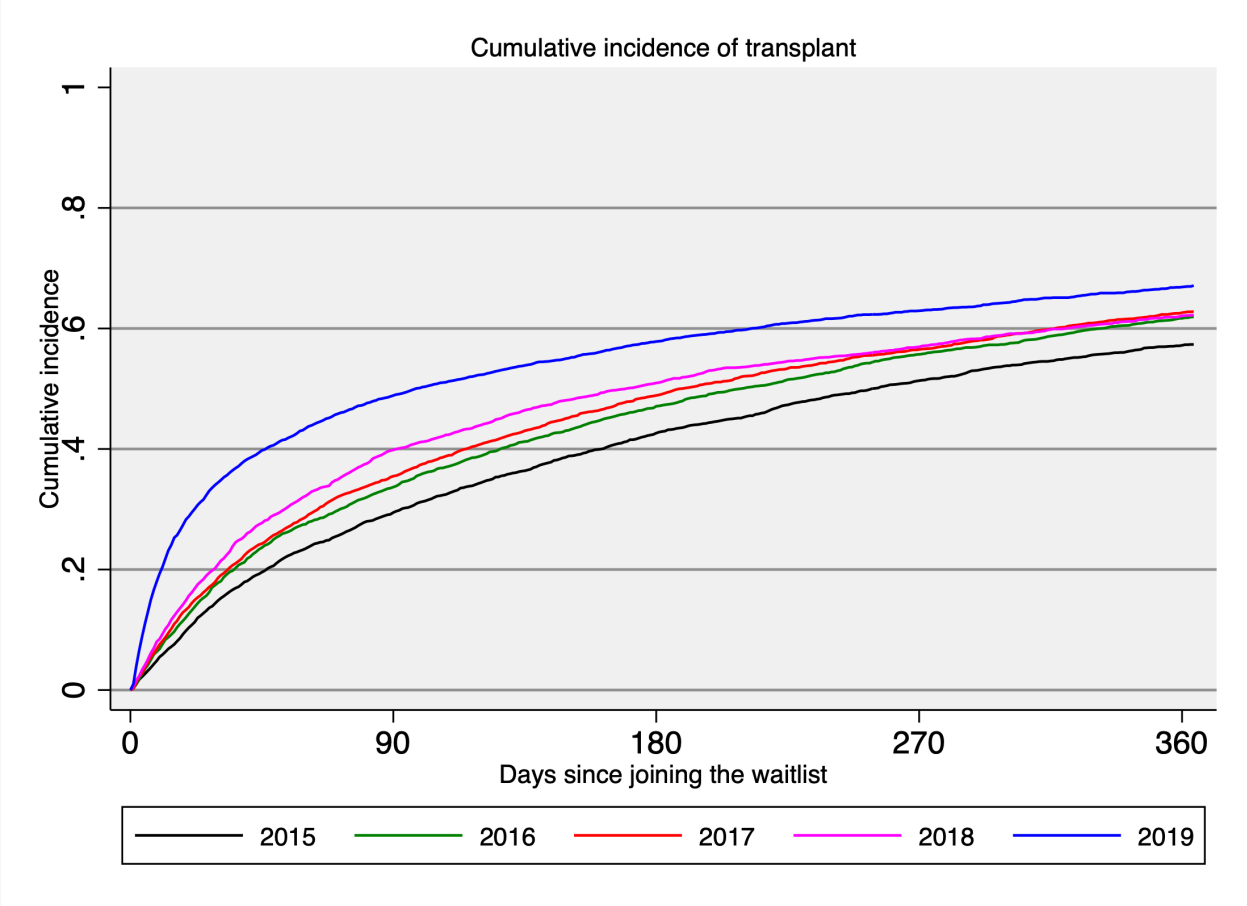


Figure B.6: This figure shows the incidence of receiving a transplant for all patients broken down by the year they entered the waitlist.

B.4 Yearly cumulative incidence of transplants

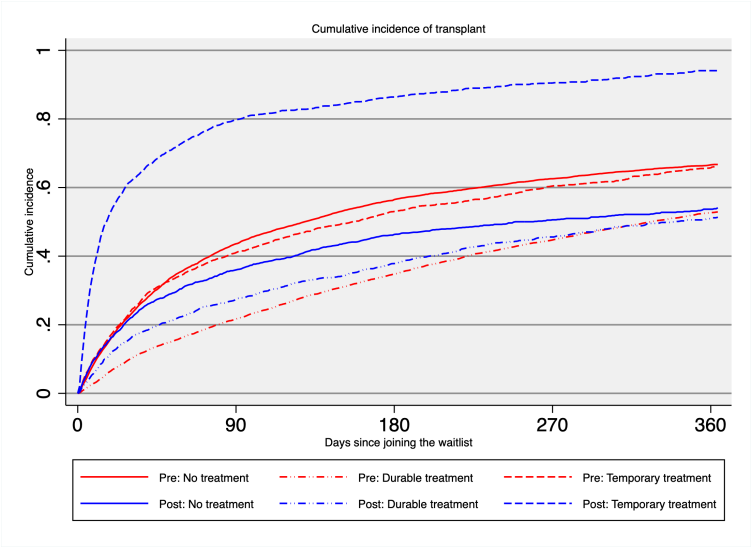
Figure B.6 contains the cumulative incidence of transplants for patients broken down by the year that they entered the waitlist. The figure demonstrates that the incidence of transplants increased slightly from year-to-year prior to the change. However, the increase in 2019 has a much larger magnitude than the previous year-to-year changes. This is especially apparent with 2016 and 2017. The increase in transplants for patients listed in 2018 could be partially a result of the change to the waitlist as it took effect in October 2018.

B.5 Change in declines following the change to the waitlist design

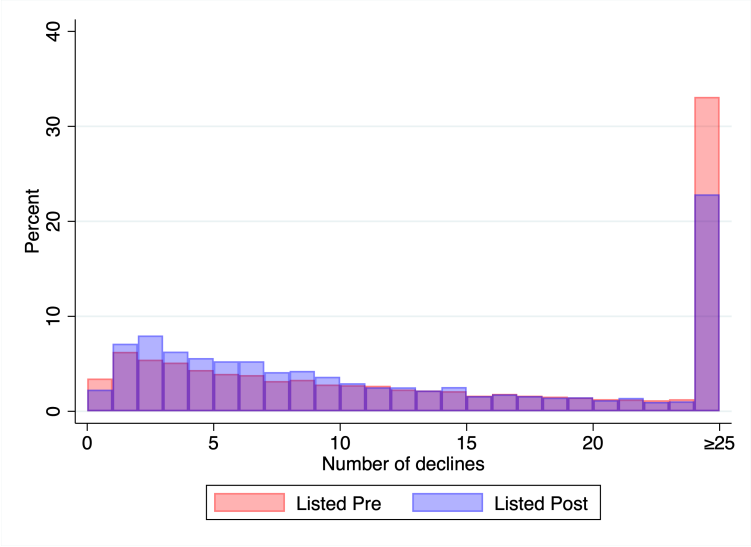
Figure B.7a contains the cumulative incidence of transplants broken down by whether the patient ever received a temporary treatment or a durable treatment. This figure demonstrates that patients that received a temporary treatment also received transplants much sooner moving from 20% being transplanted within the first month to 60%. Patients on durable treatments saw a small increase in transplants though the incidence within the first year is similar. Meanwhile, patients that never received a treatment receive fewer transplants. It is unsurprising that patients on temporary treatments received transplants much sooner under the current design since they receive higher priority. For patients on durable treatments, it is possible that they received transplants sooner because they declined fewer offers.

Figure B.7b depicts the histogram of the number of offers declined by each patient under the previous and current waitlist design. About 33% of patients declined at least 25 offers under the previous waitlist design while only about 23% of patients did under the current waitlist design. This suggests that declines across all patient groups decreased. Appendix B.5 breaks this down further by which treatment the patient received and demonstrates that this pattern holds for patients on temporary and durable treatments. This is expected if patients on temporary treatments received higher quality offers, and if patients on durable treatments received fewer offers and accepted lower quality offers sooner. The characteristics of offers and the rates at which patients receive them are discussed further below.

Figure B.8 contains histograms of the number of offers declined by each patient on the waitlist under the previous and current waitlist designs depending on whether the patient never received a treatment or ever received a durable or temporary treatment. The figures are consistent with the evidence from the cumulative incidence of transplants broken down by treatment and histogram of declines in Figure B.7. That is, patients on temporary treatments decline far fewer offers while patients on durable treatments or not treatment are similar. This results in the overall decrease in the amount of offers declined.

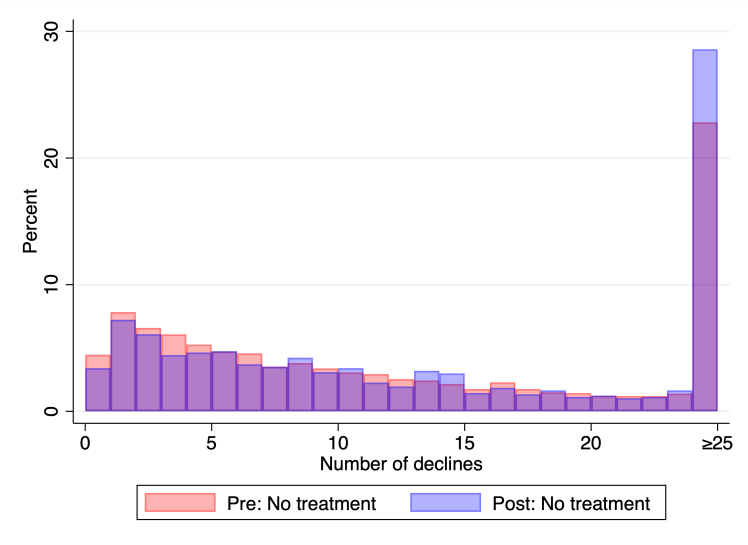


(a)

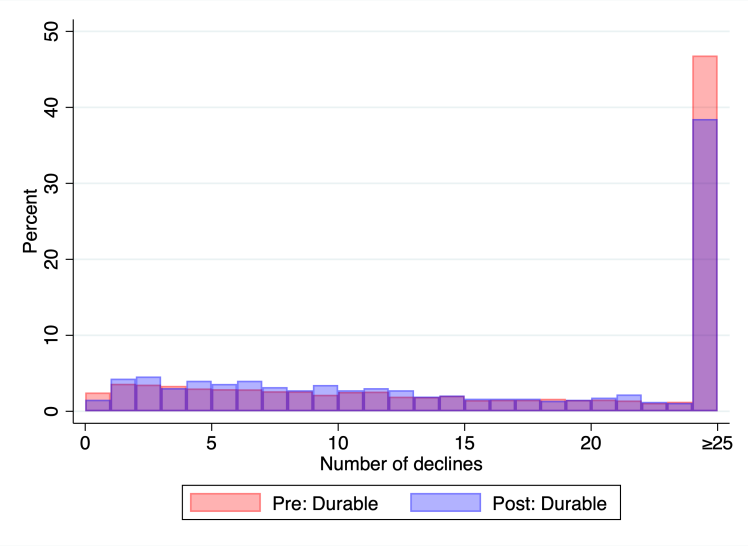


(b) Histogram of number of offers declined broken down by whether the patient was listed under the previous or current waitlist design and whether they ever received a durable or temporary treatment.

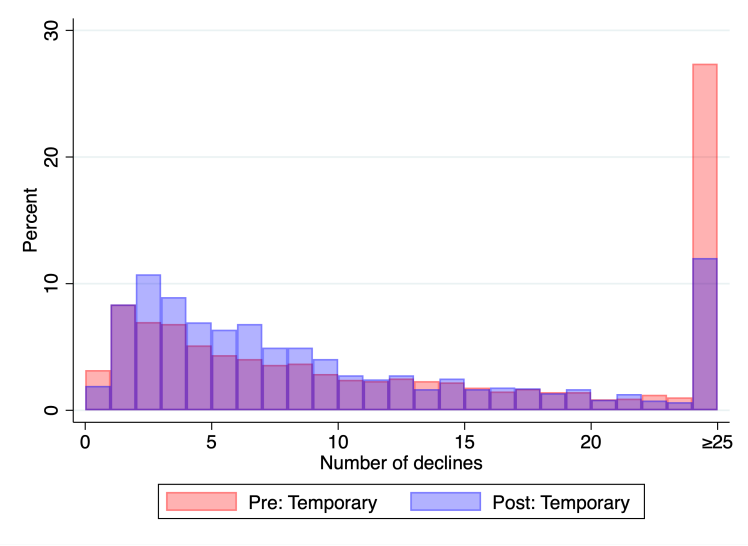
Figure B.7



(a)



(b)



(c)

Figure B.8: Histogram of number of offers declined broken down by whether the patient was listed under the previous or current waitlist design and whether they ever received a durable or temporary treatment.

B.6 Summary of characteristics used in estimation

Table B.1 summarizes the characteristics used in estimation and the components of the model. The first set of rows presents the covariates used in the model. The second set of rows summarizes the distributional assumptions on the state transitions. The third set of rows summarizes the components that appear in the flow utility and transplant value.

Characteristics	
Patient characteristics: x_i	Weight, BMI, age, sex, diagnosis, insurance type, blood type, kidney function, and mobility status.
Treatment and treatment days: y_{it} and $\tilde{y}_{it}$	2-dimensional vector with each component being an indicator for patient i receiving the corresponding treatment on day t (y_{it}) or the number of days they have spent on the treatment ($\tilde{y}_{it}$).
Waitlist design indicator: μ_{it}	Indicator that is 1 if patient i is on the current waitlist design on day t.
Patient-donor characteristics: w_{ij}	Left-ventricular ejection fraction, cause of donor's death, Hepatitis C positive donor, donor's age, weight ratio, height ratio, blood type concordance, gender concordance, , distance from recipient hospital
State transitions	
Number of offers: N_{it}	Multinomial logit dependent on x_i, $y_{i,t-1}$, $\tilde{y}_{i,t-1}$, t, and μ_{it} with probabilities of 0, 1, or 2 offers to arrive on each day.
Post-transplant survival: S_{ijt}	Gompertz survival model dependent on x_i, $y_{i,t-1}$, $\tilde{y}_{i,t-1}$, t, z_j, and their interactions.
Waitlist survival: A_{it}	Probit dependent on x_i, $y_{i,t-1}$, $\tilde{y}_{i,t-1}$, t, and their interactions.
Dynamic choice	
Flow utility: $U(\cdot)$	Treatment-combination specific flow utility dependent on x_i, disutility of implant/explant, and iid T1EV preference shocks.
Value of transplant: V_{ijt}	Terminal value dependent on distance between donor and recipient, predicted 10th, 30th, 50th, 70th, and 90th-percentiles of post-transplant survival time.

Table B.1: Description of the characteristics and unobserved heterogeneity included in each component of the model.

B.7 Post-transplant survival

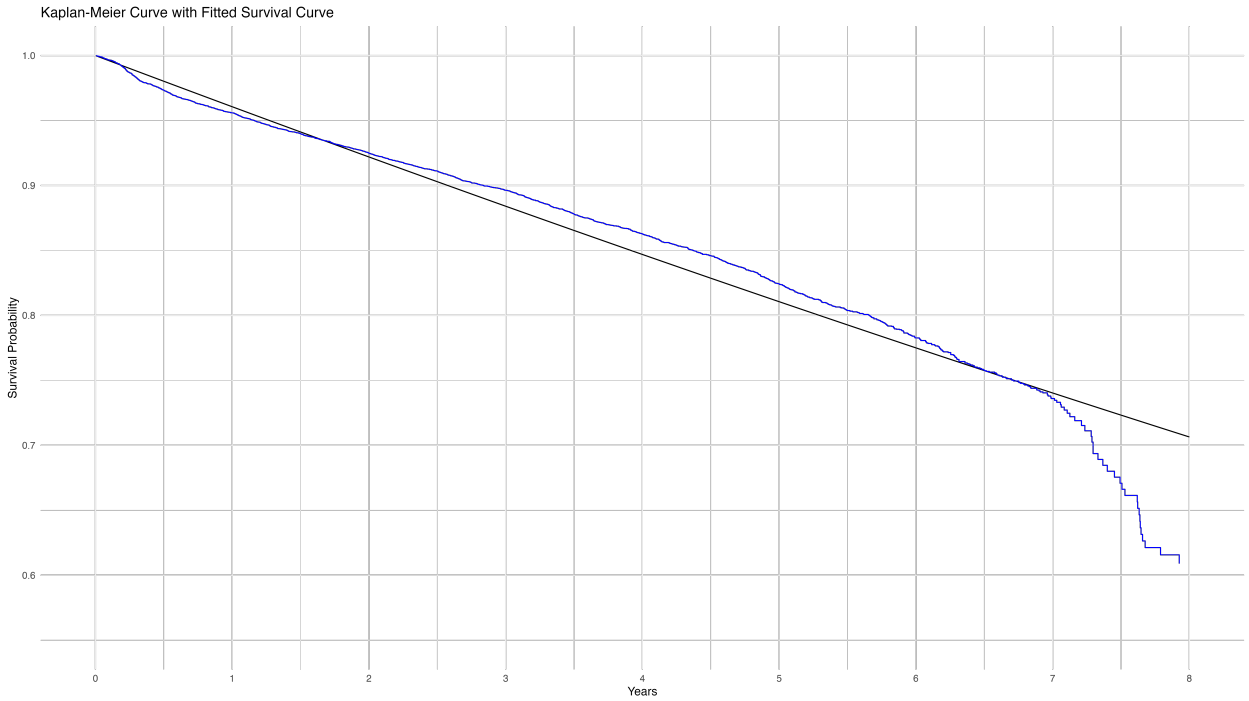
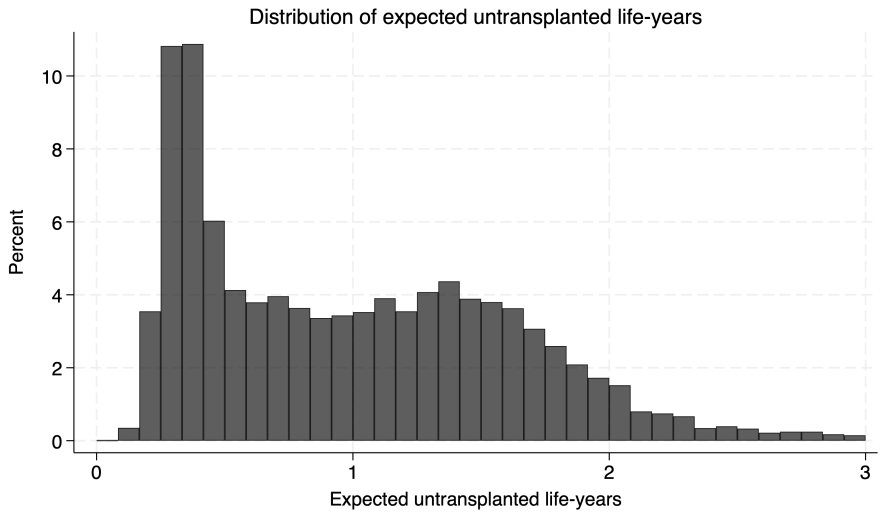
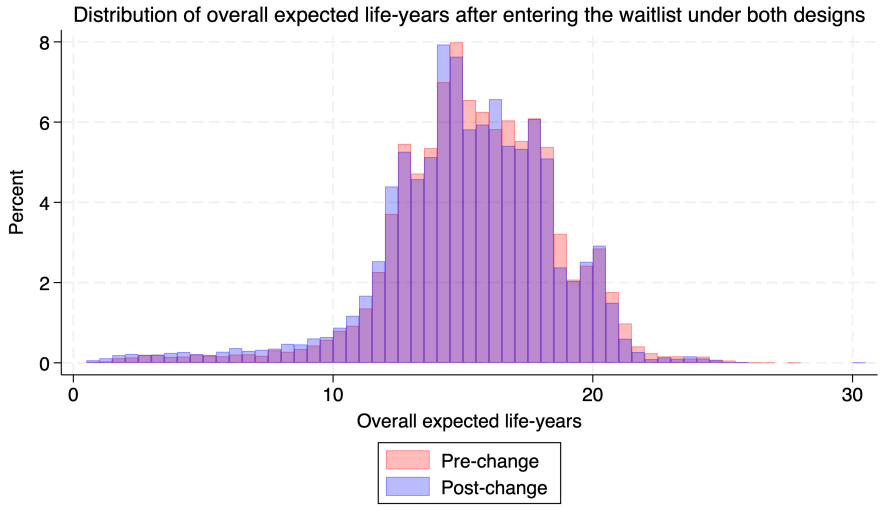


Figure B.9: This figure demonstrates the out-of-sample goodness of fit of the predicted post-transplant survival model. The Kaplan-Meier post-transplant survival curve for the 14,658 patients in the main sample is shown in blue and the predicted post-transplant survival is shown in black. This demonstrates that the predict post-transplant survival closely matches the actual post-transplant survival even though the parameters are estimated on an earlier sample. The rightmost portion of the figure matches poorly because there is a large amount of censoring that takes place since patients do not always have followup data regularly recorded this long after a transplant.

C Additional results



(a) The distribution of expected untransplanted life-years for all patients in the sample. The median untransplanted is 1 year which is the median survival for an individual with end-stage heart failure (Friedrich and Böhm, 2007). The distribution is concentrated at lower values but has a long, relatively flat right tail of patients with longer expected untransplanted survival times.



(b) The distribution of expected overall life-years for all patients in the sample under each waitlist design.

Figure C.10

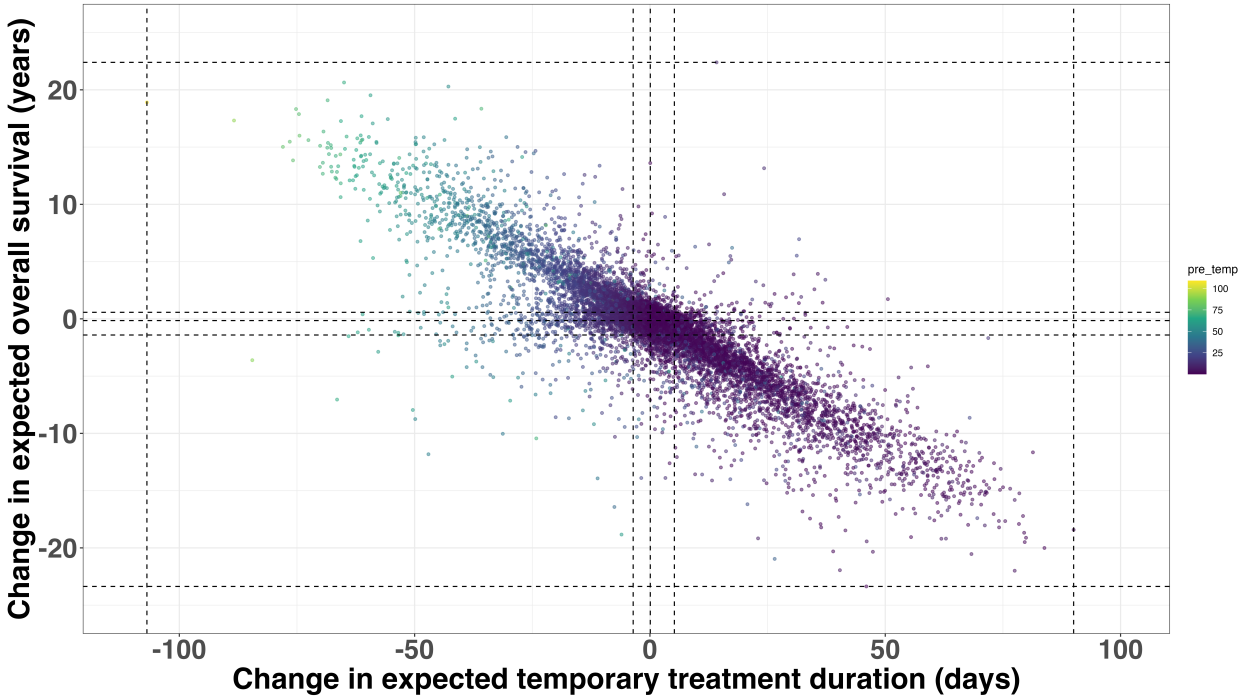


Figure C.11: This figure demonstrates the change in expected duration on a temporary treatment (in days) against the change in expected survival after entering the waitlist (in years) where the color denotes the amount of time the patient was expected to spend on the temporary treatment under the previous waitlist design. The vertical lines and horizontal lines denote quartiles of the respective axis so that each rectangle enclosed by a pair of horizontal lines and vertical lines contains 6.25% of patients (i.e. about 900 patients). This first demonstrates that the bulk of patients experience little change in both (shown in the small inner rectangles). However, the top left (bottom right) portions of the plot demonstrate that patients that previously were expected to spend a long (short) time on the temporary treatment are expected to spend much less (more) time and have improved (worsened) survival following the change. This is a more granular depiction of the results demonstrated by the clustering exercise in Figure 5.

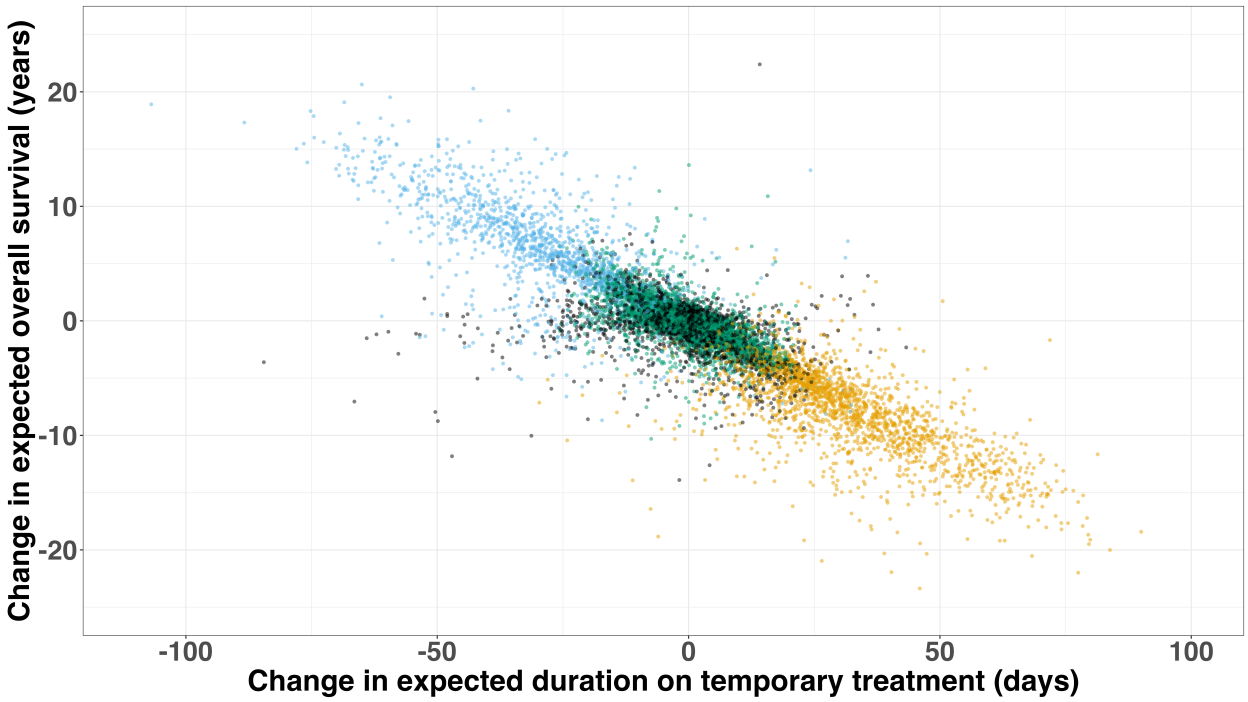


Figure C.12: This figure demonstrates the change in expected duration on temporary treatment (in days) against the change in expected survival after entering the waitlist (in years) where each color gives the cluster that each point corresponds to as demonstrated in Figure 5.

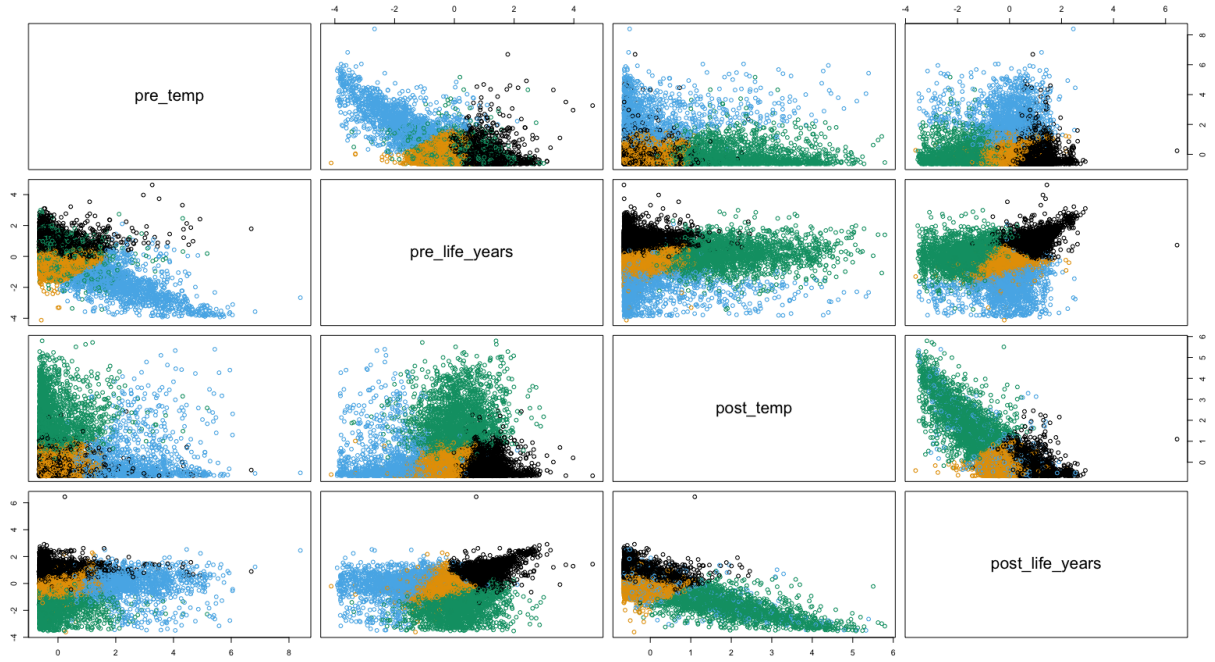


Figure C.13: This figure demonstrates where each patient lies along the four dimensions on which patients were clustered. Each color gives the cluster that each point corresponds to as demonstrated in Figure 5. The variables here have been scaled so that axes denote a standard deviation change in that variable.

D Estimation procedure

The structural model of patient survival and treatments is estimated using the nested pseudo-likelihood procedure described by Aguirregabiria and Mira (2002). This involves solving a dynamic program which is done using simulation and interpolation similar to Hotz et al. (1994) and Keane and Wolpin (1994). This section of the appendix first describes the parameterization of the components of the model in greater detail along with the likelihood functions used in the estimation procedure. The details of the estimation procedure are given in the next subsection.

D.1 Parameterization and likelihood functions

Before describing the likelihood functions that I use in my estimation, I first lay out some important definitions that appear frequently.

Define the following:

- i, t: indices to denote patient i on their tth day on the waitlist
- x_i: patient characteristics on the day that the patient arrives to the waitlist.
- y_{it}: treatment bundle vector of indicators denoting which treatments the patient is receiving as described in Section A.2.
- $\tilde{y}_{it}$: vector of the number of days that the patient has spent on each treatment.
- $\mathcal{Y} = \{(0,0),(1,0),(0,1),(1,1)\}$: set of potential treatment bundles.
- N_{it}: the number of deceased donor heart offers i receives on day t.
- z_j: the characteristics of deceased donor j.
- c_{it}: the choice made by i in period t which may be a treatment bundle or z_j if they receive a transplant from donor j.

- a_{it}: an indicator variable that is 1 if the patient is alive.

- A_{it}: a latent variable such that $a_{it} = 1$ if and only if $A_{it} > 0$.

- ε_{it}: vector of iid T1EV shocks for donor i in period t.

D.1.1 Flow utility

Recall that flow utility the patient receives each period in which they are on the waitlist is given by the following:

$$u(x_i, y_{i,t-1}, y_{it}) + \varepsilon_{it}^{y_{it}} = \gamma_{u,y0} + \gamma'_{u,yx} x_i + \gamma'_{uI} \mathbb{I}\left[y_{it} - y_{i,t-1} = \vec{1}\right] + \gamma'_{uE} \mathbb{I}\left[y_{i,t-1} - y_{it} = \vec{1}\right] + \varepsilon_{it}^{y_{it}}.$$

The observed component of flow utility is given by a treatment bundle-specific function of observed patient characteristics that is linear-in-parameters along with an implant/explant cost if they receive a new treatment.

D.1.2 Waitlist survival

The probability that a patient dies while on the waitlist depends on their characteristics (x_i) and the treatments that they receive (y_{it}). I use the following latent variable in the survival process:

$$\alpha_{it} = W\left(x_i, y_{it}, \tilde{y}_{it}, t; \gamma_A\right) + \eta_{it}^a$$

where $a_{it} = 1$ iff $\alpha_{it} > 0$, η_{it}^a is a $N(0,1)$ error term, and W is a known function that is linear-in-parameters γ_A.

D.1.3 Value of death

If the individual dies, then the physician receives a fixed value associated with their death that depends on observed characteristics: $V_{it}(a_{it} = 0)$. It is assumed that the value of death

does not depend on any treatments that the patient has received. In all that follows, the normalization that the value of death is 0 will be made so that the utility is relative to the patient dying.

D.1.4 Post-transplant survival

The expected survival time of a patient following a transplant is estimated using a Gompertz survival model on observed characteristics. This survival model is estimated on patients listed from January 1, 2010 to December 31, 2014.

The survival function of patient i with a transplant from donor j on period $\bar{t}$ is given by

$$F\left(t; \gamma^0_{\text{post-tx}}, \gamma_{\text{post-tx}} \,|x_i, y_{i\bar{t}}, \tilde{y}_{i\bar{t}}, \bar{t}, z_j\right) = \exp\left\{ -\exp\left(\gamma'_{\text{post-tx}}\lambda_{ij\bar{t}}\right)(\gamma^0_{\text{post-tx}})^{-1}\Big(\exp\left(\gamma^0_{\text{post-tx}}t\right) - 1\Big)\right\}$$

where $\lambda_{ij\bar{t}}$ denotes a vector of $x_i, y_{i\bar{t}}, \tilde{y}_{i\bar{t}}, \bar{t}, z_j$, and interactions between these terms. The parameters to be estimated are $\gamma^0_{\text{post-tx}}$ and $\gamma_{\text{post-tx}}$. They are straightforward to estimate using maximum likelihood.

D.1.5 Transplant value

The value that individual i receives from a transplant on period t from donor j with characteristics z_j also depends on the estimated quantiles of post-transplant survival, denoted $S_{ijt}(\alpha)$ for the α-quantile. It also depends on the distance between the donor hospital and recipient hospital, d_{ij}. The value of a transplant given in vector notation is then

$$V_{ijt} = \gamma_{\text{tx,0}} + \sum_{a=0}^{4} \gamma_{\text{tx,a}} S_{ijt}(0.1 + 0.2a) + \gamma_{\text{tx,d}} \log\left(1 + d_{ij}\right) + \varepsilon_{ijt}.$$

D.1.6 Heart arrival

Patients may receive 0, 1, or 2 offers on any given day (I drop outliers in which there are more than 2 offers received on a day, accounting for 0.59% of offers made since 2015). I

assume that heart arrival follows a multinomial logit as shown below:

$$\Pr(N_{it} = n|x_i, \tilde{y}_{i,t-1}, \mu_{it}, t; \gamma_N) = \begin{cases} \frac{\exp(R(x_i, \tilde{y}_{i,t-1}, y_{i,t-1}, t, \mu_{it}; \gamma_{Nn}))}{1+\sum_{\hat{n}=1}^{2} \exp(R(x_i, \tilde{y}_{i,t-1}, y_{i,t-1}, t, \mu_{it}; \gamma_{N\hat{n}}))} & n > 0 \\ \frac{1}{1+\sum_{\hat{n}=1}^{2} \exp(R(x_i, \tilde{y}_{i,t-1}, y_{i,t-1}, t, \mu_{it}; \gamma_{N\hat{n}}))} & n = 0 \end{cases} \tag{6}$$

where $R(x_i, \tilde{y}_{i,t-1}, y_{i,t-1}, t, \mu_{it}; \gamma_{Nn})$ is a linear-in-parameters (γ_{Nn}) function of patient characteristics (x_i), the time patient i has spent on each treatment while on the waitlist ($\tilde{y}_{i,t-1}$), the treatments that the patient was most recently on ($y_{i,t-1}$), the time spent on the waitlist (t), and an indicator variable for whether period t is after the waitlist change on October 18, 2018 (μ_{it}). The vector of parameters to be estimated is given by $\gamma_N = (\gamma_{N1}, \gamma_{N2})$.

Conditional on a heart arriving, the characteristics of the deceased donor offer that the patient receives is assumed to be drawn from the empirical distribution of deceased donor hearts conditional on the patient's blood type and the likelihood of the patient receiving an offer for a heart, i.e. $\Pr(N_{it} > 0|x_i, \tilde{y}_{i,t-1}, \mu_{it}, t)$.

D.1.7 Likelihood function

An observation depends on whether the patient is alive, the number of offers the patient receives, and the choice made from the choice set. The joint likelihood for a patient i is given by

$$\begin{aligned} f_{i,F}(\gamma_N, \gamma_A, \gamma_C) = &\prod_{t=1}^{T_i} \Pr(N_{it}|x_i, \tilde{y}_{i,t-1}, \mu_{it}, t; \gamma_N) \\ &\times \Pr(a_{it}|x_i, \tilde{y}_{i,t-1}, t; \gamma_A) \Pr(c_{it}|x_i, \tilde{y}_{i,t-1}, t; \gamma_N, \gamma_A, \gamma_C) \\ = &f_N(x_i, \tilde{y}_{i,t-1}, \mu_{it}, t; \gamma_N) \\ &\times f_A(x_i, \tilde{a}_{iT}, \tilde{y}_{iT}; \gamma_A) f_C(x_i, \tilde{a}_{iT}, \tilde{y}_{iT}; \gamma_N, \gamma_A, \gamma_C) \end{aligned} \tag{7}$$

where f_N, f_A, and f_C denote the conditional likelihood of the donor arrival process, survival process, and choice process, respectively, and T_i denotes the final time period for patient i.

It is clear that $f_N(x_i, \tilde{y}_{i,t-1}, \mu_{it}, t; \gamma_N) = \prod_{t=1}^{T_i} \Pr(N_{it}|x_i, \tilde{y}_{i,t-1}, \mu_{it}, t; \gamma_N)$ can be written using Equation (6) above.

Given the assumption of $N(0,1)$ error terms for the latent variable α_{it}, the likelihood of the survival process for individual i who is alive in period T_i is given by

$$\begin{aligned} f_A(x_i, \tilde{a}_{iT}, \tilde{y}_{iT}; \gamma_A) &= \prod_{t=1}^{T_i} \Pr(a_{it}|x_i, \tilde{y}_{i,t-1}, t; \gamma_A) \\ &= \prod_{t=1}^{T_i} \Pr\left(W\left(x_i, \tilde{y}_{i,t-1}, y_{it}, t; \gamma_a\right) + \eta_{it}^a > 0\right) \\ &= \prod_{t=1}^{T_i} \left[1 - \Phi\big(-W\left(x_i, \tilde{y}_{it}, y_{it}, t; \gamma_a\right)\big)\right] \end{aligned}$$

where Φ denotes the standard normal cdf. If the patient dies in period T_i this becomes

$$\begin{aligned} f_A(x_i, \tilde{a}_{iT}, \tilde{y}_{iT}; \gamma_A) &= \prod_{t=1}^{T_i} \Pr(a_{it}|x_i, \tilde{y}_{i,t-1}, t; \gamma_A) \\ &= \prod_{t=1}^{T_i-1} \Pr\left(W\left(x_i, \tilde{y}_{it}, y_{it}, t; \gamma_a\right) + \eta_{it}^a > 0\right) \\ &\times \Pr\left(W\left(x_i, \tilde{y}_{iT_i}, y_{iT_i}, T_i; \gamma_a\right) + \eta_{iT_i}^a < 0\right) \\ &= \prod_{t=1}^{T_i-1} \left[1 - \Phi\left(-W\left(x_i, \tilde{y}_{it}, y_{it}, t; \gamma_a\right)\right)\right] \\ &\times \Phi\left(-W\left(x_i, \tilde{y}_{iT_i}, y_{iT_i}, T_i; \gamma_a\right)\right). \end{aligned} \tag{8}$$

Given the assumption of iid T1EV preference shocks, the likelihood of the choice model is given by

$$\begin{aligned} f_C(x_i, \tilde{a}_{iT}, \tilde{c}_{iT}; \gamma_A, \gamma_C, \gamma_N) &= \prod_{t=1}^{T_i} \Pr(c_{it}|x_i, \tilde{y}_{i,t-1}; \gamma_N, \gamma_A, \gamma_C) \\ &= \prod_{t=1}^{T_i} \frac{\exp\left[v(c_{it}, x_i, \tilde{y}_{i,t-1}, t; \gamma_C)\right]}{\sum_{\hat{c} \in C_{it}} \exp\left[v(\hat{c}, x_i, \tilde{y}_{i,t-1}, t; \gamma_C)\right]} \end{aligned} \tag{9}$$

where $v(c, x_i, \tilde{y}_{i,t-1}, t)$ is the choice-conditional value function for individual i with previous

choices. The choice-conditional value function is approximated as described in the next subsection.

The full log-likelihood for the estimation procedure is given by

$$\sum_i \Big\{ \log\left[f_N(x_i, \tilde{y}_{i,t-1}, \mu_{it}, t; \gamma_N)\right] + \log\left[f_A(x_i, \tilde{a}_{iT}, \tilde{y}_{iT}; \gamma_A)\right] + \log\left[f_C(x_i, \tilde{a}_{iT}, \tilde{y}_{iT}; \gamma_N, \gamma_A, \gamma_C)\right] \Big\}.$$

Since this is additively separable in the state transition and choice likelihoods, it can be estimated by first estimating γ_N and γ_A before estimating γ_C conditional on consistent estimates of γ_A and γ_N. This results in a consistent but inefficient estimate of γ_C. An iterative procedure similar to Aguirregabiria and Mira (2002) is employed to improve the precision of the estimates rather than a two-step procedure similar to Hotz and Miller (1993).

D.2 Nested Pseudo-Likelihood Estimation

The estimation of choice parameters requires estimating the choice-conditional value functions for any value of the parameter γ_C. The state variables are patient characteristics at listing, the time the patient has spent on the waitlist, and the amount of days spent on each treatment. The inclusion of the last three results in a nonstationary dynamic program with a continuous state space. As a result, much of the algorithm is devoted to speeding up estimating the choice-conditional value function.

Figure D.14 summarizes the steps of the estimation procedure. The procedure begins by estimating the state-transition parameters of the dynamic program given by γ_N and γ_A by maximizing their associated partial likelihoods. An approximate solution to the dynamic program is needed to estimate the choice parameters γ_C which requires conditional choice probabilities as nonstationarity precludes estimation via a nested fixed point. Due to the large size of the state space, the approximate solution is obtained via forward simulation on a grid given estimated conditional choice probabilities. Given estimated model parameters, the CCPs are iteratively updated to obtain model-based CCPs and improve the precision

of the choice parameters. The remainder of this subsection provides further details on the estimation.

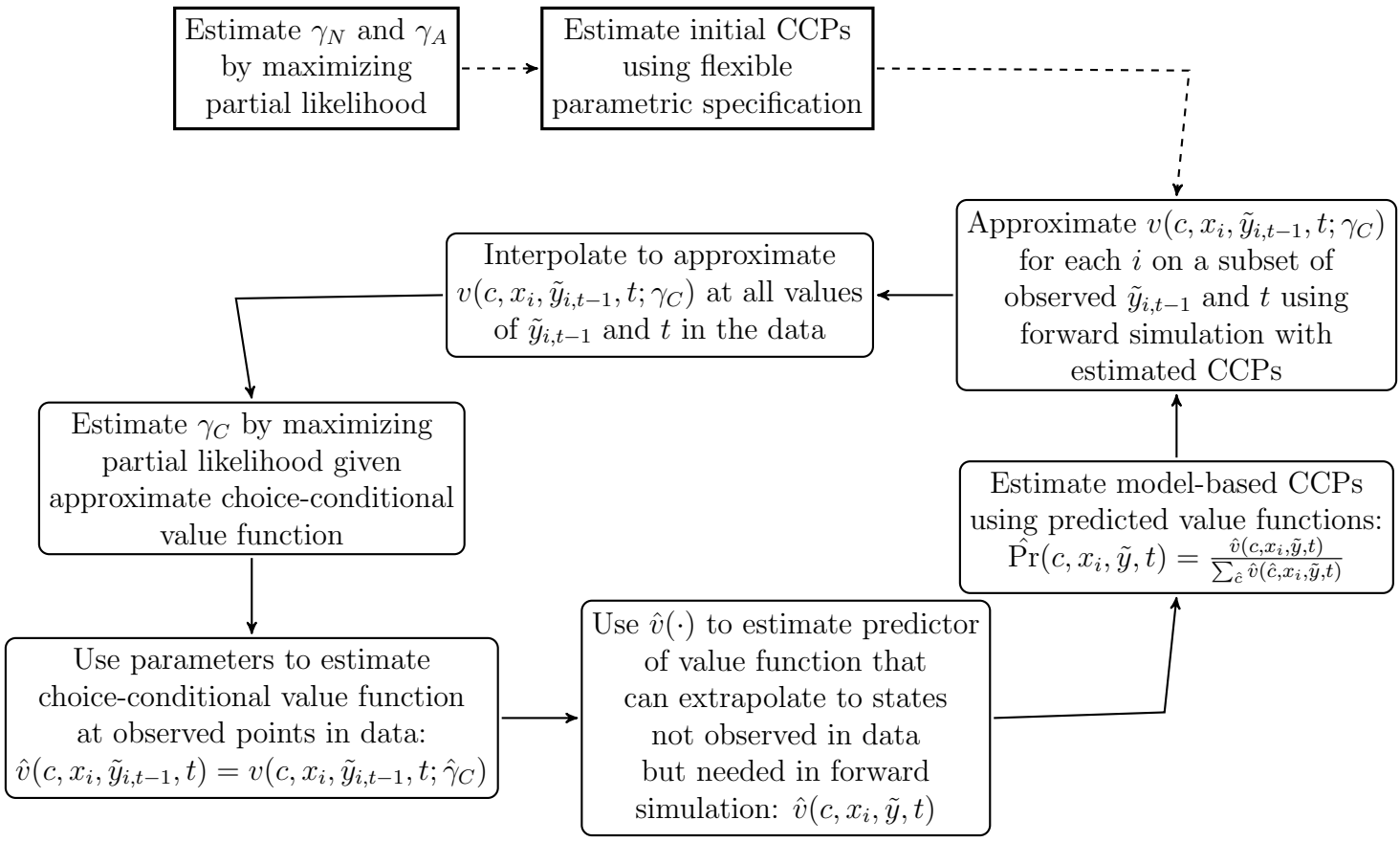


Figure D.14: Demonstration of steps in estimating the model where rectangles with rounded corners and solid paths denote steps taken on each iteration of the estimation algorithm while rectangles with dashed lines denote steps taken only on the initial iteration.

D.2.1 Deceased donor arrival process estimation

Recall that the number of deceased donor offers that arrive on a particular period is assumed to follow a multinomial logit where 0, 1, or 2 offers can arrive. These parameters are straightforward to estimate using maximum likelihood by solving the following mathematical program:

$$\max_{\gamma_N} \sum_{it} \log \left[\Pr(N_{it} | x_i, \tilde{y}_{i,t-1}, \mu_{it}, t; \gamma_N) \right] \tag{10}$$

where $\Pr(N_{it}|x_i, \tilde{y}_{i,t-1}, \mu_{it}, t; \gamma_N)$ is given by equation (6).

It is also important to estimate the characteristics of deceased donor hearts that arrive as this is important in the forward simulation procedure described below. This is done nonparametrically using the empirical distribution of blood type compatible donor hearts for a given patient. To account for the fact that higher priority patients receive offers from a larger pool of donors (including 'better' donors), this empirical distribution is conditional on the likelihood a patient was offered a heart from a particular donor. That is, for each donor j, compute $\Pr(N_{\iota\tau} \geq 1|x_\iota, \tilde{y}_{\iota,\tau-1}, \mu_{\iota\tau}, \tau; \hat{\gamma}_N)$ for each patient ι offered this donor on their τ-th period on the waitlist where $\hat{\gamma}_N$ denotes the solution to (10). Let $\widehat{\mathcal{P}}_j = \min_{\iota \text{ offered } j} \Pr(N_{\iota\tau} \geq 1|x_\iota, \tilde{y}_{\iota,\tau-1}, \mu_{\iota\tau}, \tau; \hat{\gamma}_N)$. This reflects the offer arrival probability of the least likely patient offered donor j. Then, the empirical distribution of donors that might be offered to patient i on their t-th period on the waitlist is given by all blood type compatible donors j such that $\Pr(N_{it}|x_i, \tilde{y}_{i,t-1}, \mu_{it}, t; \hat{\gamma}_N) \geq \widehat{\mathcal{P}}_j$. This ensures that patient i is only offered donors that were offered to patients who were less likely to receive offers than them, i.e. had lower priority.

D.2.2 Patient survival process estimation

The survival parameters γ_A are estimated by maximum likelihood using the likelihood described above implied by the normally distributed iid survival shocks. That is, they solutions to the following mathematical program:

$$\max_{(\gamma_A} \sum_{i,t} \log \Pr(a_{it}|x_i, \tilde{y}_{i,t-1}, t; \gamma_A) \tag{11}$$

where $\Pr(a_{it}|x_i, \tilde{y}_{i,t-1}, t; \gamma_A)$ is given in Equation 8.

D.2.3 Forward simulation

Estimating choice parameters requires first estimating the choice-conditional value function that appears in the choice likelihood. The approach taken here is a CCP-based forward

simulation approach to aid in integrating over the fairly high-dimensional state space without being as computationally burdensome as it would be to solve the dynamic program or evaluate the value function on all state-choice paths.

In general, the forward simulation should be repeated for every state variable observed in the data. These state variables can be decomposed into patient-specific observed heterogeneity, i.e. patient characteristics that are held fixed, and time-varying state variables including time spent on the waitlist and time spent on a durable or temporary treatment. The forward simulation should be repeated for all patient-days in the sample and all choices available to them, resulting in about 10 million forward simulations in my sample. This is computationally infeasible, so the forward simulation is instead done on a subset of the state space where the time-varying state variables lie on a grid.

The forward simulation procedure will be described for patient i on their t-th day on the waitlist conditional on choosing c_t which corresponds to some grid point. Interpolation at additional grid points will be discussed after description of the forward simulation. For convenience, I typically drop dependence on state variables in favor of using subscripts with the variables incorporated implicitly in the subscripts. Superscripts are used to denote the iteration of the NPL algorithm and to denote that a particular quantity is randomly drawn in the simulation procedure. The choice c_t is written explicitly for the choice-conditional value function and as a state variable in the continuation value. The lowercase v is used to denote the choice-conditional value function while V is used to denote the optimal V that approximates the solution of the dynamic program. The aim is to calculate the choice-conditional value function (net of the unobserved iid shock ε)

$$v_{it}(c_t; \gamma_C) = u_{it}(c_t; \gamma_C) + \beta \mathbb{E} V_{i,t+1}(c_t; \gamma_C)$$

using Monte Carlo simulations to calculate $\mathbb{E}V_{i,t+1}(c_t; \gamma_C)$.

This is done in two steps for each future period:

1. simulate the number of deceased donor hearts to arrive and the characteristics of donor hearts that arrive, and

2. simulate acceptance of a deceased donor offer and treatments that the patient is put on.

The rest of this subsubsection first demonstrates how each of these steps is done in the next period in further detail to estimate the choice-conditional value function. It is then shown how these simulations proceed further and are averaged across simulated state-choice paths. Then, it is shown how functional form assumptions on the flow utility and value of a transplant allow the simulation process to be performed a single time for each iteration of the NPL algorithm rather than repeatedly for every iteration of the choice estimate solver.[25] Finally, the interpolation procedure is described.

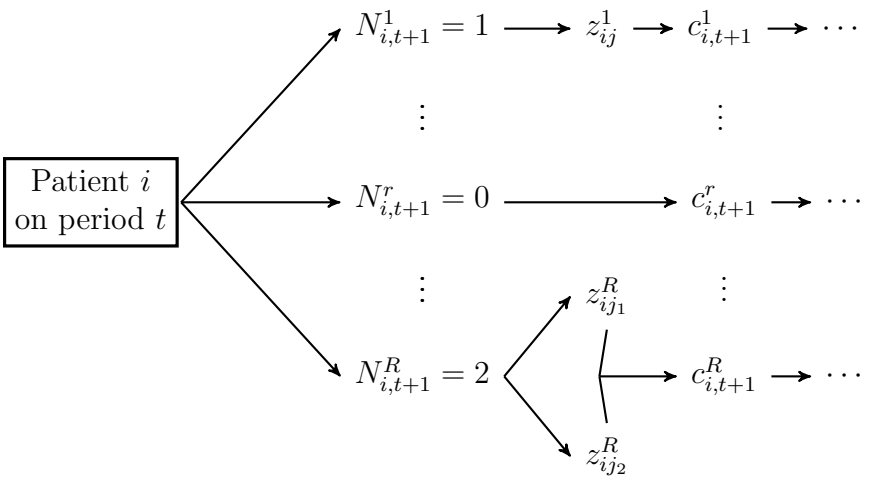
Simulation in $t+1$: Given $\hat{\gamma}_N$, randomly generate the number of offers that arrive in each period to arrive, $N^1_{i,t+1}, \ldots, N^R_{i,t+1}$. For each $r = 1, \ldots, R$, if $N^r_{i,t+1} > 0$ then next draw one or two random blood type compatible deceased donor hearts from the empirical distribution based on whether one or two donor heart offers arrived conditional on i's characteristics and $\Pr(N^r_{i,t+1} \geq 1)$. The characteristics of donor j offer to patient i in simulated path r are denoted by z^r_{ij}.

Given estimated CCPs $\widehat{\Pr}_{it}(c)$ for each c, randomly generate a treatment decision based on the estimated conditional choice probability given the simulated number of offers that arrive and their characteristics. These CCPs depend on the choice made but do not depend on the type, so they are denoted by $c^r_{i,t+1}(c)$ for $r = 1, \ldots, R$.

Simulated state-choice paths: This process continues in all future periods $\hat{t} > t+1$ by drawing randomly drawing the number of deceased donors that arrive, the characteristics of

[25] In the implementation, the matrix form of the choice-conditional value function and the estimation of the choice-conditional value function are performed concurrently. These are separated in the paper for expositional clarity.

the donor(s), and the patient's choice. Once an offer is accepted, no more random numbers need to be generated along this path since there are no more deceased donor hearts arriving or choices being made once the patient has received a transplant. Let $\bar{t}^r(c)$ denote the period in which this happens and $h^r(c)$ denote the associated donor heart where both depend on the initial choice c through the CCPs. It can be visualized using the graph below where a particular branch terminates once a random number is generated such that a patient accepts an offer for a deceased donor heart.



Each branch implies a simulated value function associated with each choice consisting of the flow utility plus the conditional expectation of the unobserved preference shocks:

$$
\begin{aligned}
V^r_{i,t+1}(c) = & \sum_{\hat{t}=t+1}^{\bar{t}^r} \beta^{\hat{t}-t-1} \Pr(a_{i\hat{t}} = 1 | c, c^r_{i\hat{t}}(c); \hat{\gamma}_A) \left[u_{i\hat{t}}(c^r_{i\hat{t}}(c); \gamma_C) + \gamma - \ln\left(\widehat{\Pr}(c_{i\hat{t}}(c) = c^r_{i\hat{t}}(c)) \right) \right] \\
& + \sum_{\hat{t}=t+1}^{\bar{t}^r} \beta^{\hat{t}-t-1} \Pr(a_{i\hat{t}} = 0 | c, c^r_{i\hat{t}}(c)) V_{i\hat{t}}(a_{i\hat{t}} = 0) \\
& + \beta^{\bar{t}^r - t - 1} \left[V_{ih^r(c)\bar{t}^r(c)}(\gamma_C) + \gamma - \ln\left(\widehat{\Pr}(c_{i\bar{t}^r(c)}(c) = h^r(c)) \right) \right]
\end{aligned}
$$

where γ denotes the Euler-Mascheroni constant, $V_{ih^r(c)\bar{t}^r(c)}$ denotes the terminal value associated with accepting a heart from donor h^r given initial choice c, and $V_{i\hat{t}}(a_{i\hat{t}} = 0)$ denotes the value associated with dying in period $\hat{t}$ which is normalized to 0 for estimation. The

probability of survival and death are estimated using previously estimated survival estimates $\hat{\gamma}_A$. The logarithm of the ratio of CCPs is included following the flow utility and value of a transplant since this is the conditional expectation of the unobserved payoff shocks estimated from the CCPs (Hotz et al., 1994). In practice, the number of periods that this simulation is conducted over is large enough that there is always some period in which a patient receives a transplant.

Finally, calculate $v_{it}(c)$:

$$v_{it}(c;\gamma_C) = u_{it}(c;\gamma_C) + \frac{\beta}{R}\sum_{r=1}^{R} V_{i,t+1}^{r}(c).$$

Matrix form of choice-conditional value function: The flow utility is assumed to be linear-in-parameters, so that there exists a vector of relevant covariates, including unobserved type θ_k^0, denoted $M_{itk}^0(c)$ such that $u_{it}^0(c,\theta_k) = \Gamma_C' M_{itk}^0(c)$ where Γ^C denotes a parameter vector as discussed in D.1.1. The parameter vector Γ_C contains the full set of treatment bundle-specific flow utility parameters.[26] Similarly, for any period $\hat{t} > t$ in simulated state-choice path r, there exists $M_{i\hat{t}k}^{0,r}(c)$ such that $u_{i\hat{t}}^{0,r}(c,\theta_k) = \Gamma_C' M_{i\hat{t}k}^{0,r}(c)$. Note that the notation used here shows the dependence of these vectors on the choice made in the observed period as an argument to a function, i.e. (c), while dependence on the simulated state-choice path is denoted using a superscript.

The same is true for the value of receiving a transplant or dying in simulated state-choice paths. The value of a transplant is linear-in-parameters so that they can be written as $V_{ih^{0,r}(c)\bar{t}^{0,r}(c)} = \Gamma_{\text{Tx}}' N_{ih^{0,r}(c)\bar{t}^{0,r}(c)k}$ where $N_{ih^{0,r}(c)\bar{t}^{0,r}(c)k}$ consists of a vector of relevant covariates for a transplant from donor $h^{0,r}(c)$ in period $\bar{t}^{0,r}(c)$ in simulation r and Γ_{Tx} denotes a vector of parameters associated with the value of a transplant. Note that dependence on the initial choice made here enters the subscripts as the donor heart accepted and the period in which it is accepted are functions of this choice. Similarly, for the value for death this gives

[26] The capital letter is used to distinguish it from the parameter vector in the log-likelihood function which does not necessarily have the same ordering or dimensions.

$V_{i\hat{t}}(a_{i\hat{t}} = 0, \theta_k^0) = \Gamma'_{\text{death}} B^0_{i\hat{t}k}$. Note that the value of death is independent of the choice made by the assumption that treatments do not affect the value of death.

This gives the simpler to compute expression for the vector of simulated value functions:

$$
\begin{aligned}
V^{0,r}_{i,t+1}(c, \theta_k^0) = \Gamma'_C & \left[\sum_{\hat{t}=t+1}^{\bar{t}^{0,r}(c)} \beta^{\hat{t}-t-1} \Pr(a_{i\hat{t}} = 1 | c, c^{0,r}_{i\hat{t}}(c), \theta_k^0) M^{0,r}_{i\hat{t}k}(c) \right] \\
& + \Gamma'_{\text{death}} \left[\sum_{\hat{t}=t+1}^{\bar{t}^{0,r}(c)} \beta^{\hat{t}-t-1} \Pr(a_{i\hat{t}} = 0 | c, c^{0,r}_{i\hat{t}}(c), \theta_k^0) B^0_{i\hat{t}k} \right] \\
& + \beta^{\bar{t}^{0,r}-t-1} \Gamma'_{\text{Tx}} N_{ih^{0,r}(c)\bar{t}^{0,r}(c)k} \\
& + \sum_{\hat{t}=t+1}^{\bar{t}^{0,r}} \beta^{\hat{t}-t-1} \Pr(a_{i\hat{t}} = 1 | c, c^{0,r}_{i\hat{t}}(c), \theta_k^0) \Big[\gamma - \ln \big(\Pr(c_{i\hat{t}}(c) = c^{0,r}_{i\hat{t}}(c)) \big) \Big] \\
& + \beta^{\bar{t}^{0,r}-t-1} \Big[\gamma - \ln \big(\Pr(c_{i\bar{t}^r(c)}(c) = h^{0,r}(c)) \big) \Big]
\end{aligned}
$$

Using this expression, it is clear that the only quantities that need to be simulated are the vectors of covariates M, N, and B, as well as the present value of the sum of the conditional expectation of preference shocks, seen in the last two lines. For a particular iteration of the QN-ESM algorithm, these quantities can be simulated a single time before solving for the parameters so that the forward simulation procedure only needs to be done once.

D.2.4 Conditional choice probability estimation

The conditional choice probabilities used in the forward simulation are estimated from observed choices and state transitions in the initial iteration and then using estimates from the model in subsequent iterations.

Initial iteration In the initial iteration, observed patient characteristics (x_i), time spent on the waitlist (t), treatments on the previous date ($y_{i,t-1}$), time spent on treatments ($\tilde{y}_{i,t-1}$), whether the time period is under the previous or current design, the number of days until the design changes, and donor characteristics (z_j). Given the observed choices in the data, the

probability of choosing treatment y_{it} is estimated using a multinomial logit with probability

$$\Pr(c_{it};\gamma_{\text{CCP}}) = \begin{cases} \frac{1}{1+\sum_{\hat{c}\in C_{it}}\exp(f(\hat{c},x_i,\tilde{y}_{i,t-1},\mu_{it},t;\gamma_{\text{CCP}}))} & \text{if } c_{it}=(0,0) \\ \frac{\exp(f(y,x_i,\tilde{y}_{i,t-1},t;\gamma_{\text{CCP}}))}{1+\sum_{\hat{c}\in C_{it}}\exp(f(\hat{c},x_i,\tilde{y}_{i,t-1},\mu_{it},t;\gamma_{\text{CCP}}))} & \text{if } c_{it}=y\in\mathcal{Y}\setminus\{(0,0)\} \\ \frac{\exp(f(z_j,x_i,\tilde{y}_{i,t-1},t;\gamma_{\text{CCP}}))}{1+\sum_{\hat{c}\in C_{it}}\exp(f(\hat{c},x_i,\tilde{y}_{i,t-1},\mu_{it},t;\gamma_{\text{CCP}}))} & \text{if } c_{it}=z_j \end{cases} \tag{12}$$

where $f(\hat{c},x_i,\tilde{y}_{i,t-1},\mu_{it},t;\gamma_{\text{CCP}})$ is a linear-in-parameters function of interactions between patient characteristics, treatments, whether the period is before or after the waitlist change, and donor characteristics.

Subsequent iterations In subsequent iterations, estimated preference parameters can be used to estimate the choice-conditional value function for each state variable observed in the data. For all patient-days, take $\hat{v}_{it}(c) = v_{it}\left(c;\hat{\gamma}_C\right)$. For each patient i and choice c, find the best linear predictor (BLP) of $\hat{v}_{it}(c)$ using a polynomial of the time spent on the waitlist and time spent on each treatment.

In particular, let $\hat{\boldsymbol{v}}_i(c)$ denote the stacked vector of $\hat{v}_{it}(c)$ across all t in the data for a specific patient i and choice c. Let $\boldsymbol{x}_{it}(c)$ denote a row vector with the product $t^j\tilde{y}_{1,it}^k\tilde{y}_{2,it}^\ell$ for any combination of $j,k,\ell\in\{0,1,2,3\}$, i.e. a constant along with interactions of time spent on the waitlist and duration spent on treatments up to the third power observed in the data. Furthermore, let $\boldsymbol{x}_i(c)$ denote the matrix of these row vectors stacked across all t observed in the data. The BLP of the choice-conditional value function solves

$$\min_{\boldsymbol{\gamma}_i(c)}\left(\hat{\boldsymbol{v}}_i(c)-\boldsymbol{x}_i(c)\boldsymbol{\gamma}_i(c)\right)'\left(\hat{\boldsymbol{v}}_i(c)-\boldsymbol{x}_i(c)\boldsymbol{\gamma}_i(c)\right)$$

where the solution $\hat{\boldsymbol{\gamma}}_i(c)$ is taken to be the solution with the smallest L^2 norm in the case of multiple solutions.

There are several things to note in approximating the value function in this way. First, the fact that the solution has the smallest norm is important as this occurs frequently in

practice. In particular, there are many individuals who are not observed with any days spent on temporary treatments so that the typical least squares solution has many solutions unless the solution is taken to be the one with the smallest norm. Second, doing so is straightforward using the singular value decomposition of the matrix $\boldsymbol{x}_i(c)$ as described in Press et al. (1992, Chapters 2 and 15). Third, this approximation provides a flexible fit by approximating from the patient-choice value function. Even if the patient is not observed using a temporary treatment, it can approximate the probability the patient receives an initial date of temporary treatment which should be a low probability choice if the flow utility parameters fit reasonably well.

There are now two cases to consider for estimating the CCPs used in the forward simulation. Let the time spent on the waitlist be t, the vector of time-treatment duration interactions denoted by $\boldsymbol{x}$, and the characteristics of deceased donors offered in the period be denoted Z^d for $d = 0, \ldots, D$ where D denotes the number of donors and Z^0 is taken to be a 0 vector if there are no donors offered. Then, if the treatment durations are observed in the data, the CCPs can be estimated directly using

$$\widehat{\Pr}(y) = \frac{\exp\left[\hat{v}_{it}(y)\right]}{\sum_{\hat{y}=0}^{3} \exp\left[\hat{v}_{it}(\hat{y})\right] + \sum_{\hat{d}=0}^{D} \hat{\Gamma}_{\text{Tx}} Z^{\hat{d}}}$$

where $y = 0, 1, 2, 3$ denotes choosing no treatment, a durable treatment, a temporary treatment, or both, respectively. Similarly, the CCP of choosing to accept an offer for a heart transplant from donor d is given by

$$\widehat{\Pr}(d) = \frac{\exp\left[\hat{\Gamma}_{\text{Tx}} Z^{d}\right]}{\sum_{\hat{y}=0}^{3} \exp\left[\hat{v}_{it}(\hat{y})\right] + \sum_{\hat{d}=0}^{D} \hat{\Gamma}_{\text{Tx}} Z^{\hat{d}}}.$$

If the time and treatment durations are not observed in the data, then the estimated

BLP parameters are used to estimate the CCP. The CCPs for treatments are given by

$$\widehat{\Pr}(y) = \frac{\exp\left[\boldsymbol{x}\hat{\boldsymbol{\gamma}}_i(y)\right]}{\sum_{\hat{y}=0}^{3}\exp\left[\boldsymbol{x}\hat{\boldsymbol{\gamma}}_i(\hat{y})\right] + \sum_{\hat{d}=0}^{D}\hat{\Gamma}_{\mathrm{Tx}}Z^{\hat{d}}}.$$

The CCP for choosing a donor is given by

$$\widehat{\Pr}(d) = \frac{\exp\left[\hat{\Gamma}_{\mathrm{Tx}}Z^{d}\right]}{\sum_{\hat{y}=0}^{3}\exp\left[\boldsymbol{x}\hat{\boldsymbol{\gamma}}_i(\hat{y})\right] + \sum_{\hat{d}=0}^{D}\hat{\Gamma}_{\mathrm{Tx}}Z^{\hat{d}}}.$$

D.2.5 Value function interpolation

The forward simulation procedure needs to be done for each value of the state variables in the data because of the dependence of the value function on time and on the duration spent on each treatment. However, each of these state variables increments by no more than 1 for each additional observation in the data. As a result, interpolation is likely to be a useful way to reduce the amount of state variables used in the interpolation process. This is done by constructing a grid for each time interval on which the treatment decision is the same so that time spent on each treatment the patient receives increments by 1. Forward simulation is done on these grid points, reducing the number of forward simulations from more than 10 million to roughly 2 million. Chebyshev interpolation is then used to approximate the value function at the remaining points in the data that are not included in the grid. This is described in greater detail below.

Grid construction The forward simulation grid is constructed by first considering all treatment spells for each patient where a treatment spell is a time interval in which the patient receives the same treatments for each day. For example, if the patient receives only a temporary treatment from $t = 5$ to $t = 10$ then $5 \leq t \leq 10$ would be a single treatment spell. If there are 20 time periods or fewer in the treatment spell, then the treatment spell is left as-is without breaking the interval into a finer grid. These treatment spells typically correspond to receiving a temporary treatment, perhaps in combination with a durable treatment, or to

receiving no treatment prior to implantation of another treatment.

Longer treatment spells use Chebyshev grids where the grid points are rounded to ensure that the state variables are integers. If the spell has K grid points, then each grid point for time spent on the waitlist in the interval $[\underline{t}, \bar{t}]$ is constructed using the formula

$$\left[\frac{1}{\cos\left(\frac{\pi}{2K}\right)}\cos\left(\frac{(2k-1)\pi}{2K}\right)+1\right]\frac{\bar{t}-\underline{t}}{2}+\underline{t}$$

for $k = 1, \ldots, K$. Each of these values is rounded to the nearest integer to obtain the grid points used in this interval. Brutman (1978) demonstrates that these grid points reduce approximation error. Full details on grid construction are available in the associated Git Repo with the number of grid points increasing until reaching 80 grid points for sufficiently large intervals.

Chebyshev interpolation Consider a particular patient i with spells $s = 1, \ldots, S$ and associated grid points t_{sk} for $k = 1, \ldots, K_s$ where K_s denotes the number of points on the grid used for spell s. The forward simulation procedure gave the approximate choice-conditional value function $v_{it_{sk}}(c)$ for each grid point, k, in each spell, s. For a particular spell s, Chebyshev interpolation at remaining state variables in the interval first requires computing Chebyshev polynomials by the recursive relationship

$$\begin{aligned}
T_0(x) &= 1 \\
T_1(x) &= x \\
&\vdots \\
T_{k+1}(x) &= 2xT_k(x) - T_{k-1}(x), \text{ for } k = 1, \ldots, K-1.
\end{aligned}$$

Given Chebyshev polynomials, the coefficients for each Chebyshev polynomial in the

interpolation are computed using

$$a_j = \frac{\sum_{k=1}^{K} v_{it_{sk}}(c) T_j\left(\frac{1}{\cos\left(\frac{\pi}{2K}\right)} \cos\left(\frac{(2k-1)\pi}{2K}\right)\right)}{\sum_{k=1}^{K} T_j\left(\frac{1}{\cos\left(\frac{\pi}{2K}\right)} \cos\left(\frac{(2k-1)\pi}{2K}\right)\right)^2}.$$

The approximation at $t \in [\underline{t}_s, \bar{t}_s]$ is then

$$v_{it}(c) = \sum_{j=0}^{K-1} a_j T_j\left(2\frac{t-\underline{t}_s}{\bar{t}_s - \underline{t}_s} - 1\right).$$

Chebyshev interpolation results in a polynomial interpolation with a small uniform error. Additional details on Chebyshev interpolation are available in Rivlin (1990) and Judd (1998).

D.2.6 NPL estimation steps

The estimation procedure consists of the following steps:

1. Estimate state transition processes for donor arrival and patient survival using maximum likelihood as in (10) and (11).
2. Estimate initial CCPs using the logit model described in (12).
3. Forward simulate and interpolate to obtain choice-conditional value functions for each observation as described in D.2.3.
4. Estimate preference parameters using maximum likelihood with (9).
5. Estimate model-based CCPs as described above.
6. Repeat steps 3-5 until convergence in the log-likelihood.

E Counterfactual estimation

There are five counterfactual scenarios estimated:

1. Untransplanted: patient survival if they were not on the waitlist.

2. Previous waitlist design: patient survival if they were on the waitlist design in which durable and temporary treatments received similar priority.

3. Current waitlist design: patient survival if they were on the waitlist design in which temporary treatments received higher priority

4. Naive outcomes: patient survival if they received offers based on the current waitlist design but were given treatments using CCPs from 2.

5. Incentive-free outcomes: patient survival if they received offers based on the current waitlist design but were given treatments using CCPs from 1.

Much of the computation of these counterfactuals consists of estimating three sets of counterfactual conditional-choice probabilities corresponding to counterfactuals (1), (2), and (3). These are then used to simulate choices in counterfactuals (4) and (5).

These counterfactuals consist of changing the donor arrival process and the CCPs, so it is helpful to introduce notation to clarify the dependence of the counterfactual value function on these quantities. The choice-conditional value function (minus the preference shocks) will then be written as

$$\begin{aligned} v_{it}\left(c_t; \Pr_\mu\left(N|\cdot\right), \Pr_\mu\left(c|\cdot\right)\right) = u(x, y_{t-1}, y) \\ + \beta \Pr\left(a_{t+1} = 1 | x, y, t, \tilde{y}_{t-1} + y\right) \\ \times \sum_{n \in \mathbb{N}} \Pr_\mu\left(N_{t+1} = n | x, y, \tilde{y}_{t-1} + y\right) \mathbb{E}V(x, y, \tilde{y}_{t-1} + y, \hat{C}_{t+1}, \hat{\epsilon}) \end{aligned}$$

where $\Pr_\mu\left(N|\cdot\right)$ is shorthand for the conditional distribution of deceased donor arrivals under waitlist μ and $\Pr_\mu\left(c|\cdot\right)$ is shorthand for the conditional choice probabilities. The CCPs enter in the expected continuation value which is again approximated via forward simulation.

The counterfactuals can now be summarized by the associated values of the donor arrival process and the CCPs as follows:

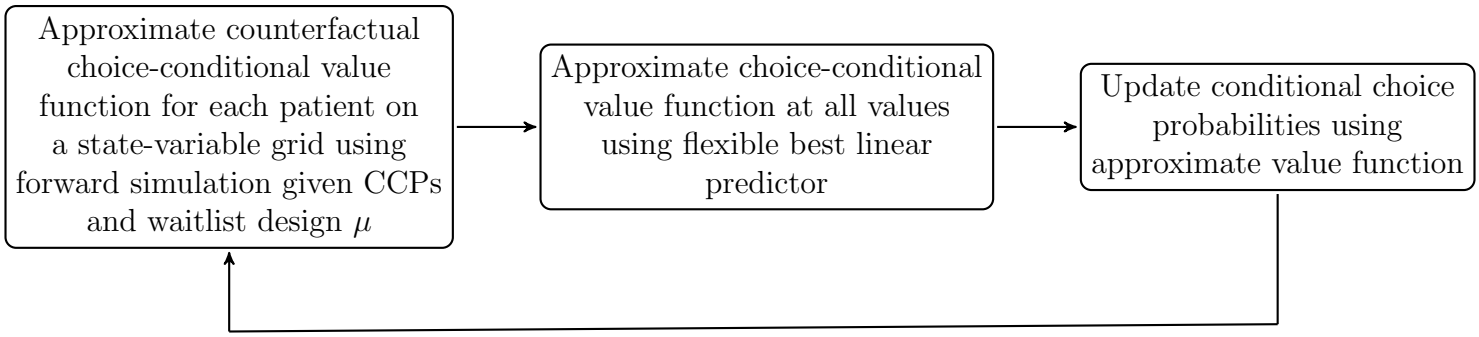


Figure E.15: Demonstration of iterative estimation of counterfactual conditional choice probabilities under no waitlist design (1), the previous waitlist design (2), or the current waitlist design (3).

1. Untransplanted: Set $\Pr_{\emptyset}(N > 0|\cdot) = 0$ and compute CCPs $\Pr_{\emptyset}(c|\cdot)$.

2. Previous: Set $\Pr_{\text{Prev.}}(N|x, y, \tilde{y})$ to the estimated arrival process under the previous waitlist design and compute CCPs $\Pr_{\text{Prev.}}(c|\cdot)$.

3. Current: Set $\Pr_{\text{Curr.}}(N|x, y, \tilde{y})$ to the estimated arrival process under the current waitlist design and compute CCPs $\Pr_{\text{Curr.}}(c|\cdot)$.

4. Naive: Set $\Pr_{\text{Curr.}}(N|x, y, \tilde{y})$ and $\Pr_{\text{Prev.}}(c|\cdot)$ to forward simulate patient outcomes.

5. Incentive-free: Set $\Pr_{\text{Curr.}}(N|x, y, \tilde{y})$ and $\Pr_{\emptyset}(c|\cdot)$ to forward simulate patient outcomes.

Given CCPs from (1)-(3), it is straightforward to estimate patient outcomes under (4) and (5) using the procedure given in Appendix D.2.3. The remainder of this section details the computation of these counterfactual CCPs.

E.1 Computing counterfactual CCPs

The procedure for estimating counterfactual CCPs is described in Figure E.15. First, the donor arrival process is set based on the corresponding counterfactual. Then, using the model-based CCPs as an initial value, the choice-conditional value function for each patient is forward simulated given the donor arrival process following the procedure described in Appendix D.2.3. The forward simulation is done at fixed values of t and $\tilde{y}_t$ for each patient.

In order to extrapolate to other points in the state space, the best linear predictor of the choice-conditional value function is estimated using a polynomial with interactions of the state variables (t and the components of $\tilde{y}_t$). This gives an approximation of the choice-conditional value function at all points in the state space that can be used to obtain CCPs at all points in the state space. These updated CCPs are then used to repeat the forward simulation and begin another iteration. This is repeated until convergence in the CCPs for each individual.