ESSAYS ON THE ECONOMICS OF ORGAN TRANSPLANTATION

By

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ABSTRACT

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Chapter 1: The Effect of Share 35 for Kidneys on Pediatric Transplant Candidates

Due to the shortage of donated kidneys in the United States, allocation policy is used to balance equity and efficiency in distribution of these scarce resources. I analyze the effect of a change in the allocation system for deceased donor kidneys called "Share 35" that gave priority to pediatric kidney transplant candidates over adult candidates for young deceased donor kidneys. Using data from the Scientific Registry of Transplant Recipients on all kidney transplant candidates in the US, I show that providing priority for pediatric candidates increased the average kidney quality by 30% and increased the likelihood of being transplanted within a year by 20 percentage points for pediatric candidates who are predicted to receive a deceased donor kidney in absence of Share 35. However, this policy also created an incentive for pediatric candidates with a living donor available to them to forgo using that donor to use a deceased donor instead. These candidates, who I estimate switch donor types, experience worse average kidney quality but no change in wait time. Additionally using the limited long run follow-up data available, the policy does not appear to have the unintended consequence of candidates with available living donors strategically "saving" their living donor for their second transplants when they would no longer have pediatric priority.

Chapter 2: The Effects of the Affordable Care Act on the Demand for Organ Transplants

Many potential transplant candidates are unable to be registered on the wait list to receive an organ for transplant due to their lack of insurance. With the introduction of the Affordable Care Act, some of these potential candidates obtained insurance coverage through state Medicaid expansions or through the introduction of the private insurance marketplace. In this paper, I estimate the effect of this increase in availability of insurance coverage on these potential transplant candidates' wait list decisions and transplant outcomes using a difference in differences model. I find that the state

expansions of Medicaid increased monthly wait list registrations by candidates insured through Medicaid by about 50 percent on average for all organs, but I find no effect of the marketplace on registrations. Additionally, I find that for candidates insured through Medicaid, the Medicaid expansion led to an increase in monthly deceased donor transplants for all organs, and a doubling of monthly living donor liver transplants.

Chapter 3: Opioids and Organs: How Overdoses Affect the Supply of Donors, Waiting Lists, and Transplant Outcomes (with Stacy Dickert-Conlin, Todd Elder, and Keith Teltser)

As the number of fatal drug overdoses has rapidly grown in recent years, patients awaiting organ transplants may be the unintended beneficiaries. In 2017, 70,237 people died due to a drug overdose, 5,795 transplant candidates died while waiting for an organ, and an additional 6,363 candidates were removed from waiting lists because they were too sick to accept a transplant. In this paper, we use mortality data from the National Vital Statistics System, merged with restricted-use data on transplant candidates and recipients from the Scientific Registry of Transplant Recipients, to study the extent to which the recent growth in fatal drug overdoses impacts the supply of deceased organ donations and transplants. We find that each opioid overdose death generates 0.019 additional organ donors, resulting in 0.053 additional organ transplants. Nearly all of this association is concentrated among donors aged 18-49, who account for the majority of opioid overdose victims. Somewhat surprisingly, opioid-driven supply shocks induce limited demand-side responses.

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The data reported here have been supplied by the Hennepin Healthcare Research Institute (HHRI) as the contractor for the Scientific Registry of Transplant Recipients (SRTR). The interpretation and reporting of these data are the responsibility of the author(s) and in no way should be seen as an official policy of or interpretation by the SRTR or the U.S. Government.

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CHAPTER 1

THE EFFECT OF SHARE 35 FOR KIDNEYS ON PEDIATRIC TRANSPLANT CANDIDATES

"The current system was not conceived as a unified allocation policy. When kidney transplantation began it was only offered to younger patients with minimal underlying comorbidities. Because all potential candidates looked more or less "the same," time spent waiting for a transplant was a reasonable proxy for need. Over time, as immunosuppression and patient management improved and the criteria for kidney transplantation became more inclusive, transplantation became the gold standard for treating end stage renal failure. With this development, the number of patients waiting for a kidney transplant swelled. In response to the increasing demand for organs, donor service areas (DSA) and [the United Network for Organ Sharing (UNOS)] regions began to modify the allocation system, through the incorporation policy variances, largely in an effort to address what was perceived as local problems with organ availability. The result was an allocation system that placed an overemphasis on waiting time, progressively downplayed biologic and immunologic considerations, failed to adapt to the changing needs of the patients being listed, and morphed into an overlapping patchwork of variances that rendered the implementation of any meaningful changes nearly impossible from an information technology perspective." - Richard Formica, MD, Yale University School of Medicine (2014)[1]

1.1 Introduction

Without a price mechanism to allocate deceased donor kidneys, the United States government mandates that the United Network for Organ Sharing [UNOS] creates an allocation policy that balances efficiency and equity in distributing this scarce resource. The difference between the supply of and the demand for these kidneys is huge. In 2017, more than 35,000 candidates entered the waiting list to receive a deceased donor kidney, but surgeons performed fewer than 15,000

[1]Source: https://www.myast.org/about-ast/presidents-blog/time-change-new-kidney-allocation-system

deceased donor transplants. This shortage highlights the critical effect that the allocation system has on candidates' lives: changes to the allocation system can determine whether a candidate ultimately receives a kidney or not.

In 2014, UNOS overhauled the kidney allocation system to implement an allocation scheme that matches the individual expected survival of a deceased donor kidney to the individual expected survival of a patient, which are both measured as continuous variables based on medical factors. This system replaced one that primarily allocated kidneys first to patients who had waited the longest, regardless of the characteristics of the patient or the donor kidney. But, there was one element of the pre-2014 system that included this "survival matching" in the allocation system. Specifically, Share 35, which UNOS introduced in 2005, gave pediatric candidates priority for young deceased donor kidneys. Share 35 recognized the longer post-transplant expected survival of children and gave them priority for kidneys that were thought of as lasting longer after transplantation. Pediatric transplant patients were a crude proxy for patients with high expected survival after transplantation and donors under the age of 35 were a crude proxy for high expected survival of a deceased donor kidney. Analyzing this first rudimentary attempt at longevity matching, provides insights into the intended and unintended consequences of the long run changes in the broader allocation reforms of 2014.

The goals of Share 35 were to have children waiting fewer days before a deceased donor transplant and also to allocate them deceased donor kidneys that were expected to last longer after transplantation (Moudgil et al., 2013). Giving pediatric patients priority for kidneys from young deceased donors reduces the cost of receiving a deceased donor transplant by reducing the wait time associated with it. Share 35 also increases the expected benefit of receiving a deceased donor transplant for pediatric patients by increasing the quality of the transplant. Unsurprisingly, the number of pediatric transplants that occurred using deceased donors that were less than 35 years old increased dramatically from 260 in 2004 to 552 in 2006. This represents an increase in the percent of pediatric deceased donor transplants that used donors who are less than 35 from 70 percent to 98 percent. Additionally, the median wait time for a pediatric deceased donor transplant

dropped from about 400 days in 2004 to only 300 days in 2006.

At first glance, these trends suggest that Share 35 achieved its intended effects of reducing wait time and improving kidney quality for pediatric candidates.[2] However, candidates can make behavioral changes in response to policy changes that can cause unintended consequences. Many examples of these behavioral changes have been previously documented: Sweeney (2011) and Choi (2019) find that candidates who receive Panel Reactive Antibody [PRA] priority in kidney allocation, which is based on their likelihood finding a match, are less likely to use a living donor as a result. Howard (2011) also finds that candidates are less likely to use a living donor when their expected wait time decreases. Fernandez et al. (2013) find that a decrease in the supply of deceased donors leads to more living donors being used. Finally, Dickert-Conlin et al. (forthcoming) find that an increase in the supply of deceased donors decreases the number of living donor transplants and that candidates are more likely to register in areas with increases in supply. It is likely that this behavioral change is also present in pediatric candidates' response to Share 35: between 2004 and 2006, the percent of annual pediatric transplants that used living donors dropped from 51 percent to 35 percent.

In this paper, I investigate whether a reallocation of high quality deceased donor kidneys from adults to children affects pediatric candidate behavior and their outcomes, as measured by wait time and kidney quality. Furthermore, I explore what the implications of the changes in pediatric candidates' behavior are for the effectiveness of the allocation policy.

Share 35 reduces expected wait time and improves expected kidney quality of a deceased donor transplant for pediatric patient. As a result, candidates who do not have a living donor, and need to use a deceased donor, should experience shorter wait times and improved kidney quality. However, because asking someone to give up a kidney may be emotionally costly, this expected improvement

[2]In fact, existing medical literature documents this reduction of wait time and improvement in kidney quality (Agarwal et al., 2009; Abraham et al., 2009). However, these estimates are not causal and do not account for the change in composition of pediatric deceased donor recipients after Share 35 that results from some pediatric candidates switching from using living to deceased donors. In this paper, I find that this change in composition counteracts the expected improvements in candidates' outcomes.

to deceased donor transplants from Share 35 may also cause some pediatric candidates to now use a deceased donor when without Share 35 they would have used a living donor. For most pediatric patients, this living donor would have been a parent. These parents, who are involved in the kidney transplant decision process, now avoid the costs of giving up their kidney. Living donor kidney transplants require less wait time and typically involve higher quality kidneys than deceased donor transplants (Hardy et al., 2009; Dale-Shall et al., 2009; Mercy Health, 2018), so these candidates who switch are potentially worse off with respect to wait time and kidney quality. Because candidates who receive a deceased donor transplant are likely better off but candidates who switch away from using a living donor are likely worse off with respect to wait time and kidney quality, the overall effects of the policy change on pediatric candidates' outcomes are ambiguous. Additionally, because children typically have many more years to live after receiving a transplant, Share 35 may incentivize children to "save" their willing living donor for a future necessary additional transplant when they no longer have pediatric priority.

I use data from the Scientific Registry of Transplant Recipients [SRTR] from 1998 to 2019 that includes the universe of all transplant candidates, recipients, deceased donors, and living donors in the United States. By comparing the outcomes of pediatric candidates to young adults' before and after Share 35, I find that Share 35 increases the likelihood that a pediatric candidate receives a transplant within a year by 10 percentage points and slightly improves average kidney quality. By additionally exploiting differences in observable characteristics between deceased and living donor transplant recipients, I also estimate that pediatric deceased donor recipients who would have used a deceased donor in absence of Share 35 are 20 percentage points more likely to receive a transplant within a year and have an average improvement in kidney quality of 8.4 points. In contrast, I estimate that candidates who switch from using a living to deceased donor are transplanted with kidneys that are 11.8 points lower quality on average, but do not have any change in their wait time. Finally, using variation in eligibility for Share 35 priority at first transplant, I find that candidates who had Share 35 priority for their first transplant are not significantly more likely to use a living donor for their second transplant although they are 17 percentage points less likely to use a living

donor for their first transplant.

The paper proceeds as follows: In section 1.2, I provide an overview of pediatric kidney transplants and a brief explanation of deceased donor kidney allocation. In section 1.3, I present a conceptual framework which motivates my empirical methods. In section 1.4, I describe the data that I use and provide descriptive statistics. In section 1.5, I estimate the effects of Share 35 on pediatric candidates' transplant outcomes and behavior. In section 1.6 I show that my results are robust to excluding groups of candidates that could potentially manipulate their treatment status. Finally, section 1.7 concludes.

1.2 Environment

When someone's kidneys stop functioning, they are diagnosed with End-Stage Renal Disease [ESRD] (MedlinePlus, 2015). Although most adults develop ESRD due to diabetes or hypertension, most pediatric patients develop ESRD due to glomerulonephritis or congenital diseases (SRTR, 2014; USRDS, 2018). Patients with ESRD have two treatment options: dialysis or a kidney transplant (MedlinePlus, 2015). If a patient choses dialysis, a dialysis machine will clean their blood, replicating the work that their functioning kidneys would do. However, patients using dialysis typically need three treatments a week, where each treatment lasts for about four hours.(NKF, 2019) A kidney transplant is associated with better survival and quality of life than dialysis, so many patients try to receive a kidney transplant instead of using dialysis long-term (SRTR, 2014). For pediatric patients with ESRD, kidney transplants also offer another benefit over dialysis: improved growth and development (Smith & Dharnidharka, 2014; Sharma et al., 2013). Kidney specialists recommend pediatric patients pursue transplants instead of using dialysis long-term because of these developmental concerns (Smith & Dharnidharka, 2014; Sharma et al., 2013).

Before transplantation, physicians evaluate match quality between potential donor kidneys and the intended transplant recipient. A necessary condition for receiving a donor kidney is that it must have a compatible blood type with the intended recipient. Potential kidney matches are also evaluated for how many of the six human leukocyte antigen [HLA] mismatches they have. A

higher number of HLA mismatches increases the chance of graft failure, which occurs when the patient's transplanted kidney stops functioning or is rejected by the patient's body. Recipients take immunosuprressive drugs after transplantation to reduce the risk of graft failure. These drugs do not completely eliminate graft failure; 51% of deceased donor kidney transplant recipients and 34% of living donor kidney recipients experience graft failure at some point within 10 years after their transplant (SRTR, 2014). Because most pediatric patients will experience graft failure at some point, this creates the need for multiple kidney transplants over their lifetime.

Kidneys used in transplants come from one of two sources: living donors or deceased donors. Because the body only needs one working kidney, one of a living person's two kidneys can be donated to a transplant candidate if they are compatible. Most of the time, living donors are family members of the transplant candidate (SRTR, 2014). Many patients who use a living donor do not register on the deceased donor waiting list. Because these patients do not need to wait for a deceased donor kidney offer and they only need to wait for their potential living donor to be evaluated for suitability for transplant, living donor recipients typically spend less time waiting to receive a transplant. Many transplant centers prefer living donor kidneys over deceased donor kidneys because living donor kidneys are associated with better patient outcomes after transplantation (SRTR, 2014).

If a transplant candidate wants to receive a deceased donor kidney, they must register on the waiting list.[3] Because of the shortage of deceased donor kidneys, most patients will spend a significant amount of time waiting for a kidney before they can undergo transplantation. For example, the median wait time for adults who registered in 2000 was 724 days and the median wait time for pediatric candidates was 342 days.[4]

For the purpose of deceased donor kidney allocation, the United States is divided into 58 Donation Service Areas [DSAs] within 11 regions (UNOS, 2017a). When an Organ Procurement

[3]Until September 1, 2014, if a candidate was receiving a living donor kidney, they were not required to register on the waiting list. Source: `https://optn.transplant.hrsa.gov/media/1281/policynotice_20140815.pdf`

[4]Source: Author's calculations from SRTR data

Organization [OPO], the governing body of the DSA, collects a deceased donor kidney, they enter the donor's information into the United Network for Organ Sharing's [UNOS] system. This system also contains information on all kidney transplant candidates currently on the waiting list. Using this information, UNOS creates a unique listing of all blood type compatible candidates for that kidney (UNOS, 2017a). The candidates on the list are ranked according to the current allocation policy, and the highest ranked candidate on the list is offered the kidney first (UNOS, 2017a). At the time of Share 35, allocation policy offered kidneys first to candidates who were registered in the same DSA as the donated kidney. If the kidney was not accepted by someone in the same DSA as the kidney, the list was expanded to candidates in the same region as the donated kidney. If no one in the same region accepted the kidney, the list was expanded to all other compatible candidates. Within each of these geographic categories, candidates were further split into categories based on the number of HLA mismatches they have with the donated kidney, and then within each of these subgroups, candidates were ranked by the number of points they have. Candidates earned points for many different reasons. For most candidates, a majority of their points would be earned from the amount of time they spent waiting to receive a transplant.[5] If the first person on a list turned down an offered kidney, the OPO offered the kidney to the next person on the list. The OPO continued making offers down the list until a candidate accepted or the kidney was discarded due to spending too much time outside of the body.

Due to concerns that pediatric candidates were not receiving transplants fast enough and that they were frequently turning down offers for deceased donor kidneys from older donors, OPTN revised the allocation system on September 28, 2005[6] to give additional priority to pediatric candidates

[5]Candidates can register on the waiting list as soon as they obtain approval from a transplant center. However, adult candidates are listed as "inactive" and do not accrue waiting time until their kidney function reaches a sufficiently low level. Pediatric candidates do not have this restriction and accrue waiting time as soon as they are placed on the list.

[6]This change to the policy document can first be seen in the November 19, 2004 document with the note that "The amendment ... shall be implemented pending distribution of appropriate notice and programming on the UNOS Computer, if and as applicable." The policy change also appears with the same note in the June 24, 2005 policy document. I follow Smith et al. (2012) who list September 28, 2005 as the start date of the policy.

for kidneys from deceased donors under 35 years of age (Smith et al., 2012).[7] Candidates received pediatric status if they were under 18 years old at the time that they registered on the waiting list and retained their pediatric status until they received a transplant or were otherwise removed from the waiting list (OPTN Policy 3.5.11.5.1; UNOS, 2010).[8] When a kidney from a deceased donor under 35 years of age became available, in each subgroup of geographic category and HLA mismatches, the allocation rule placed pediatric patients above adult patients, regardless of the number of points assigned to the adult candidates (OPTN Policy 3.5.11.5.1).[9] This allocation change is illustrated using a hypothetical wait list in Appendix Figure D.1.

1.3 Conceptual Framework

Suppose a pediatric candidate needs a kidney transplant. If the parent of the pediatric candidate has a compatible blood type with their child, the parent can decide to donate one of their kidneys to their child.[10] To make this decision, the parent compares the costs and benefits of donating their own kidney to the costs and benefits of their child receiving a deceased donor kidney. The parent cares about three aspects of the donated kidney that their child receives: the expected wait time associated with the kidney (less time on dialysis is better), the expected quality (expected graft survival) associated with the kidney, and the costs associated with the donation of the kidney. If a parent donates one of their kidneys, they have emotional costs from going through surgery and

[7]The age of 35 was picked to try to give pediatric patients priority for kidneys with the best expected graft survival. Since there was no official measure of expected graft survival at the time, the age of 35 was selected as a proxy for expected graft function (Anne Paschke, personal communication, March 22, 2017).

[8]Organ allocation policy from the past is not publicly available. I received the deceased kidney allocation policy from November 18, 2005 through correspondence with UNOS. This section is based off of information contained in that policy document.

[9]If there were multiple pediatric patients in a group for a kidney from a donor who was less than 35 years old, candidates who were less than 10 years old at the time of the match received one additional point (OPTN Policy 3.5.11.5.1).

[10]If a parent is incompatible with their child, the child will either need to wait to receive a deceased donor kidney or the family can choose to seek out a different compatible living donor. For simplicity I do not model the search for a different living donor. Approximately 80% of pediatric living donors are the parent of the patient so this simple model is representative of a majority of pediatric candidates.

from losing a kidney.[11] If a child receives a deceased donor kidney, the family does not have any costs associated with that donation.[12] Because of this, suppose the cost for a parent of donating their own kidney is higher than the cost of using a deceased donor.

By giving pediatric candidates priority for kidneys under 35 years old, Share 35 reduces the expected wait time for a deceased donor kidney and improves the expected quality of a deceased donor kidney, all else equal.[13] There are at least two margins along which all else may not be equal: pediatric candidates may change the types of kidneys they are willing to accept after Share 35 or the deceased donor waiting list may change. If pediatric candidates expect to receive more kidney offers, they may become more selective with the types of kidneys they will accept. If Share 35 induces more pediatric candidates to register on the wait list then these marginal pediatric wait list additions could be placed above originally wait listed pediatric candidates. Both of these changes in candidate behavior could counteract the expected reduction in wait time from Share 35. However, because pediatric candidates have an incentive to avoid extended dialysis use (Smith & Dharnidharka, 2014; Sharma et al., 2013), and because the effects of these two behavioral changes should be small compared to the mechanical effect of Share 35, pediatric candidates should still expect to have shorter wait times with deceased donor transplants after Share 35. Because of this, I hypothesize that after Share 35, pediatric deceased donor recipients will on average receive higher quality kidneys and shorter wait times. In section 1.5.4 I empirically test this hypothesis.

To justify why I might expect to see additional pediatric candidates join the wait list for a deceased donor kidney, suppose a parent is considering donated their kidney to their child. They chose to donate their kidney if their expected utility from donating is greater than their expected utility from their child joining the wait list and receiving a deceased donor kidney. Then a parent will donate if the benefits of a better quality kidney and shorter wait time for their child outweigh

[11] The child's insurance will pay for the surgery that removes the kidney from the living donor but will not cover any lost wages while the donor is recovering from the surgery.

[12] Transplant recipients do not pay for the donated organs that they receive.

[13] Appendix Figure D.2 shows that there were enough deceased donors younger than 35 for every pediatric candidate to receive a kidney from one so pediatric candidates should not have concerns about there not being enough kidneys from donors less than 35.

the additional cost of donating their own kidney. After Share 35, the expected quality and wait time for a deceased donor kidney improves, which increases the expected utility from a deceased donor kidney without changing the expected utility of a parent donating their own kidney. Because of this, I hypothesize that Share 35 reduces the number of living donor transplants. I empirically test this hypothesis in Section 1.5.2.

Living donor kidneys are associated with better quality and shorter wait times than deceased donor kidneys before Share 35 (SRTR, 2014). Because Share 35 improves the expected wait time and kidney quality of deceased donor kidneys, pediatric candidates who have their parent no longer donate to them as a result of Share 35 have an ambiguous effect on their wait time and kidney quality. I estimate this effect empirically in Section 1.5.5.

Because I have two competing effects of Share 35 on pediatric candidates: one that improves deceased donor transplants, and one that induces some candidates to switch from potentially higher quality and shorter wait time living donors to deceased donors, the overall effect of Share 35 on pediatric candidates' outcomes is ambiguous. I empirically estimate this effect in Section 1.5.1.

The decision of a parent to donate to their child may also incorporate the expected future subsequent transplants of the child. Consider instead if candidates need two transplants: one as a pediatric candidate and one as an adult. Parents decide both if and when they want to donate by maximizing their total expected utility of the two transplants. This leaves a parent with three options: never donate, donate when their child has pediatric status, or donate when their child is an adult. If Share 35 improves expected outcomes for pediatric deceased donor transplants, then parents have less of an incentive to donate when their child is pediatric. If a parent does not donate when their child is pediatric, the parent will be available to donate when their child is an adult. Because of this, I hypothesize that after Share 35, pediatric candidates should be more likely to use a living donor when they are an adult. I empirically test this in Section 1.5.6.

1.4 Data and Descriptive Statistics

This study uses data from the Scientific Registry of Transplant Recipients (SRTR). The SRTR data system includes data on all donors, waitlisted candidates, and transplant recipients in the US, submitted by the members of the Organ Procurement and Transplantation Network (OPTN). The Health Resources and Services Administration (HRSA), US Department of Health and Human Services, provides oversight to the activities of the OPTN and SRTR contractors. The SRTR dataset contains individual level information on all kidney transplant candidates and transplant recipients in the United States. From October 1987 to March 2019, I observe basic demographic information and clinical information about every candidate who registers on the waiting list. Additionally, I observe candidate information at any transplants they receive and the characteristics of the donor. I also can link all recipients to any follow up visits, future waiting list registrations, and transplants. All candidates registered on the wait list are followed until their death regardless of transplant status, upon which I observe the date and cause of death.

I restrict my sample to kidney-only transplant recipients who are 0 to 21 years old.[14] Additionally, I restrict my sample to first time transplant recipients because the choice of living or deceased donor is more similar among candidates without prior transplants than for candidates with prior transplants.[15] I define a candidate as being "pediatric" if they are less than 18 and "young adult" if they are 18 to 21 years old. I also restrict my sample to candidates who receive a transplant between the years 1998 and 2013 due to inconsistency in the recording of key variables before 1998 and the substantial change in the allocation rules in 2014.[16] I define each candidate as belonging to the "Pre-Share 35 cohort" if they received a transplant before September 28, 2005 or as belonging to

[14] Because dual-organs are allocated differently from only kidneys, I exclude candidates who are listed for dual-organs from my sample. These dual-organ registrations are rare among pediatric candidates; between October 1987 and March 2018, there have only been 118 kidney-pancreas pediatric registrations.

[15] 15% of pediatric candidates before Share 35 had prior kidney transplants. 25% of young adult candidates had prior kidney transplants.

[16] I further restrict my sample to recipients who are not missing information on their diabetes type. This removes 38 recipients from my sample.

the "Share 35 cohort" if they received a transplant after September 28, 2005.[17]

In this paper, I evaluate Share 35's effect on two outcomes for transplant recipients: wait time and kidney quality.[18] A candidate's wait time captures the amount of time a candidate spends waiting before their transplant. I observe transplant dates for all candidates who receive a transplant, regardless of their donor type, but because not all living donor recipients register on the waiting list before their transplant, I use the candidate's HLA typing test date for the start of wait time instead of registration on the waiting list.[19] Additionally, I use this date to define a candidate's age.[20] The HLA typing test is a blood test that is one of the first things that is done when someone needs a transplant, regardless of whether they plan to obtain a deceased or living donor transplant(NIDDK, 2018). The results of this test are used to determine the number HLA mismatches a candidate has with a potential donor kidney.

To measure kidney quality I combine two measures of quality: the Kidney Donor Profile Index [KDPI] and the Living Kidney Donor Profile Index [LKDPI].[21] For deceased donor kidneys I use the official measure of kidney quality, KDPI. This measure is used by the new kidney allocation

[17]Some candidates register in the Pre-Share 35 era and receive a transplant in the Share 35 era. I define these candidates as part of the Share 35 cohort since they receive Share 35 priority after it is introduced.

[18]Previous papers (Choi, 2019; Dickert-Conlin et al., forthcoming; Teltser, forthcoming) use graft survival instead of kidney quality. I use kidney quality because it is only calculated from donor factors so it is independent of the transplant recipient. Graft survival can reflect both kidney quality and characteristics or behaviors of the recipient.

[19]I present summary statistics of my measure of wait time and the measure of wait time that uses registration date in Appendix Table D.1. The first column looks at how the two measures differ for deceased donor recipients. The second column shows the two measures for living donor recipients who registered on the waiting list before their transplant. For both groups of recipients, the average test date measure of wait time is longer than the average registration version of wait time, however, the average difference between the two measures is not statistically different from zero. Additionally, the average difference between the two measures across donor types is not statistically significant.

[20]I do not observe a candidate's age at this date or a candidate's birthday. Instead I observe a candidate's age in months at their transplant date and subtract from this age the number of months between the transplant date and the HLA test date.

[21]Some candidates in the early years of my data are missing information in variables needed to compute KDPI and LKDPI. I impute values for donor weight, height, creatinine level, and systolic blood pressure using sample means conditioned on donor age, gender, and race.

system introduced in 2014 to help match kidneys with longer expected graft survival to patients with longer expected post-transplant survival (OPTN, 2017).[22] The KDPI uses ten donor factors to compare the quality of a deceased donor kidney to all other recovered deceased donor kidneys (OPTN/UNOS, 2016). These ten factors include donor age, height, weight, ethnicity, and other medical characteristics of the donor (OPTN/UNOS, 2016).[23] The KDPI incorporates all of these factors into a single number that ranges from 0 to 100 where lower KDPI scores are associated with a lower risk of post transplant graft failure (OPTN/UNOS, 2016). One limitation of using this measure of kidney quality is that KDPI "is not a precise enough tool to differentiate with high confidence the quality of kidney donors with only slight differences in KDPI" (OPTN/UNOS, 2016).

For living donor kidney quality I use the measure proposed by Massie et al. in their 2016 article. By extending the KDPI, they allow comparisons between both living and deceased donor kidneys.[24] The LKDPI is constructed on the same scale as the KDPI, but, unlike the KDPI, LKDPI is not restricted to lie between 0 and 100. Massie et al. allow the LKDPI to be unbounded to account for the fact that living donor kidneys have better expected graft survival than deceased donor kidneys.[25] Hereafter I refer to both KDPI and LKDPI as KDPI. A kidney with a lower KDPI score represents a better quality kidney with respect to expected graft survival, regardless of whether the donor was deceased or living.

To difference out any other changes that might be happening over time I use young adults as a comparison group for the pediatrics because they are close in age. There is no control group in this setting that is completely unaffected by Share 35. When one candidate is moved up the wait

[22] Although the measure was officially introduced in 2014, I can use the formula to also compute this measure for kidneys used before the measure was introduced.

[23] Specifically, the KDPI calculation includes the age, height, weight, ethnicity, history of hypertension, history of diabetes, cause of death, serum creatine, Hepatitis C Virus status, and donation after circulatory death status of the deceased donor (OPTN/UNOS, 2016).

[24] The LKDPI calculation includes the following donor factors: age, eGFR, race, history of cigarette use, gender, blood type, relation to potential recipient, HLA mismatches with the potential recipient, and the donor/recipient weight ratio (Massie et al., 2016).

[25] Among pediatric and young adult living donor recipients in my sample, LKDPI ranges from -67.9 to 84.2.

list, mechanically, at least one candidate must be moved down the wait list. Because young adults are only affected by Share 35 through pediatric patients potentially being moved above them on the wait list, the effect of Share 35 on them is likely to be very small.[26] Additionally, although OPTN defines a patient as "pediatric" if they are under 18, the United States Renal Data System [USRDS] defines a patient as "pediatric" if they are under 22 (SRTR, 2014; USRDS, 2018). Several pediatric transplant centers also advertise that they accept "young adult" patients.[27] Table A.1 presents summary statistics on pediatric and young adult candidates in my sample. For comparison, I also include summary statistics on adult candidates (older than 21 years old) who are not in my estimation sample. Although all three groups are similar in terms of sex, race, blood type, and insurance distributions, adult candidates are on average more than 35 years older than pediatric candidates. Additionally, adult candidates are 27 percentage points more likely to have diabetes than pediatric or young adult candidates. Because of these large differences between pediatric and adult candidates, I restrict my comparison group to only young adults, instead of including all adult candidates.

[26] Appendix Figure D.1 illustrates this with a hypothetical wait list change as a result of Share 35. The pediatric candidates are moved up significantly on the wait list but the young adult only moves down one position. Note that this hypothetical wait list only contains 15 candidates. In reality, wait lists usually contain at least 100 candidates, and many wait lists have several thousand candidates on them (Source: `https://optn.transplant.hrsa.gov/data/view-data-reports/build-advanced/`). Since real wait lists are much longer than this example, the effect of being moved up the wait list for pediatric candidates would be even larger than this figure illustrates, and the effect of young adult candidates being moved down would be even smaller in proportion to the size of the wait list.

[27] For example, Seattle Children's Kidney Transplant Program accepts ages up to 21, Driscoll's Children's Hospital Kidney Transplant Program and Kidney Center say their recipients "range in age from 1 to 21 years old", and Texas Children's Hospital "has transplanted kidney in children from newborns to young adults". Additionally, children up to age 21 are eligible for Medicare coverage of their ESRD treatment (Source: `https://www.medicare.gov/people-like-me/esrd/children-and-esrd.html`)

1.5 Effect of Share 35 on Pediatric Kidney Transplant Recipients

1.5.1 Effect of Share 35 on all Pediatric Recipients

My conceptual framework implies that the overall effect of Share 35 on wait time and quality for pediatric candidates is ambiguous because of two competing effects: the improvement of deceased donor transplants for pediatric recipients because of Share 35 and the behavioral change of candidates switching from using a living to a deceased donor. The panel on the left in Figure A.1 shows the improvement from Share 35: approximately 200 more pediatric candidates were receiving transplants that used younger deceased donor kidneys every year while there was not any change in the amount of young adults receiving young deceased donor kidneys. But, as is evident in the panel on the left in Figure A.2, the behavioral change as a result of Share 35 is significant: it appears that about 100 pediatric candidates switch from using living donors to using deceased donors instead every year while there is no change in the living donor use of young adults. These two effects potentially counteract each other when considering the effect of Share 35 on all pediatric recipients. For example, Figure A.3 shows the percent of pediatric and young adult recipients in my sample who are transplanted within a year over time. In the figure, pediatric wait time does not appear to change after Share 35 but young adult wait time increases. Figure A.4 illustrates the trends in average KDPI across years among recipients in the same sample. Pediatric and young adults trend similarly with respect to kidney quality both before and after Share 35 is introduced.

In order to obtain estimates of these effects I now move to a regression model. To difference out unobserved changes that are common across transplant recipients, like changes in deceased donor kidney supply or quality, I use a difference in differences model where my comparison group is

young adult kidney transplant recipients.[28] Specifically, I estimate the following model:

$$y_i = \beta_1 Share_i + \beta_2 Pediatric_i + \beta_3 Share_i * Pediatric_i + \mathbf{x_i}\gamma + u_i, \tag{1.1}$$

where $y_i = 1$ if recipient i was transplanted within 3, 6, 12, or 18 months or where y_i is the KDPI of the kidney that was used in recipient i's transplant. $Share_i$ is a dummy variable that indicates whether individual i received a transplant before or after Share 35. $Pediatric_i$ =1 if individual i is less than 18 years old when they start waiting for a transplant. β_3 is my coefficient of interest; it represents the causal effect of Share 35 on wait time or kidney quality. $\mathbf{x_i}$ includes age at start of wait time, gender, insurance type, race, blood type, transplant year, diabetes status, highest PRA score, citizenship status, functional status, diagnosis that lead to ESRD, DSA level fixed effects, an indicator for if candidate i was ever inactive on the wait list, and an indicator for whether candidate i opted into receiving Expanded Criteria Kidney[ECK] offers.[29]

Table A.2 shows the estimated coefficients of equation (1.1) on the entire sample of pediatric and young adult deceased and living kidney recipients. Columns 1 through 4 show that Share 35 significantly improved wait time before transplant for pediatric recipients relative to young adults. The estimated coefficient on $Share * Pediatric$ in Column 1 implies that Share 35 increased the

[28] By using a sample of only transplant recipients, there is the potential for bias in my estimates if Share 35 changes who among pediatric and young adult candidates receives a transplant. I am not concerned about this change for pediatric candidates because an overwhelming majority of them were receiving transplants before Share 35. In Section 1.5.3 I elaborate on this argument. The main concern that one might have about young adult recipients is that by giving pediatric candidates priority, young adult candidates are moved down the wait list, and therefore might be less likely to receive a transplant. The right hand panel of Figure A.1 illustrates that this is not the case. Young adults receive the same number of deceased donor transplants after Share 35 as they did before it was introduced. Additionally one might believe that young adult candidates might have an increased incentive to find a living donor after Share 35. The right hand panel of Figure A.2 shows that even if this is the case, they are not able to find these living donors; young adults are receiving approximately the same number of living donor transplants before and after Share 35.

[29] ECK status kidneys were introduced on October 30, 2002 to address the growing shortage of deceased donor kidneys. ECK status kidneys are older than kidneys that were previously accepted as deceased donor kidneys. Only 6% of pediatric deceased donor recipients between 2002 and 2013 opted into receiving these offers. However, among young adult deceased donor recipients in this same time period, 25% opted into these offers. This difference in opt in rate is not surprising since it is logical that older candidates would be more willing to accept older kidneys.

likelihood of a pediatric patient receiving a transplant within 3 months, relative to a young adult recipient, by 4 percentage points. Compared to the percent of pre Share 35 pediatric recipients receiving a transplant within 3 months of 16%, this is a substantial increase in likelihood. Columns 2, 3, and 4 show even larger increases in likelihood receiving a transplant within 6, 12, or 18 months after Share 35 for pediatric recipients.

Column 5 of Table A.2 shows the estimated coefficients of equation (1.1) on the same sample of pediatric and young adult deceased and living kidney recipients, where $y_i = KDPI_i$. The estimated coefficient on $Share * Pediatric$ implies that Share 35 slightly improved average kidney quality of pediatric recipients by 1.7 points, relative to young adult recipients. This is consistent with my hypothesis that the improvement in quality for pediatric deceased donor recipients could counteract any decline in quality that candidates who switch from using a living donor kidney to a deceased donor kidney experience.

The key assumption of my difference and difference design is that pediatric and young adult deceased donor recipients would have had parallel trends in wait time and kidney quality in the absence of Share 35. To assess the plausibility of this assumption, I estimate a variation of equation (1.1) that allows for the effect of Share 35 to vary by transplant year. For ease of notation, I introduce the subscript t for the year during which recipient i receives their transplant and the subscript a for the age of recipient i:

$$y_{ita} = \alpha_t + \delta_a + \sum_{\tau=1998}^{2002} \beta_\tau 1(\tau = t) * Pediatric_i + \sum_{\tau=2004}^{2014} \beta_\tau 1(\tau = t) * Pediatric_i + \mathbf{x_i}\gamma + u_{ita} \quad (1.2)$$

If the assumption of parallel trends holds then the estimated pre Share 35 transplant year β_τ's should be approximately zero, representing that pediatric and young adult candidates have parallel trends in wait time or kidney quality before the policy change. Figures A.5 and A.6 plot the estimated betas from equation (1.2), where the betas measure the change in that year compared to the base year of 2003. I use 2003 as the base year because the policy was announced publicly before it was implemented.[30] In Figures A.5 and A.6, the coefficients are approximately zero before the policy

[30] 2003 is the year before the policy was announced, and therefore is before any changes in

change, representing that there are no significant differences in trends in wait time and kidney quality between pediatric and young adult recipients before Share 35. The lack of evidence of differential trends before Share 35 supports my assumption of parallel trends before Share 35. The coefficients start to diverge after Share 35 was introduced, representing the differential effect that the priority had for pediatric recipients over young adult ones.

These results suggest that although Share 35 improved wait time for pediatric candidates, on average, candidates did not experience large improvements in kidney quality. One likely explanation for the lack of quality improvement is that some candidates switched from using a living donor to using a deceased donor, changing the composition of who receives a deceased donor transplant after Share 35. The composition of pediatric deceased donor recipients after Share 35 may include new transplants recipients who would not have received a transplant in absence of Share 35, deceased donor transplant recipients who would have received deceased donor transplants in the absence of Share 35, and deceased donor recipients who would have received living donor transplants in absence of Share 35. I now turn to considering the effect of Share 35 on each of these different groups of recipients separately.

1.5.2 Crowd out in Living Donors for First Transplant

Because Share 35 improves expected kidney quality and wait time for pediatric deceased donor transplants, some pediatric candidates are likely to switch from using a living donor to using a deceased donor instead. Figure A.7 shows that this switch was very dramatic. The percent of pediatric first transplants that used a living donor drops by about 20 percentage points after Share 35 while the percent for young adults remains constant. 75% of pediatric living donors before Share 35 are the parent of the pediatric recipient and 52% of young adult living donors are parents

transplant decisions might be changed as a result of Share 35. For example, a pediatric candidate might decide not to use their living donor after hearing that they would be receiving Share 35 priority next year. This candidate would register on the wait list in anticipation of the implementation of the policy but could receive and accept an offer of a young deceased donor kidney before Share 35 takes effect.

of the recipient.[31] These parents would be likely to consider the future transplants that their child might need so although the decline in living donors in Figure A.7 may be due to the improvement in expected wait time and quality of deceased donor transplants from Share 35, it also could be due to pediatric recipients strategically "saving" their living donors for future transplants.

To quantify this decline for pediatric candidates, I estimate equation (1.1) where y_i is $LivingDonor_i$. $LivingDonor_i = 1$ if recipient i uses a living donor for their first transplant and = 0 if recipient i uses a deceased donor. The vector $\mathbf{x_i}$ includes the same controls as it did in Section 1.5.1. I estimate equation (1.1) using OLS on my whole sample of deceased and living donor recipients before and after Share 35. Here β_3 represents the change in likelihood of a pediatric recipient using a living donor because of the introduction of Share 35.

The estimated coefficients from equation (1.1) where y_i is $LivingDonor_i$ on the entire sample of pediatric and young adult deceased and living kidney recipients are presented in Table A.3. The estimated coefficient on $Share * Pediatric$ implies that Share 35 caused a statistically significant decrease in the probability that a pediatric candidate uses a living donor by 17 percentage points, relative to young adult candidates, on average. Multiplying this coefficient by the approximately 800 pediatric transplants that occur each year, means that about 136 fewer pediatric transplants use a living donor each year after Share 35. I hypothesize that this decline in the probability of using a living donor is due to these candidates saving that living donor for a future transplant. I look for evidence of this effect in Section 1.5.6.

In order for β_3 to have a causal interpretation, pediatric and young adult candidates must have common trends in likelihood of using a living donor. To assess the plausibility of this assumption, I estimate equation (1.2) where y_{ita} = is $LivingDonor_i$. Figure A.8 plots these estimated betas. The estimated betas are approximately zero before Share 35, supporting the assumption that there is no difference in trends in living donor use between pediatric and young adult recipients before Share 35.

[31] Other potential living donor sources include siblings, children, other relatives, spouses, or friends.

1.5.3 Effect of Share 35 on New Pediatric Transplants

One assumption that I need to make for my estimation of the effect of Share 35 on pediatric candidates who always would have received a deceased donor transplant is that Share 35 did not create any new pediatric deceased donor transplants. Because of this assumption, before moving to estimating the effects of Share 35 on wait time and kidney quality on pediatric deceased donor recipients, I first argue that Share 35 did not create any new pediatric transplants. Because Share 35 improved deceased donor transplants for pediatric candidates, one might expect that this led to more pediatric candidates receiving transplants who would not have received one without Share 35. The rest of this section shows that this is unlikely. First, Figure A.9 adds an additional line onto Figure A.2 that shows the total number of pediatric transplants over time. This figure shows that although there are more yearly pediatric transplants after Share 35, the increase in transplants is actually a trend that started before Share 35. Starting in 2000, the number of pediatric transplants increased until 2006, after which the total number of transplants starts to decline. This suggests that Share 35 did not increase the total number of transplants.[32]

Additionally, if Share 35 did create new transplants, they could come from two sources: increasing the proportion of pediatric wait list registrations that lead to transplants or from inducing more pediatric patients with ESRD to try to get a transplant earlier or even, rather than remaining on dialysis in the near future. Figure A.10 shows the trend in the percentage of wait list registrations by all pediatric candidates that registered on the waiting list between 1995 and 2010 that lead to either a deceased or living donor transplant. The figure shows that not only was there not a significant change in the trend after Share 35 in 2005, but also that pediatric candidates already had a high rate of transplantation before Share 35. It would be difficult to create more pediatric transplants from registrations when about 96% of these registrations already end in transplantation.[33] This evidence

[32] Although there does appear to be a jump in transplants in 2006, this jump is exclusive to 2006. Additionally, in Section 1.6 I show that my results are robust to excluding 2005 and 2006 so this jump in transplants in 2006 is not driving my results.

[33] The remaining 4% of registrations that do not end in transplantation can be due to the candidate still waiting, improvement to where the candidate no longer needs a transplant, deterioration to where the candidate is too sick for a transplant, candidate dies, candidate listed in error, or refused

makes it unlikely that a higher proportion of registrations end in transplantation.

Next, Figure A.11 shows that there is little change in the dialysis use of pediatric ESRD patients after Share 35.[34] Furthermore, it shows that any increase in transplantation among pediatric ESRD patients follows the general increasing trend in ESRD development in the pediatric population, not from more pediatric patients with ESRD choosing to get a transplant instead of using dialysis because of Share 35. Additionally, opting for a transplant instead of remaining on dialysis approximately doubles the expected remaining lifetime of pediatric patients with ESRD (USRDS, 2018). For example in 2014, for a 14- to 17-year-old child with ESRD, receiving a transplant instead of dialysis increases their expected remaining lifetime from 20.9 years to 48.8 years (USRDS, 2018).[35] Given that there already was a substantial benefit to receiving a transplant over using dialysis for pediatric patients, it is unlikely that the benefits of Share 35 induced many ESRD children to try to receive a transplant instead of using dialysis.

Because I've shown that it is unlikely that Share 35 creates new transplants, I proceed assuming that the group of pediatric deceased donor recipients after Share 35 is only composed of candidates who would have received a deceased donor transplant even in absence of Share 35 ("Stayers") and candidates who switched from using a living donor to using a deceased donor because of Share 35 ("Switchers").

1.5.4 Effect of Share 35 on Stayers

In this section, I estimate the effect of Share 35 on "stayers", the candidates who would have received a deceased donor transplant without Share 35. These are the candidates who the Share

transplant.

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

[35]This is not a causal estimate of the survival benefit of receiving a transplant over remaining on dialysis. It is possible that patients who select into receiving a transplant also have different characteristics or behaviors that lead to better survival regardless of whether they receive a transplant or use dialysis. However, it is unlikely that these characteristics or behaviors would account for the entirety of the 28 year survival benefit of transplantation over using dialysis.

35 policy change was intended to benefit. Figures A.12 and A.13 show the trend in likelihood of transplantation within a year and the average KDPI over time for all pediatric and young adult deceased donor recipients. From Figure A.12, it appears that there was a decrease in wait time for pediatric recipients after Share 35. Figure A.13 shows that there is a improvement in the average kidney quality for pediatric recipients. The rest of this section quantifies these effects for pediatric recipients who are more similar to pre-Share 35 deceased donor recipients.

First, note that I cannot directly observe "stayers" and "switchers" because these designations are based on counterfactual outcomes. However, looking at Tables A.4 and A.5, there are observable differences between deceased and living donor recipients. For example, comparing the pre Share 35 pediatric recipients in column 1 in these two tables, pediatric living donor recipients are on average more likely to be white, have type A blood, and use private insurance than pediatric deceased donor recipients. To take advantage of these observable differences, I use a two-step estimation technique. I first calculate weights for the post Share 35 pediatric deceased donor recipients so that they are more similar with respect to observable characteristics to pre-Share 35 pediatric deceased donor recipients. Next, I use those weights in the difference in difference model in equation (1.1).[36]

To generate the weights I use propensity-score matching[PSM].[37] The basic idea behind matching methods is that comparison units with similar observable characteristics to a treated unit can be used to estimate a counterfactual version of the treated unit. PSM reduces the number of dimensions that a unit needs to be matched on by estimating an estimated probability of being treated called the propensity score. Comparison units with a close propensity score to the propensity score of a treated unit are matched to that treated unit. I use a variation of PSM called kernel matching, which instead of forming pairs of treated and comparison units, creates weights for all comparison units for each treated unit, where comparison units with closer propensity scores to the treated unit receive larger weights.[38] I restrict my sample for the matching step to pediatric deceased

[36]Stuart et al. (2014) use a similar methodology but allow both treatment and comparison groups to change as a result of a policy change. An and Winship (2017) also combine propensity score matching with a difference in difference model but they use it in a panel data setting.

[37]Imbens and Wooldridge (2009) provides an overview of propensity score matching methods.

[38]For more information on kernel matching, see Jann, B. (2017). kmatch: Stata module for

donor transplant recipients before and after Share 35. I assign "treatment" status to recipients who received a transplant before Share 35. This means that I am using post Share 35 pediatric deceased donor recipients to estimate what outcomes for a pre Share 35 pediatric deceased donor recipient would be in the post Share 35 period. I estimate propensity-scores using a logit model and match observations based on the following recipient characteristics: age, gender, insurance type, race, blood type, diabetes status, highest PRA score, citizenship status, functional status, diagnosis that lead to ESRD, DSA, an indicator for if candidate i was ever inactive on the wait list, and an indicator for whether candidate i opted into receiving Expanded Criteria Kidney[ECK] offers. [39] For each treated unit, all comparison units are given a weight that is a function of how close their propensity score is to that of the treated unit.

The second step of my estimation procedure is to estimate equation (1.1) using the sample of pediatric and young adult deceased donor recipients before and after Share 35, weighting the observations with the weights I create in step 1. Pre Share 35 pediatric recipients receive a weight of 1. Post Share 35 pediatric recipients receive a weight equal to the sum of all the weights they receive for each pre Share 35 pediatric recipient. This re-weights the post-Share 35 group so that it is similar to the pre Share 35 pediatric recipient group with respect to observable characteristics. This weighting is done to counteract the composition change that results in the post Share 35 pediatric group containing both Stayers and Switchers because of Share 35. Since the young adult recipients do not experience a compositional change as a result of Share 35, all young adult recipients receive a weight of 1. Because the weights used in this step are estimated, I bootstrap standard errors over both steps.

multivariate-distance and propensity-score matching. Available from `https://ideas.repec.org/c/boc/bocode/s458346.html`.

[39] Figure D.3 shows how well the matching in the first step rebalances the recipients' propensity scores. In particular, the red line shows the distribution of propensity scores for "treated" individuals. These are pre Share 35 pediatric deceased donor recipients. The blue line shows the propensity score distribution for post Share 35 pediatric deceased donor recipients. Note that a higher propensity score represents a higher predicted likelihood of being a pre Share 35 deceased donor recipient. The right hand panel of Figure D.3 shows that the propensity score matching successfully re-weights the post Share 35 recipients so that their propensity score distribution is more similar to that of the pre Share 35 recipients.

Table A.6 presents the estimated coefficients from the two step estimation procedure: equation (1.1) is estimated, weighting the observations with the weights I created from PSM. $\mathbf{x_i}$ includes contains the same controls that I used in the matching step plus an additional control for transplant year. The coefficient on $Share * Pediatric$ implies that Share 35 increased the likelihood that a pediatric deceased donor recipient was transplanted within a three months by 6 percentage points, within six months by 15 percentage points, within a year by 20 percentage points, and within 18 months by 22 percentage points, compared to young adult deceased donor recipients. These are substantial effects, especially considering only 44% of pediatric deceased donor recipients were transplanted within a year before Share 35. The coefficient on $Share * Pediatric$ in Column 5 implies that Share 35 improved the quality of kidneys used in pediatric deceased donor transplants by about 8.4 points on average. This represents a 30% improvement in quality, given the pre Share 35 pediatric sample mean quality of 28.

Table D.2 compares these estimates to the estimates of equation (1.1) without re-weighting the observations. The estimated unweighted coefficients on $Share * Pediatric$ are smaller, in general, than the weighted one. This suggests that the stayers have shorter wait times for deceased donor transplants and accept higher quality deceased donor kidneys than switchers, on average.

The event study analysis shown in Figures A.14 and A.15 supports the assumption of parallel trends in wait time and quality between pediatric and young adult recipients before Share 35. However, the introduction of the matching procedure adds another key assumption that must hold for my estimated coefficients to have a causal interpretation. With the matching, I am assuming that post Share 35 pediatric recipients have the same outcomes as what pre Share 35 pediatric recipients would have in the post period, conditional on observable characteristics. Because the set of post Share 35 pediatric recipients has both Stayers and Switchers in it, this could potentially violate this assumption. However, both Stayers and Switchers are receiving the same kidney offers through the same allocation system, conditional on observables like on being in the same locality and having the same blood type. This would make it difficult for Stayers and Switchers have have different deceased donor kidney quality or wait time unless they have differences in kidney offer acceptance

rules. (For example, if Switchers were more willing to turn down offers in order to wait for a higher quality offer.) This is unlikely to be the case because Share 35 offers all pediatric candidates high quality kidneys that they should be willing to accept. It is unlikely that candidates would be willing to wait longer, without functioning kidneys, in order to receive an offer that would be even higher quality.

These results imply that Share 35 did achieve its goals among pediatric candidates who are similar to pre-Share 35 candidates. These candidates experienced reduced wait times and received higher quality kidneys. These results are especially encouraging given the large number of pediatric candidates who switched from living donors to deceased donors; there was the potential that the addition of these pediatric deceased donor candidates could crowd out the benefits for the candidates who the policy was intended to benefit.

1.5.5 Effect of Share 35 for Switchers

In this section, I estimate the effect of Share 35 on "Switchers": the recipients who were induced to use a deceased donor instead of a living donor by Share 35. To do this, I follow the methodology introduced in Jones (2015). First, consider the following model of the effect of Share 35 on wait time or kidney quality for a pediatric recipient:

$$Y_i = \beta Share_i + \mathbf{x_i}\gamma + e_i \tag{1.3}$$

where $Share_i = 1$ if recipient i received a deceased or living donor transplant after Share 35 and $= 0$ if they received a transplant before Share 35. β in this equation represents the average effect of Share 35 on all pediatric transplant recipients. Note that there are three different subgroups of pediatric recipients: the Stayers, the Switchers, and the living donor recipients who would use a living donor with or without the introduction of Share 35. Since β is the average effect, it can be rewritten as the weighted average effect on these three different subgroups of pediatric recipients:

$$\beta = \theta_{Stayer}\beta_{Stayer} + \theta_{Switcher}\beta_{Switcher} + \theta_{AlwaysLiving}\beta_{AlwaysLiving} \tag{1.4}$$

where θ_{Stayer} represents the proportion of pediatric recipients that are Stayers, $\theta_{Switcher}$ is the proportion that are Switchers, and $\theta_{AlwaysLiving}$ is the proportion that would always use a living donor. β_{Stayer}, $\beta_{Switcher}$, and $\beta_{AlwaysLiving}$ represent the effect of Share 35 on each of these subgroups.

Now, assume $\beta_{AlwaysLiving} = 0$ because Share 35 only affects wait time or quality for recipients who use deceased donors. Then equation (1.4) can be rearranged to solve for $\beta_{Switcher}$:

$$\beta_{Switcher} = \frac{\beta}{\theta_{Switcher}} - \beta_{Stayer}\frac{\theta_{Stayer}}{\theta_{Switcher}} \tag{1.5}$$

Therefore, I can estimate $\beta_{Switcher}$ by estimating the average effect of Share 35 on pediatric recipients, the effect of Share 35 on Stayers, and the proportion of recipients who are Stayers and Switchers. I previously estimated β in Section 1.5.1 and the effect of Share 35 on Stayer in Section 1.5.4. Finally, to estimate θ_{Stayer} and $\theta_{Switcher}$ I estimate the following model, using the my entire sample of pediatric and young adult recipients:

$$DeceasedDonor_i = \alpha_{YA} + \alpha_P Pediatric_i + \theta_{Switcher} Share_i * Pediatric_i + \gamma Share_i + u_i \tag{1.6}$$

In this model, $\theta_{Stayer} = \alpha_{YA} + \alpha_P$.

Table A.7 contains my estimates of $\beta_{Switcher}$ using this process. Standard errors are bootstrapped over the whole process. The estimates on wait time are not statistically significant at conventional levels but they imply that pediatric candidates who switched from using a living donor to using a deceased one as a result of Share 35 are able to receive transplants faster as a result of this switch. However, looking at column 5, these candidates received transplants with kidneys that were, on average, 11.8 points worse quality than what they would have received otherwise. This is a substantial reduction in quality for these candidates. Given how highly transplant teams value higher quality living donor kidneys, it seems unlikely that Share 35 would induce so many candidates to switch unless they are strategically saving their living donor for their next transplant or unless the costs of finding or using a living donor are very large. In the next section, I investigate whether any candidates who switch are saving their living donor for their next transplant.

1.5.6 Potential Saving of Living Donors for Second Transplant

Now that I've discussed how switchers are affected by their switching donor types at their first transplant, I estimate whether they are more likely to use a living donor for their second transplant. To do this, I use data on the second transplant of deceased donor recipients in my original sample. Table A.8 shows that although my original sample of deceased donor transplant recipients contained about 8,600 pediatric and young adult recipients, I only observe the second transplant of 1,696 of them. Unsurprisingly, given that this sample contains recipients whose first transplant had the worse graft survival, these recipients' first transplant used slightly worse quality kidneys than the average among all deceased donor recipients in my sample. My hypothesis is that the decrease in the likelihood that a pediatric patient uses a living donor for their first transplant from Section 1.5.2 is because these patients save their living donor for their next transplant. Figure A.16 shows the trend in the likelihood that pediatric and young adult recipients who used a deceased donor for their first transplant use a living donor for their second transplant. This figure shows that pediatric and young adult deceased donor recipients had similar likelihood of using living donors for their second transplants before Share 35. However, after Share 35, it does look like pediatric recipients are slightly more likely to use living donors while young adults are slightly less likely to use living donors for their second transplants. In order to estimate this potential effect, I first estimate the following difference in differences model using the second transplants of deceased donor recipients in my sample from Section 1.5.2:

$$LivingDonor_i = \beta_1 ShareFirst_i + \beta_2 PediatricFirst_i + \beta_3 ShareFirst_i * PediatricFirst_i + \mathbf{x_i}\gamma + u_i \tag{1.7}$$

where $ShareFirst_i = 1$ if recipient i's first transplant occurred after Share 35 and $PediatricFirst_i = 1$ if recipient i was considered pediatric at their first transplant. The vector $\mathbf{x_i}$ includes age at start of wait time, gender, insurance type, race, blood type, transplant year, diabetes status, citizenship status, functional status, diagnosis that lead to ESRD, DSA level fixed effects, an indicator for receiving Share 35 priority for the second transplant, and an indicator for whether the recipient

receives EPTS priority in the new allocation system.[40] β_3 represents the difference in likelihood of using a living donor for their second transplant between pediatric and young adult candidates who used a deceased donor for their first transplant after Share 35. If some candidates save their living donor for their second transplant, I expect $\hat{\beta_3}$ to be positive.

Table A.9, column 1 shows the estimated coefficients from equation (1.7) using OLS on the second transplant observations of candidates who were pediatric or a young adult in my sample who used a deceased donor for their first transplant. The coefficient on $ShareFirst * PediatricFirst$ is positive but not statistically significant, implying that Share 35 might have increased the likelihood that deceased donor recipient use a living donor for their second transplant.

Because I only observe approximately 20% of second transplants for the deceased donor recipients in my original sample, my estimates will be biased if selection into receiving a second transplant earlier is correlated with receiving a transplant after Share 35. This is likely to be true because recipients who have earlier graft failure might exhibit worse compliance with post-transplant care, and this reduced compliance might be correlated with whether or not they had a parent as a willing living donor available to them at their first transplant. Recipients with parents willing to donate a kidneys for them might also have parents helping them adhere to their post transplant care. There also is a correlation between family and personal health (Case & Paxson, 2002). If a recipient's parents do not meet the criteria to be living donors because of their health, the recipient might be unhealthier than other transplant recipients on average. Because of the crowd out in living donors created by Share 35, deceased donor recipients after Share 35 are more likely to have had a willing donor available to them than recipients before Share 35. Hence, it is plausible that earlier graft failure (i.e. inclusion in my sample) is negatively correlated with having a willing living donor available and having a willing living donor available is positively correlated with being transplanted after Share 35. Therefore, my OLS estimate of the coefficient on Share 35

[40]The new Kidney Allocation System introduced in 2014 gives priority to candidates who have Estimated Post Transplant Survival [EPTS] scores less than 20. Most of the candidates in my sample will still be young enough in 2019 to qualify for this priority at their second transplant. Source: `https://optn.transplant.hrsa.gov/resources/allocation-calculators/epts-calculator/`

is negatively biased.

To correct the bias due to the selection problem, I use a two step Heckman procedure. First, using all observations of candidates who used a deceased donor for their first transplant, I estimate the probability of selection using the following Probit model:

$$Pr(\text{Received Second Transplant}_i|\mathbf{z_i}) = \Phi(\mathbf{z_i}\gamma) \tag{1.8}$$

where $\mathbf{z_i}$ contains the vector $\mathbf{x_i}$ plus the additional explanatory variables of KDPI of first transplant, year of the first transplant, and an indicator for dialysis use within the first week after a candidate's first transplant. These additional variables satisfy the exclusion restriction: they are correlated with earlier graft failure but are plausibly independent of the decision to use a living donor for a candidate's second transplant. Next, I use $\hat{\gamma}$ to estimate inverse Mills ratios for candidates who received a second transplant. Finally, I estimate equation (1.7) including these estimated inverse Mills ratios as an additional covariate.

Table A.9, column 2 shows the estimated coefficients from equation (1.7) with the estimated Mills ratio as an additional covariate. The coefficient on $ShareFirst * PediatricFirst$ is positive, although it is smaller and still statistically insignificant. However, 80% of the recipients in my sample who received a first transplant have not received a second transplant yet. It is possible that with more years of data in the future, there will be better evidence of these recipients saving their living donor for their second transplant.

1.6 Robustness

One might be concerned that candidates can affect their treatment status and that this manipulation is driving my results. Two potential ways a candidate could manipulate their treatment status is by registering on the wait list before they turn 18, or by waiting to receive a transplant until after Share 35. Figure A.17 shows that eighteen year olds are still registering at a similar rate after Share 35 while the number of seventeen year old registrations increases. This suggests that the increase in seventeen year old registrations is not driven by young adults who might register earlier to get Share 35 priority, but rather by pediatric candidates who are choosing deceased donors over living

donors. Additionally, kidney transplant candidates gain wait list points for how long they have been on the waiting list. These points move them higher up the kidney offer list; therefore, it has always been optimal to register on the wait list as soon as possible. To provide additional evidence that this manipulation is not driving my results, I re-estimate my specifications from Sections 1.5.1, 1.5.2, and 1.5.4 excluding all candidates aged 17 or 18. Column 2 of Table A.10 presents the estimated coefficient on $Share * Pediatric$ from this re-estimation. These coefficients are very similar to the original coefficients in column 1, providing evidence that it is unlikely that candidates manipulating their registration age is driving my results.

It is also unlikely that pediatric candidates wait until after Share 35 to accept a deceased donor kidney. Waiting until after the policy takes effect would involve candidates waiting longer, which their transplant team would not recommend. However, as a specification check, columns 3 in Table A.10 addresses any concerns that candidates may be manipulating their treatment status by waiting to receive a transplant by omitting candidates who were transplanted within one year on either side of Share 35's introduction. Because median wait time is approximately one year, this eliminates any candidates who might change their behavior to take advantage of Share 35. The estimated coefficients on $Share * Pediatric$ in column 3 are again very similar to the original estimated coefficient in column 1 suggesting that candidates manipulating their treatment status through their transplant year does not drive the results.

1.7 Conclusion

In this paper, I am the first to analyze the effect of the Share 35 policy separately on deceased donor pediatric recipients who always would have used a deceased donor, and on those who were induced to switch from living to deceased donors as a result of Share 35. I find that the Share 35 policy change improved the kidney quality and reduced wait time for pediatric candidates who are predicted to have received a deceased donor kidney in absence of the policy change but does reduce kidney quality for pediatric patients who switch from using a living donor to using a deceased donor kidney because of Share 35. This means that although Share 35 achieves its intended effect

for its intended recipients, it induces some pediatric patients to substitute away from living donors, resulting in worse kidney quality for these candidates. Although there is strong evidence of pediatric patients being less likely to use a living donor after Share 35, I find very little evidence of these patients saving that donor for their second transplant.

Creating policy that balances efficiency and equity in allocating a growing shortage of donated kidneys is challenging, especially when there are unintended effects that result from the policy. The population affected by Share 35 is small; pediatric candidates were only about 3% of the new candidates added to the wait list in 2004. Because pediatric candidates are such a small proportion of the wait list, the distortion in living donor use might not be too concerning as a side effect of Share 35, given the improvements I find to wait time and quality for deceased donor pediatric recipients. But, now there are more candidates on the wait list and in 2014 the allocation system was revised to give priority to candidates in the top 20% of Expected Post Transplant Survival [EPTS]. This is a much larger group of candidates than the pediatric candidates affected by Share 35, but since the calculation for EPTS is heavily based off of age, these candidates should be similar to the pediatric candidates affected by Share 35. If the proportion of candidates who switch when given EPTS priority is similar to what it is for candidates given Share 35 priority, then we should anticipate a larger crowd out in living donors from the new EPTS priority. 20% of candidates is a very large proportion of the wait list to have potentially crowd out of using living donors. My crowd out estimate implies that the EPTS priority potentially crowds out 3,224 living donor transplants.[41]

When these candidates who have living donors available to them receive deceased donor kidneys, this denies the candidates on the wait list without living donors the opportunity to receive those deceased donor kidneys. Although some priority rules improve survival matching between candidates and deceased donor kidneys, this improvement comes with a cost of reducing the total number of transplants that can take place and a change in the equity in allocation.

[41] 3,224=(current number of kidney wait list candidates)*(percent of candidates given EPTS priority)*(estimated crowd out from Share 35 priority)=94,835*0.2*0.17

Source for current number of kidney wait list candidates: `https://optn.transplant.hrsa.gov/data/view-data-reports/national-data/`

CHAPTER 2

THE EFFECTS OF THE AFFORDABLE CARE ACT ON THE DEMAND FOR ORGAN TRANSPLANTS

2.1 Introduction

Before the passage of the Affordable Care Act [ACA] in 2010, many low income, childless households had difficulty finding insurance coverage if they were unemployed or if their employers did not sponsor a plan for them. One of the goals of the ACA was to introduce more options for these households to obtain insurance coverage. This was done primarily through state expansions of Medicaid and through the introduction of a centralized marketplace for private insurance plans. Previous literature documents that the ACA was successful at reducing the number of uninsured (Simon et al., 2017; Duggan et al., 2017; Miller & Wherry, 2019; Courtemanche et al., 2017; Sommers et al., 2015; Wherry & Miller, 2016) and that the Medicaid expansions were successful at increasing some forms of preventative and dental care, increasing diagnosis of chronic health conditions, and increasing access to timely care for some common surgical conditions, like appendectomy surgeries, among low-income childless adults (Simon et al., 2017; Wherry & Miller, 2016; Loehrer et al., 2018).[1] However, some individuals have chronic illnesses and may need more than preventative care.

In this paper, I look at the effects of increased access to insurance from the ACA for individuals who have organ failure and need an organ transplant. Low income individuals can develop organ failure (Crews et al., 2014; Clark et al., 2009; Raju et al., 2019; Scaglione et al., 2015). For most of these individuals, an organ transplant is their only treatment option. However, these transplants are expensive and most transplant centers require patients to have insurance coverage (Thibodeau et al., 2013; Laurentine & Bramstedt, 2010; Glueckert et al., 2013). These low income individuals

[1] Further evidence that uses the Oregon Health Insurance Experiment shows that an increase in access to Oregon's Medicaid program increases cancer screenings, dental care, and preventive care (Wright et al., 2016; Baicker et al., 2018; Finkelstein et al., 2012).

are likely to have been able to gain insurance through the state Medicaid eligibility expansions or the private insurance marketplace subsidies introduced with the ACA. Previous literature finds that the states that expanded Medicaid on January 1, 2014 had increased wait list registrations for transplants (Tumin et al., 2017; Breathett et al., 2017; Ising et al., 2018; Trivedi et al., 2018; Harhay et al., 2018; Oliveira et al., 2016). Although some of these papers use a difference in differences design to causally look at the effects of Medicaid expansion, some simply compare pre ACA counts of Medicaid insured listings to post ACA counts of listings. Additionally, this literature has not yet looked at whether these registrations lead to transplants and no papers look at the effects of the private insurance marketplace on wait list registrations or transplants.

In this paper, I use a difference in differences model based on timing of Medicaid expansions to access whether Medicaid expansions increase wait list registrations and transplants. Additionally, I use variation in requirements for private insurance plans to cover transplants to identify the effects of the newly available subsidized private marketplace plans on registrations and transplants. Using the universe of all transplant candidates and recipients in the United States, I find that the state expansions of Medicaid increased monthly wait list registrations by candidates insured through Medicaid by 20 to 60 percent for each organ, but I find no effect of the marketplace on privately insured individuals' registrations. I also find an increase in the number of Medicaid insured deceased donor transplants for Medicaid expansion states, although this increase is not statistically significant for all organs. Finally, I find the number of Medicaid insured living donor liver transplants after Medicaid expansion more than doubles.

The paper proceeds as follows: In section 2.2, I provide an explanation of transplantation and allocation of organs in the United States. Additionally, I describe the changes to health insurance that result from the ACA that would impact transplant candidates. In section 2.3, I describe the data that I use and provide descriptive statistics. In section 2.4, I estimate the effects of the Medicaid expansions and private insurance marketplace on wait list registrations. In section 2.5, I estimate the effects the ACA on deceased donor transplants. In section 2.6 I estimate the effects of the ACA on living donor transplants. Finally, section 2.7 concludes.

2.2 Environment

2.2.1 Transplantation in the United States

The most commonly transplanted organs in the United States are kidneys, livers, hearts, and lungs. In order to receive a transplant, individuals with organ failure need to be accepted at a transplant center. Each transplant center sets its own patient acceptance criteria, which typically includes physical, psychological, and social evaluations. Most transplant centers also require the patient to have insurance before accepting them because the transplant procedure involves many costs. For example, the American Kidney Fund states that kidney transplant evaluations may be denied due to lack of adequate insurance coverage (Samoray & Satarino, 2016). Thidbodeau et al. (2013) surveyed heart transplant centers and found that 84% of the centers that they surveyed required insurance in order for a potential candidate to register on the waiting list. Even among centers that would allow uninsured candidates to register, 81% of these centers required the candidate to pay a deposit before they could be added to the waiting list (Thibodeau et al., 2013).[2] In 2017, billed charges for a transplant averaged from $415,000 for a kidney transplant to $1,382,000 for a heart transplant (Bentley & Phillips, 2017). These costs include both upfront costs for the surgery and expensive medications used to maintain the transplant for the rest of the recipient's life. Once a patient has been accepted at a transplant center, they can be registered on the waiting list. While on the waiting list, a candidate receives organ offers based on the current organ allocation policy, which varies by organ. In general, organs are allocated first to candidates in the same locality as the recovered organ. There is a shortage of deceased donor organs, so candidates need to wait to receive an organ offer before their deceased donor transplant can take place.[3]

Because organs are allocated locally first, this creates an incentive for candidates to strategically choose which transplant center they list at. Data are publicly available on how quickly candidates

[2] The median amount that these centers required was $200,000 (Thibodeau et al., 2013).

[3] 80% of kidney candidates, 45% of heart candidates, 35% of lung candidates, and 55% of liver candidates wait longer than a year to receive a transplant.

receive transplants on average from specific centers.[4] This data can help candidates list at centers in locations with faster times to transplant. Some candidates even register at multiple transplant centers in different localities. This behavior is commonly called "multilisting". In order to multilist, a candidate needs to be accepted as a patient at both centers. If the center is located a substantial distance away from the candidate's home, the transplant center requires that the candidate has transportation that will allow them to travel to the center quickly in case they receive an organ offer.

Kidney and liver transplant candidates can try to find a living donor instead of, or in addition to, waiting to receive a deceased donor organ offer. By finding a willing and blood type compatible living donor, these candidates can avoid the long wait to receive a deceased donor transplant. Additionally, living donor transplants are associated with better post-transplant outcomes than deceased donor transplants (SRTR, 2014). In 2014, 32% of kidney transplants and 4% of liver transplants used a living donor.[5]

After receiving a transplant, candidates require immunosuppressants to prevent their body's immune system from attacking the transplanted organ. These medications help prevent graft failure, where the transplanted organ ceases functioning. Billed charges for these medications can range from $20,000 to $50,000 a year (Bentley & Phillips, 2017). Because transplant recipients take these medications until the transplanted organ ceases functioning, a transplant recipient will benefit from insurance coverage after the transplant procedure.

2.2.2 Health Insurance before the Affordable Care Act

Before the 2014 implementation of most provisions of the ACA, 90% of all privately insured adults were covered by employer sponsored plans (Buchmueller & Monheit, 2009). Individuals who did not have access to an employer's group plan could buy a plan in the individual health insurance marketplace. The non-employer sponsored plans were typically expensive and pre-existing conditions could be used to deny an individual coverage.

[4] See https://www.srtr.org/reports-tools/program-specific-reports/

[5] Source: https://optn.transplant.hrsa.gov/data/view-data-reports/build-advanced/

If a person did not have private insurance, they might qualify for one of two public options: Medicaid or Medicare. Medicaid primarily targeted low-income households with children. In order to qualify, a household must meet their state's eligibility levels, which depend not only on income, but also on household size. Most states did not offer Medicaid to households without children.[6] For households with children, 26 states required the household's income to be below 64 percent of the Federal Poverty Level [FPL] in 2010.[7] For example, in order to qualify for Medicaid in 2010, a family of three in Michigan would need to have an income less than $11,718.[8] Cost sharing in Medicaid programs varies by state, however there are some federal restrictions. For example, in 2013, The Centers for Medicare and Medicaid Services [CMS] prohibited deductibles from exceeding $2.65 and prohibited cost sharing on preferred drugs from exceeding $4.[9] CMS caps all out of pocket costs at 5 percent of a family's income.

All US citizens are eligible to enroll in Medicare when they are 65 years old. If an individual or their spouse has paid payroll taxes for at least 10 years, they can enroll in Medicare part A without having to pay premiums. Medicare part A will cover 100% of the costs of an inpatient hospital stay for a transplant after the enrollee covers an deductible ($1,364 in 2019).[10] Medicare Part B will cover 80% of outpatient costs, like transplant evaluations or transplant follow-up care, after the enrollee pays the Part B deductible ($185 in 2019). Medicare Part B will also cover 80% of the costs of immunosuppressants after the transplant.[11]

Candidates who need a kidney potentially qualify for End State Renal Disease [ESRD] Medicare without a minimum age requirement. CMS rules require these candidates have paid payroll taxes

[6] Refer to Appendix Tables E.1 and E.2 for income eligibility levels by state and household size.

[7] 34 states required the household's income to be below 100 percent of the Federal Poverty Level.

[8] =(0.64)*(18310)
FPL obtained from https://aspe.hhs.gov/prior-hhs-poverty-guidelines-and-federal-register-references

[9] Source: https://www.medicaid.gov/medicaid/cost-sharing/out-of-pocket-costs/index.html

[10] Source: https://www.cms.gov/newsroom/fact-sheets/2019-medicare-parts-b-premiums-and-deductibles

[11] Source: https://www.medicare.gov/node/35206

for the required number of years to Social Security in order to qualify (U.S. Centers for Medicare & Medicaid Services, 2019). The required number of years varies by how old the potential enrollee is. Any dependents of someone who has met the contribution requirement are also eligible for ESRD Medicare. ESRD Medicare covers 80% of the costs of dialysis treatments, without any time limits, and if a patient opts for a kidney transplant, ESRD Medicare will cover the costs of the transplant as outlined previously. However, ESRD Medicare only covers the costs of immunosuppressants for 36 months after the transplant.

2.2.3 Health Insurance after the Affordable Care Act

The ACA introduced three major changes to health insurance that potentially affected transplant candidates. First, the ACA mandated that all insurance plans must cover ten Essential Health Benefits [EHB]. States have discretion over which services were included in the 10 EHB categories. States determined these services by choosing an existing health plan available in that state as the "EHB Benchmark Plan". Table B.1 shows whether or not a state's benchmark plan included coverage for transplants. Although most states' benchmark plans included coverage for transplants starting in 2014, eight states' plans did not until 2017.

Second, the ACA encouraged states to expand the income level at which households were eligible for Medicaid to 138 percent of the FPL by providing states funding for newly eligible enrollees. This expansion would especially benefit childless individuals who were previously ineligible for Medicaid at any income level in most states. 25 states expanded their eligibility level for Medicaid on January 1, 2014, but an additional 12 states expanded their eligibility level since then.[12] Because many potential transplant candidates have low incomes (Crews et al., 2014; Clark et al., 2009; Scaglione et al., 2015; Raju et al., 2019), these expanded eligibility levels make it more

[12]Note that although for most states, this "expansion" increased the income eligibility level for Medicaid for childless individuals, some states reduced their income eligibility level Medicaid for households with children. This would result in it being harder for these households to be eligible for Medicaid after the expansion. However, these households who are no longer eligible for their state's Medicaid program would be eligible for subsidies on the newly introduced Marketplace for private insurance.

likely for potential transplant candidates, especially ones without children, to be eligible to receive Medicaid coverage, and in turn register at a transplant center.

Finally, the ACA introduced a centralized marketplace for private insurance plans. Unlike private insurance plans of the past, the ACA required these plans to cover the EHBs outlined in the state's benchmark plan and these plans cannot deny individuals with pre-existing conditions coverage. Plans on the marketplace are categorized into Bronze, Silver, Gold, or Platinum plans based on how the insurance company splits costs with the purchaser. Cost sharing ranges from the purchaser paying 40 percent of costs with a Bronze plan to 10 percent with a Platinum plan. Individuals who need a transplant are likely to want to buy a plan with reduced cost-sharing because they would expect to have higher medical costs.[13] Tax subsidies are available to help cover the cost of the premium of these plans for households with incomes between 100 and 400 percent of the FPL, adjusted for the household's size. These tax subsidies are calculated so that a household does not spend more than a certain percentage of their household income on the premium for the second lowest cost Silver plan in their county. This percentage ranges from 3 percent of income for households at 133 percent of the FPL to 9.5 percent for households at 400 percent of the FPL. This subsidy is given to the household, regardless of whether they choose to buy a silver plan or a bronze, gold, or platinum plan instead.

2.3 Data

This study uses data from the Scientific Registry of Transplant Recipients (SRTR). The SRTR data system includes data on all donors, waitlisted candidates, and transplant recipients in the US, submitted by the members of the Organ Procurement and Transplantation Network (OPTN). The Health Resources and Services Administration (HRSA), US Department of Health and Human Services, provides oversight to the activities of the OPTN and SRTR contractors.

For each transplant candidate from 2008 to 2018, I observe their age, primary source of payment

[13]There is variation in how many different insurance companies offer plans on the marketplace and also in which categories of plans are offered in each county. Future work will explore how this availability of plans effects transplant candidates ability to register on the wait list.

for the transplant, and state of permanent residence.[14] For each transplant candidate I also observe their wait list registration date and the date of their transplant, if they receive one. Table B.2 shows that 72 to 82 percent of candidates are between the ages of 18 and 64. These candidates are of an age that would benefit the most from the provisions of the ACA because they are too young to qualify for Medicare. The racial distribution of candidates varies by organ needed. Although 82 percent of lung candidates are white, only 46 percent of kidney candidates are white. Additionally, with the exception of kidney candidates, who are eligible for Medicare before they turn 65, approximately 50 percent of candidates had private insurance as their primary source of payment and depending on the organ needed, 7 to 17 percent of candidates had Medicaid insurance before the ACA. Because kidney candidates can use dialysis to help replace the function of their kidneys before they receive a transplant, kidney candidate mortality is low compared to other organ candidates. Only 4 percent of kidney candidates die within a year of registering on the wait list. However, for other organs, approximately 15 percent of candidates die within a year of listing. For candidates who need a heart, liver, or lung, receiving a transplant quickly can be a deciding factor in whether they live or die. Because of these differences between the candidates of different organ types, I expect that my estimates of the ACA on transplant candidates will also vary by organ type needed.

I use population estimates from the National Cancer Institute to create population adjusted counts of wait list registrations and transplants for each state.[15] Population counts are only available at a yearly level, so I linearly interpolate the increase in population between years into estimated monthly counts. I also use information obtained from the Henry J Kaiser Family Foundation on the Medicaid expansion dates of each state.[16]

[14] Although I can also observe the secondary source of payment for some candidates, for over 60% of candidates it is unobserved. For this reason, I am unable to look at changes in wait listing or transplants among candidates who might have gained private or Medicaid insurance as their secondary insurance as a result of the ACA. However, the Medicaid expansions and private insurance marketplace subsidies were targeted at benefiting people who would otherwise be uninsured. These candidates would gain private or Medicaid insurance as their primary source of payment which I can observe reliably.

[15] Source: `https://seer.cancer.gov/popdata/download.html`

[16] Source: `https://www.kff.org/health-reform/state-indicator/state-activity`

2.4 Wait List Registrations

With the introduction of the ACA, many potential transplant candidates have new options for insurance coverage through either the Medicaid expansions or through the Marketplace for private insurance.[17] This creates an opportunity not only for previously uninsured individuals to gain coverage, but also for individuals who already had coverage to switch to being insured through one of these channels instead. I expect that a majority of new registrations come from previously uninsured candidates who are gaining insurance from the ACA, not from candidates switching from other insurance types to Medicaid or Marketplace private insurance.[18] Courtmanche et al. (2017) provides some support for this assumption. They estimate that only 27 percent of people who bought private insurance on the Marketplace already had some form of insurance coverage. If these people are switching insurance coverage to a private plan on the Marketplace, it is likely that they are doing so because the Marketplace plans offer better coverage or lower expected costs to the individual. If this is the case, these individuals' prior insurance coverage might not have been good enough to allow them to register to receive a transplant, which would mean that these are still new registrations. Additionally, Courtmanche et al. find that increase in Medicaid insured individuals after Medicaid expansion does not come from a crowd out of private insurance.[19] I

-around-expanding-medicaid-under-the-affordable-care-act/

[17] This is conditional on transplant centers being willing to accept Medicaid patients or patients with insurance from the Marketplace. This not necessarily the case. Medicaid payments lower than those from Medicare for many procedures (Mabry et al., 2016). There are also documented cases of people with insurance from the Marketplace having difficulties finding physicians who would accept their insurance. (See https://www.nytimes.com/2016/05/15/sunday-review/sorry-we-dont-take-obamacare.html)

[18] Future work will explore if I see any evidence of candidates switching between insurance types as a result of the ACA. To do this, I will compare the insurance type that a candidate uses when they register on the wait list before the ACA to the insurance type that a candidate uses when they receive a transplant after the ACA.

[19] One might also be concerned that individuals are switching insurance from Medicare due to disability to private insurance or Medicaid. I do not find any evidence of this when I look for a change in the number of registrations by candidates who are less than 65 years old who have insurance through Medicare. Additionally, I find no evidence of a decrease in the number of candidates who join the wait list with their primary source of payment listed as self, donation, or free care after the ACA. This suggests that candidates are also not switching from these payment

hypothesize that new candidates that join the wait list after the ACA should increase the number of private insurance registrations in all states and also increase Medicaid insurance registrations in expansion states. Future work will also explore how existing candidates respond to the expected increase in Medicaid and privately insured candidates on the wait list. If candidates expect that wait lists will get longer in Medicaid expansion states, candidates who are not Medicaid insured might choose to register in non-expansion states.

I expect Medicaid expansion to increase the number of Medicaid insured candidates on the wait list in states that expand Medicaid, but not in non-expansion states. Column 1 of Figure B.1 shows that this seems to be the case: on average, Medicaid expansion states have an increase in Medicaid insured candidates after the ACA, but non-expansion states do not have a similar increase in registrations. I also expect that both Medicaid expansion states and non-expansion states should see an increase in the number of privately insured candidates after transplants are declared an EHB and due to the increase in the availability and affordability of private insurance plans on the Marketplace. With the exception of heart candidates, Column 2 of Figure B.1 does not show any noticeable increases in privately insured candidates after the ACA.[20]

To estimate the effects of the changes implemented with the ACA on the monthly number of registrations, I estimate the following model for each transplantable organ separately[21]:

$$WL_{st} = \beta_1 EHB_{st} + \beta_2 PostMedicaidExpansion_{st} + \gamma x_{st} + \mu_s + \theta_t + u_{st}, \tag{2.1}$$

where y_{st} is either the monthly number of Medicaid or private insured wait list registrations per 1 million state population. $EHB_{st} = 1$ if state s defines a transplant as an Essential Health Benefit in their Benchmark Plan in month t and $PostMedicaidExpansion_{st}$ is a dummy variable that equals one after a state expands their Medicaid program. $x_{st} = 1$ if state s requires adults to wear

types to private insurance or Medicaid.

[20]Figure B.1 also highlights that even before the ACA, states that expanded Medicaid eligibility had more than twice the number of transplant candidates per population than states that did not expand Medicaid. Future work will explore how these wait list size differences interact with the Medicaid expansions.

[21]Results for intestines and pancreas transplants are not included in this paper due to the small number of recipients of these transplants. Results for these organs are available upon request.

motorcycle helmets in month m. μ_s and θ_t are state and month-year fixed effects. β_1 represents the effects of states mandating coverage for transplants in private insurance plans after the ACA. β_2 represents the effects of a state expanding its Medicaid program to cover individuals up to 138 percent of the FPL.

Table B.3 presents estimates of equation (2.1). The coefficient in row 1, column 1 for kidneys implies that after the ACA requires private insurance plans on the marketplace to cover transplants, on average, there is no change in Medicaid registrations, but, row 2 shows there is an increase in Medicaid registrations after a state expands their Medicaid eligibility. Furthermore, the estimated increases in Medicaid registrations is substantial; These estimates for kidneys implies that on average, after a state expands their Medicaid program, monthly Medicaid wait list registrations per million state residents increases by 0.29. This represents a 59 percent increase in registrations, comparing this effect size to the pre-ACA monthly average number of registrations of 0.49. The estimated increases in Medicaid registrations for other organs are similar. After Medicaid expansion there is a 19 percent increase in Medicaid insured heart candidates, a 60% increase in Medicaid insured lung candidates, and a 41 percent increase in the Medicaid insured liver candidates. These estimates suggest that the Medicaid expansions allowed significantly more low-income individuals to gain Medicaid coverage and register on the wait list for a transplant for all organs as a result.

Row 1, Column 2 for kidneys in Table B.3 shows that there is no significant effect of mandating transplants as an EHB on the monthly privately insured wait list registrations per million state residents. This also holds true for for heart, lung, and liver candidates. The coefficient in row 2 for kidneys and lungs implies that after a state expands their Medicaid program, on average, there is no significant increase monthly wait list registrations per million state residents by privately insured candidates. Effects for hearts and livers are negative and statistically significant. These negative effects could result from one of the following scenarios: The first scenario is privately insured candidates are not able to, or choose not to, register on the wait list after the Medicaid expansion. This seems unlikely because transplant centers do not have limits on how many candidates they can accept. Furthermore, candidates are unlikely to willingly choose not to pursue a lifesaving

transplant as a result of Medicaid expansions. The second scenario is that there is a differential effect of the private insurance marketplace between expansion and non-expansion states. Then, the negative coefficient on Medicaid expansion could represent that candidates in non-expansion states are more likely to gain private insurance coverage than candidates in Medicaid expansion states. Figure B.1 lends some support to this theory: it does appear that there is an increase in private insurance registrations in non-expansion states after 2014 that is not present in expansion states. Future work will explore alternative specifications that would allow a differential effect of EHB designation on candidates in expansion and non-expansion states. Future work will also explore whether Medicaid expansions induce some non-Medicaid insured candidates to register at centers that are not in expansion states. It is possible that non-Medicaid insured candidates recognize that Medicaid expansion will lead to more Medicaid candidates joining the wait lists and as a result non-Medicaid candidates might seek out centers that they expect will have shorter wait lists.

In order to interpret my Medicaid expansion results as causal, expansion and non-expansion states need to have parallel trends in registrations. To test the plausibility of this assumption, I estimate the following event study model, which allows the Medicaid expansion treatment effect to differ in every year:

$$y_{st} = \beta_1 EHB_{st} + \sum_{y \in \mathcal{Y}} \beta_y 1(t \in y) * Expansion_s + \gamma x_{st} + \mu_s + \theta_y + u_{st}, \tag{2.2}$$

This equation is identical to equation (2.1) except $PostMedicaidExpansion_{st}$ has been replaced with a series of dummy variables for each year ($1(t \in y)$) interacted with $Expansion_s$ which equals 1 if state s expanded Medicaid. $\mathcal{Y}$ includes all years from 2008 to 2018 except 2013, the year before the introduction of the ACA. Therefore β_y represents the difference between expansion and non-expansion states in year y, normalized the difference in 2013. If expansion and non-expansion states have parallel trends in registrations, estimates of β_y should be approximately zero before 2014, representing that expansion and non-expansion states do not differ differentially over time before 2014. Figure B.2 plots the estimated β_y's for Medicaid registrations and private insurance registrations by organ. The estimated β_y's before 2014 are approximately zero supporting my assumption of parallel trends. Furthermore, in column 1, the estimated β_y's after 2014 are visually

more positive than before 2014, which is consistent with the estimated coefficients in Table B.3. Note that although this figure supports my assumption of parallel trends, a state's decision to expand their Medicaid eligibility or define transplants as an EHB could be correlated with differential organ demand or supply trends between expansion and non-expansion states. Future work will explore alternative specifications that are robust to these types of differential trends.

2.5 Deceased Donor Transplants

Although I find an increase in Medicaid candidates as a result of Medicaid expansion, joining the wait list does not guarantee that a candidate will receive a transplant. There is a shortage of deceased donor organs, so candidates need to wait to be offered an organ before they can receive a transplant. It is also possible that while candidates are waiting for an organ offer, they could become to sick to receive a transplant.[22] As a result, although I expect to see an increase in the number of transplants occurring for Medicaid candidates after Medicaid expansion, I expect the increase in transplants to be smaller in magnitude than the increase in the number of candidates who joined the wait list. Additionally, because the supply of organs is constrained, if more Medicaid candidates receive transplants, this means that fewer candidates with other insurance types would be able to receive transplants.[23]

Figure B.3 illustrates the differences between yearly private or Medicaid deceased donor transplants over time by a state's Medicaid expansion status. These figures preview my results: there appears to be a positive effect of Medicaid expansion on Medicaid insured deceased donor transplants, but Medicaid expansion does not have clearly visible effect on privately insured deceased donor transplants.

Table B.4 estimates equation (2.1) where y_{st} is now the monthly number of Medicaid insured or private insured deceased donor transplants per 1 million state population. As expected, there

[22] Future work will look at how the health of candidates on the wait list changes as a result of the new Medicaid candidates.

[23] It is possible that the additional candidates added after the ACA are more willing to accept "worse" quality organs that would not have been accepted by other candidates, resulting in an increase in the supply of organs. Future work will explore this possibility.

is no increase in private insurance transplants, likely because there is no increase in private insurance registrations after the introduction of the Marketplace. For all organs, the estimated effect of Medicaid expansions on deceased donor transplants is positive.[24] Although this increase is only statistically significant for lung and liver transplants, the estimated increase in transplants is clinically significant: the increases in transplants represents a 28 percent increase in the number of Medicaid deceased donor kidney transplants, a 7 percent increase for heart transplants, a 47 percent increase for lungs, and a 41 percent increase for liver transplants. Additionally, these increases imply that 12 percent of the new kidney Medicaid candidates, 25 percent of new heart candidates, 58 percent of new lung candidates, and 54 percent of new liver candidates are able to receive transplants as a result of the Medicaid expansions. Table B.4 also provides some evidence that the new Medicaid candidates crowd out transplants for candidates with private insurance. For all organs, I estimate a negative effect of Medicaid expansion on the number of privately insured transplants of a similar magnitude to the increase in Medicaid transplants, supporting my theory that these private insurance transplants are being crowded out.

As discussed in the previous section, the assumption of parallel trends needs hold in order for these estimates to be causal. To access the plausibility of this assumption, I estimate equation equation (2.2), where y_{st} is now the monthly number of Medicaid insured or privately insured deceased donor transplants per 1 million state population. Figure A.4, shows the estimated trends in number of transplants between expansion and non-expansion states are approximately parallel before the ACA, supporting this assumption. Additionally the figure shows that over time the effect of the Medicaid expansions on transplants increases. This is likely due to fact that candidates need to wait on the wait list to receive an organ offer before they can receive a transplant.

[24] As shown in Table B.2, candidates can frequently need to wait longer than a year to receive a transplant after joining the wait list. As a result of this, I expect the effect of Medicaid expansion on transplants to increase over time. Figure B.3 supports this hypothesis, as does Figure B.4. Note that although I expect the magnitude of the effect increase over time, the functional form I estimate averages the size of the effect in all post expansion years.

2.6 Living Donor Transplants

Patients who need a kidney or liver transplant have the option of finding someone currently living who is willing to donate one of these organs to them. These living donors need to be blood type compatible with the potential recipient and the living donor usually needs to have insurance coverage for after they donate.[25] Some patients who need a transplant before the ACA and who did not have insurance are likely to have had someone who was willing to donate to them, but due to the candidate's lack of insurance, the transplant did not take place. If these candidates gain insurance after the ACA, these living donor transplants are more likely to occur. Moreover, these transplants represent new transplants that increase the total number of transplants because they do not use one of the limited number of deceased donor organs.

Table B.5 presents estimates of equation (2.1) where y_{st} is the monthly number of Medicaid insured or privately insured living donor transplants of kidneys or livers. I find that Medicaid expansion more than doubles the number of Medicaid insured liver living donor transplants. Additionally, although the effect on Medicaid insured kidney transplants is not statistically significant, it does represent a 35% increase in the number of Medicaid insured kidney living donor transplants. Figure B.5 supports the assumption of parallel trends. Although the estimated effect of Medicaid expansion on privately insured living donor kidney transplants is negative, Figure B.6 makes it clear that this is not a causal effect because expansion and non-expansion states do not have parallel trends in privately insured living donor kidney transplants. This pretrend is also visible in Figure B5. Future work will explore different specifications that address this differential pretrend.

2.7 Conclusion

One aim of the ACA was to increase insurance coverage for previously uninsured low income individuals. The increase in access to insurance should allow individuals to receive needed transplants if they experience organ failure. Using the universe of organ transplant candidates

[25] Although the organ recipient's insurance will pay for the donor's surgery to remove the organ for transplant, some transplant centers want the donor to have insurance in case they have complications after the surgery.

and recipients, I find that state Medicaid eligibility expansions allowed about 50 percent more Medicaid insured candidates to register on the wait list to receive a transplant. This increase in access to Medicaid insurance also allows more Medicaid deceased donor transplants to take place and a significant increase in living donor liver transplants to occur. However, I do not find evidence that the introduction of the private insurance marketplace increases the number of individuals with private insurance registering.

More work should be done to understand why there is no effect of the marketplace on private insurance registrations and should explore heterogeneity in these results by the proportion of uninsured individuals in counties and also by availability of different metal level marketplace plans across counties.[26] Future work might also look at additional outcomes like patient and graft survival, or the wait time of candidates before transplant.[27]

The increase in the ability of low income individuals to register on transplant wait lists after the ACA is especially encouraging considering the organ allocation policy is created to be "equitable". Although the chances of receiving an organ are equal across insurance sources after candidates join the waitlist, candidates face different barriers to being waitlisted based on the source of their insurance. Uninsured individuals do not even have access to the pool of organs. Ansell et al. (2014) highlight this disparity in their blog post, stating "Studies estimate the uninsured receive less than 1 percent of all organs but comprise almost 20 percent of all organ donors". With truly equitable

[26] I also might explore heterogeneity by change in the income eligibility level for Medicaid. For example, Vermont actually decreased their eligibility level when they "expanded" Medicaid eligibility so this might lead to a different effect even though it's an "expansion" state. An additional example is Wisconsin, which isn't an "expansion" state, but they started offering Medicaid coverage for childless individuals with income up to 100 percent of the FPL around the same time as the introduction of the ACA.

[27] Even though I don't see an effect of the marketplace on private insurance wait list registrations, it might have an effect on candidates who receive transplants with other insurance types. For example, if a candidate loses their insurance after they receive a transplant, they might be able to purchase a plan on the marketplace that would help them pay for the immunosuppressants they need to help maintain their transplant. This would be especially relevant for ESRD Medicare kidney transplant recipients who lose Medicare coverage 3 years after they receive their transplant.

Existing candidates on the wait list might be made worse off by the inflow of new Medicaid candidate registrations, leading to longer wait times for them.

allocation, all individuals should have equal access to the organs being allocated. By increasing access to Medicaid insurance, the ACA helps improve equity in the organ allocation system.

CHAPTER 3

OPIOIDS AND ORGANS: HOW OVERDOSES AFFECT THE SUPPLY OF DONORS, WAITING LISTS, AND TRANSPLANT OUTCOMES (with Stacy Dickert-Conlin, Todd Elder, and Keith Teltser)

3.1 Introduction

The Organ Procurement and Transplant Network (OPTN) proclaimed that "US organ transplant and deceased donors set new records in 2016."[1] The source of the record-setting number of donors and transplants includes a dramatic increase in donors who died of drug intoxications. Figure C.1 shows that the share of all deceased donors who experienced drug intoxication rose from less than 1 percent in 1995 to 13.1 percent in 2018. In Figure C.2 we see that the number of donations arising from drug intoxication is quickly approaching the number that arise from motor vehicle donations. The news is sobering in the midst of an opioid epidemic, in which the number of drug overdose deaths more than tripled in the 15 years since 1999 (Centers for Disease Control Prevention, 2018).

Quantifying the effect of the increase in opioid overdoses on donations and transplants leads to significant equity and efficiency questions, given the allocation system of organs in the United States. Notably, donated organs from deceased donors are allocated first, in most cases, to transplant candidates in the geographic region where the organ came from. Given that the opioid epidemic is more widespread in some parts of the United States, OPTN's often competing goals of increasing "the number of transplants", providing "equity in access to transplants", and improving "waitlisted patient, living donor, and transplant recipient outcomes" (OPTN, 2017) may be further tested. For example, in Massachusetts opioid overdose deaths rose by 248 percent between 2010 and 2017, while the number of donors from drug intoxication rose by 389 percent. In contrast, opioid overdose deaths rose by only 40 percent in Iowa over the same period, and the number of donors from drug intoxication remained unchanged. Differential growth rates have the potential to differentially

[1] https://optn.transplant.hrsa.gov/news/us-organ-transplants-and-deceased-donors-set-new-records-in-2016/

impact waiting list behaviors and outcomes of transplant candidates.

In this paper, we use mortality data from the National Vital Statistics System and restricted-use data on transplant candidates and recipients from the Scientific Registry of Transplant Recipients to study the extent to which the recent growth in fatal drug overdoses affects the supply of deceased organ donations. We find that every 100 additional opioid deaths leads to 1.9 additional donors, allowing 5.3 additional transplants to take place. With the increase in donations and transplants arising from the opioid epidemic, we further consider whether organ transplant candidates respond to the increased supply. Local administrators allocate organs from deceased donors within their geographic areas via a waiting list process. Existing research (Dickert-Conlin et al., forthcoming; Fernandez et al., 2013; Lemont, 2019; Choi, 2019) shows that transplant candidates respond dramatically to supply shocks by increasing their likelihood of listing in areas with the supply increases and, in the case of kidneys, choosing to pursue an organ from a deceased donor rather than from a living donor. We find surprisingly little measurable response to the opioid related shocks. In particular, there is no evidence that the higher supply of organs from drug intoxication deaths crowds out living donors. Overall wait list additions do increase in response to increased organ donors in a geographic area, but this is primarily driven by kidney, liver, and lung candidates, although the response from kidney candidates is not statistically significant.

3.2 Institutional Details/Literature Review

3.2.1 The Opioid Epidemic

The number of drug overdose deaths more than tripled from 1999 to 2017 (CDC WONDER, 2017).[2] Opioids represent a major contributor, as 68 percent of the 70,237 drug overdose deaths in the U.S. in 2017 involved an opioid.[3] This is up from 55 percent of the 38,329 overdose deaths

[2]Source: United States Department of Health and Human Services (US DHHS), Centers for Disease Control and Prevention (CDC), National Center for Health Statistics (NCHS), Multiple Cause of Death 1999-2017 on CDC WONDER Online Database, released 2018. Data are compiled from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program. Accessedathttp://wonder.cdc.gov/mcd-icd10.html.

[3]Source: Authors' calculations from CDC WONDER data

in 2010, which is an aggregate increase of 126 percent over those seven years. This growth from 1999 to 2017 was overwhelmingly driven by deaths involving non-methadone synthetic opioids (for example, fentanyl) and heroin (CDC WONDER, 2017).

While the epidemic is a matter of national concern, there is considerable cross-state variation in opioid overdose death rates (CDC WONDER, 2017). In 2017, the states with the highest rates of opioid overdose deaths were West Virginia, Ohio, and District of Columbia (460, 370, and 350 per million population, respectively). The states experiencing the most rapid per-capita growth from 2010 to 2017 were District of Columbia, New Jersey, and Connecticut (518%, 421%, and 329%, respectively). Meanwhile, the states with the lowest opioid overdose death rates were Nebraska, Montana, and Hawaii (30, 40, and 40, per million population, respectively). The states with the least growth from 2010 to 2017 were Montana, Hawaii, and Oklahoma who all experienced declining opioid overdose death rates (-35%, -31%, and -27%, respectively).

3.2.2 Link to Organ Donation and Transplantation

Almost all deceased organ donors are brain dead at the time of organ recovery, which means that all brain function has irreversibly stopped. Because the heart continues to beat after brain death occurs, current medical technology allows for respiration via a ventilator, so that the internal organs receive oxygenated blood and remain viable for transplantation.[4] When a person experiences an opioid overdose their breathing often slows or stops, which causes hypoxia (reduced oxygen to the brain) and can cause brain death.[5] We hypothesize that there is a mechanical relationship between opioid overdose deaths and organ donation: more brain deaths due to opioid overdoses will increase the number of organ donors.

Initial published links between the opioid epidemic and organ donation were made circumstan-

[4]In contrast, organs deteriorate rapidly following cardiac deaths and are therefore unsuitable for transplantation except in extraordinary circumstances in which patients with non-survivable brain injuries who are not brain dead because they retain some minimal brain stem function become donors. See `http://www.organtransplants.org/understanding/death/`.

[5]See `https://www.drugabuse.gov/publications/drugfacts/heroin`

tially or anecdotally. For example, the April 2016 issue of *Journal of Transplantation* reprinted a Morbidity and Mortality Weekly Report from the Center for Disease Control and Prevention entitled "Increases in Drug and Opioid Overdose Deaths-United States. 2000-2014" (Rudd et al., 2016), which is entirely about the rise in overdose deaths, with the following abstract inserted before the reprint: "Deaths from opioid overdoses are increasing in the United States, which may have an impact on the organ donor pool." Around the same time in 2016, numerous newspaper articles appeared that highlighted the link between drug overdoses and organ donors and addressed the health of drug overdose donors. The *Washington Post* (Izadi, 2016) quotes David Klassen, the chief medical officer for the United Network for Organ Sharing as saying, "[T]ruthfully, people who are dying of drug overdoses are young and tend to be otherwise healthy. In many ways, they are ... potentially excellent donors, from an organ quality standpoint." In the same article Klassen cautions that long-term drug use can have damaging effects on organs. Seelye (2016) in the *New York Times* and Wenner (2016) in PennLive.com report that victims of drug overdose may be higher risk because they practice other risky behaviors that are associated with HIV and hepatitis C, but even these diseases can be treated or cured in the small chance that the transplant recipient contracts the disease.[6] Further, the risk of contracting a disease from the organ may be preferable to the outcome of death if the transplant candidate does not receive an organ at all.[7]

Goldberg et al.'s (2016) Personal Viewpoint article in the *American Journal of Transplantation* systematically documents the rise in the number of donors whose deaths are due to drug intoxication between 2003 and 2014 and shows vast geographic and organ differences in the changes in organ donation from drug overdose. They also document that donors who died from a drug overdose have the highest overall donation rate, yet do not have the highest mean number of organs transplanted

[6]Additionally, OPTN reports that the risk of contracting these diseases from an organ is smaller than the individual's lifetime risk of dying from a traffic accident. (`https://optn.transplant.hrsa.gov/media/2270/dtac\_guidance\_risks\_201706.pdf`)

[7]The webpage organdonor.gov notes that "[T]here are very few conditions that would prevent someone from being an organ eye or tissue donor - such as HIV infection, active cancer, or a systemic infection. Even with an illness, you may be able to donate your organs or tissues." Note that the risk of waiting for a lower risk organ differs by organ. Kidney patients have dialysis, which allows them to survive without a transplant, but other patients who need other organs do not.

per donor. They conclude by urging the medical community to maximize the utilization of potential donors in the face of organs from drug overdose donors often being labeled as "increased risk". In a "Special Article" for the *Transplantation* Journal, Weiner et al. (2017) make the same plea, suggesting that "due to concerns over disease transmission (HIV, hepatitis B, and hepatitis C virus), these donors are underused by the transplant community."[8]

Of course, for a potential organ donor to become an actual organ donor, the individual or their family must consent to the donation. Individuals can do so by indicating their preference on their driver's license or by registering on a state registry. First person consent laws, which exist in most states, require health care professionals to abide by the potential donor's consent to recover organs. If no such indication exists, health care professionals will seek permission from the potential donor's next-of-kin.[9] Wenner (2016) interviews the vice president for clinical services for a Pennsylvania Organ Procurement Organization (a local administrative body of OPTN) who reports that 83 percent of potential donors who died of drug overdose ultimately become donors while only 63 percent of the general population of potential donors do. He hypothesizes that this is in part due to higher donor registrations rates among overdose victims, who are more likely to be from young, white, higher income backgrounds than the overall population: 46 percent of overdose victims are registered donors, compared to 29 percent of the overall population of potential donors. In addition, he suggests that family members may be more likely to consent to donation after a drug overdose so that something positive comes from a tragic experience.[10,11] After consent for

[8]See the reference to Volk in this article and the following: https://www.healio.com/hepatology/transplantation/news/online/\%7Bc95305eb-691c-409c-9cad-d184ed02ade9\%7D/organs-donated-after-drug-overdose-safe-for-transplantation
https://consultqd.clevelandclinic.org/harvesting-life-from-a-deadly-epidemic-protocol-ups-heart-transplants-from-overdose-deaths/
https://annals.org/aim/fullarticle/2678899/drug-overdose-epidemic-deceased-donor-transplantation-united-states-national-registry.

[9]Howard (2007) estimates that donation rates among all potential donors range from 51 to 60 percent, primarily due to low consent rates.

[10]Siminoff et al. (2001) find that a family was more likely to consent to donation if the death was due to trauma compared with non-trauma related deaths.

[11]Future work might consider whether the probability transplant candidates/physicians accept

donation has been given, the organ needs to be offered to potential recipients.

3.2.3 Transplants

Transplant candidates seeking a deceased donor transplant must first register with a transplant center in order to join the national waiting list. Each transplant center is located in one of 58 donation service areas (DSAs), which broadly follow state boundaries, although large states have multiple DSAs, while some DSAs include multiple states or portions of states. When a deceased donor organ becomes available, it is first offered to candidates who are registered in the same DSA from which the organ was recovered.

Because organs are allocated first to these local candidates, transplant candidates may also want to register on multiple waiting lists in different DSAs, a process known as "multilisting". In order to do this, candidates need to be able to arrive in time to the center to receive a transplant if an organ was to become available and they also need to be accepted at the additional center. Some centers do not accept candidates who have already been registered at another center.[12] Although only 6 percent of all candidates multilist, those who do generally have higher resources than those who do not, with higher education and employment and lower Medicaid insurance coverage.

3.3 Data and Descriptive Statistics

This study uses data from the Scientific Registry of Transplant Recipients (SRTR). The SRTR data system includes data on all donors, waitlisted candidates, and transplant recipients in the US, submitted by the members of the Organ Procurement and Transplantation Network (OPTN). The Health Resources and Services Administration (HRSA), US Department of Health and Human Services, provides oversight to the activities of the OPTN and SRTR contractors. The SRTR data, which comes from hospitals and immunology laboratories, include detailed donor level data such as

organs from drug intoxication deaths evolves over time and how this affects the rate at which donated organs are transplanted.

[12] See `http://optn.transplant.hrsa.gov/learn/about-transplantation/transplant-process/` for more details.

cause, circumstance, and mechanism of death, age, gender, geographic location of donation, which organs were recovered, discarded, and transplanted, and relevant health markers. SRTR data also include transplant candidate-level information such as time spent on the waitlist, transplant centers at which each candidate is registered, health markers, demographics such as zip code of residence, reason for leaving the waitlist, and follow-up health data for those who receive a transplant. All donors can be matched with the transplant recipient when a transplant took place. In our analysis of the SRTR data, we use the years 2000, when data began being consistently collected on our variables of interest, through calendar year 2018.[13]

The *mechanism of death* is a key variable that includes the following categories: drug intoxication, gunshot/stab wounds, asphyxiation, blunt injury, cardiovascular, drowning, electrical, intracranial hemorrhage/stroke, natural causes, seizure, SIDS, none of the above, or not reported. We count donors whose mechanism of death is coded as "drug intoxication" as donors who arose from a drug overdose. In addition, SRTR codes a cause of death and circumstance of death for each donor. Not surprisingly, approximately 93 percent of all donors whose death is coded as a "drug intoxication" receive "anoxia" (defined as injury to the brain due to lack of oxygen) as their cause of death; "cerebrovascular/stroke" and "other" make up the remainder. Among the donors whose mechanism of death is "drug intoxication", almost half have no circumstance of death listed, almost 30 percent are listed as non-motor vehicle accidents, approximately 20 percent are suicides and the small remainder list natural causes as their circumstance of death.

Figure C.3 shows the dramatic rise in the number of organ donors whose death results from drug intoxication (DI). While the number of donors from all other mechanisms combined have been relatively flat and even falling in some years over the past decade, the donors from drug intoxication deaths have been dramatically rising in every year. Figure C.3 also supports the argument that donors whose death results from drug intoxication are often young, meaning that these organs are good organs to use in transplants.

Table C.1 shows that an average of 3.138 organs are transplanted per donor who died due to drug

[13] We have SRTR data through 2018, but the 2018 Mortality data are not yet available.

intoxication, which is consistent with these donors being young and otherwise healthy. However, Table C.1 also shows that organs transplanted per donor who died due to drug intoxication is relatively low compared to many other mechanisms of death. Among deaths that occur from a gunshot wound and blunt injuries, 4.340 and 3.687 organs are transplanted per donor, respectively.[14]

We also use Vital Statistics mortality micro data with county identifiers and population data from the National Cancer Institute at the individual level from 1999 to 2017 from the National Vital Statistics System (NVSS) multiple cause of death mortality files.[15] These data include every reported death of a resident in the United States and for each death, the files record information obtained from the individual's death certificate. This information includes the individual's county of residence and their cause of death. We map these counties into the Donation Service Area that covers that county. Following the CDC, opioid-related deaths are indicated by the following *International Classification of Disease, Tenth Revision (ICD-10)* multiple cause of death codes: T40.0 (opium), T40.1 (heroin), T40.2 (other opioids), T40.3 (methadone), T40.4 (other synthetic narcotics), and T40.6 (other and unspecified narcotics) (Rudd et al., 2017). Again, following the CDC, we classify a death as an opioid overdose if it is opioid-related and the underlying cause of death code is one of the following: X40-44 (unintentional drug poisoning), X60-64 (intentional self-poisoning using drugs), X85 (homicide by drugs), or Y10-14 (drug poisoning with undetermined intent).

The two panels of Figure C.4 preview our regression results. In both panels, we divide 57 DSAs into quintiles based on their 2016 opioid deaths per capita as calculated in the Vital Statistics Data.[16] In the top panel, we show the DSAs in the top quintile of opioid deaths in 2016 also tended to be in the top quintile of opioid deaths between 2000 and 2010. However, the differences between

[14]Goldberg (2016) reports a finding similar to this one; that the organs per donor are higher for asphyxiation, gunshot wounds, and blunt injuries than for drug intoxication deaths in spite of drug intoxication deaths leading to higher donation consent rates.

[15]Data are from the Multiple Cause of Death Files with County Identifiers, 1999-2017. as compiled from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program.

[16]There are 58 DSAs in the United States; however, we do not have mortality data for the DSA that includes Puerto Rico for all years in our sample, so we exclude this DSA from our analysis.

the top quintile and the other four began to widen dramatically around 2010. For example, prior to 2010, the ratio of opioid deaths per capita between the top quintile and bottom quintile ranged between 1.9 and 2.9. By 2016, the number of deaths per capita in the top quintile was 302, while the number of deaths per capita in the bottom quintile was 52, which increased the ratio of deaths to over 6.3.

The bottom panel shows that the DSA-level correlation between opioid deaths and DI organ donors is positive, although not perfectly so. For example, the DSAs in the top quintile of 2016 opioid deaths per capita have the highest level of DI organ donors per capita in most years since 2010, including in 2016. Again, there has been dramatic divergence over time across groups.

3.4 Do Overdoses Lead to Increases in the Supply of Organ Donors and Transplants?

We next turn to assessing whether drug overdoses affect the supply of organ donors and transplants. Our primary empirical strategy involves estimating DSA- and year-specific organ donation and transplantation rates as a function of the number of deaths due to drug overdoses in that DSA and year. We begin by estimating the following model:

$$Donors_{st} = \alpha_s + \delta_t + \gamma(Deaths)_{st} + \epsilon_{st}, \tag{3.1}$$

where $Donors_{st}$ is a measure of the number of deceased organ donors, s indexes the DSA, t indexes the year, and $Deaths_{st}$ is a measure of the number of drug-related deaths in that DSA and year. All specifications include a full set of DSA and year indicators (α_s and δ_t, respectively). We weight each observation by the DSA's population in that year using U.S. Census Bureau estimates. Estimates of γ based on (1) capture the association between organ donation rates and drug-related deaths over time within DSAs.

Table C.2 presents estimates of γ from specification (3.1) separately for donations due to DI and donations due to all other mechanisms. The top row presents our central estimates, in which $Donors_{st}$ includes only DI donors. In all cases, we measure $Donors_{st}$ and $Deaths_{st}$ per million state residents, so the estimates measure the effect of one additional death on the supply of organ

donors. In column (1), we use the number of opioid-related deaths as our measure of $Deaths_{st}$. This variable includes all deaths in which one of the multiple causes of death is coded as opioid-related (ICD-10 codes T40.0, T40.1, T40.2, T40.3, T40.4, and T40.6).[17] The estimate of 0.019 implies that each opioid-related death increases the supply of organ donors by 0.019, with a standard error of 0.002.

In column (2), we use opioid overdoses as our measure of $Deaths_{st}$. The set of opioid overdoses is a subset of opioid deaths, as it includes deaths that 1) have the ICD-10 codes listed above, and 2) have drug overdose listed as the underlying cause of death (ICD-10 codes X40-44, X60-64, X85, or Y10-Y14). The point estimate in this column is again 0.019, with a standard error of 0.002. Finally, column (3) shows estimates from models in which all drug overdoses is the measure of $Deaths_{st}$. This is a superset of the deaths in column (2) that also includes deaths due to anesthetics, sedatives, and stimulants. The resulting point estimate is 0.021 (0.003). Clearly, the estimates are insensitive to the particular measure of $Deaths_{st}$ that we use, and this pattern holds for all specifications that we estimate throughout the paper. As a result, below we focus on models similar to column (1), in which opioid deaths is our measure of $Deaths_{st}$.

In all cases, the estimates in the top row of Table C.2 imply that an increase of 100 drug-related deaths increases the supply of DI organ donors by only roughly two donors.[18] Viewed in this context, this implies that very few overdose victims eventually become organ donors. Nonetheless, each drug-related death increases the supply of DI organ donors by roughly 1.4 percent (= 0.019 / 1.365) of the baseline donation rate of 1.365 per million state residents.

The principal threat to the internal validity of estimates based on specifications such as (3.1) stems from differential unmeasured time trends in organ donation rates that may be correlated

[17] Specifically, ICD-10 code T40.0 refers to poisoning by opium, while T40.1, T40.2, T40.3, T40.4, and T40.6 refer to poisoning by heroin, other opioids, methadone, synthetic narcotics, and "other and unspecified narcotics", respectively.

[18] An increase of 100 deaths is approximately the size of the yearly increase in opioid-related deaths in a DSA during each year of the recent opioid crisis. In 2014, there were an average of 520 opioid-related deaths in a DSA. In 2015, the number of deaths increased to 599. In 2016 and 2017, the number of deaths were 762 and 857.

with drug-related deaths. These time trends could reflect hospitals improving their procedures for organ recovery, education campaigns encouraging informed consent, or endogenous law changes in response to declining donation rates. Based on the "All Others" row of the table, we do not think it is likely that differential trends drive the positive point estimates in the top row of the table. In all three specifications, the point estimates on measures of drug deaths are negative. The estimates are also small relative to the sample mean donation rate of 24.141 per million state residents.

Figure C.3 and Table C.3 show, the incidence of drug-related deaths varies widely by age and gender, so in Table C.4 we present age- and gender-specific estimates of specification (3.1) above. The top row shows that each drug-related death increases the supply of male organ donors who died due to drug intoxication by 0.0097 (0.0014) and increases the supply of female organ donors who died due to drug intoxication by 0.0091 (0.0009). These estimates lie between 13 and 15 percent of the respective sample means, shown in brackets. As another check on the plausibility of the results shown above, the remaining rows in Table C.4 present estimates of equation (3.1) separately by age categories. We expect the absolute effects of opioid overdose deaths on DI donation rates to be largest among individuals most likely to be involved in overdose deaths, who tend to be 25 to 54 years old (Hedegaard et al., 2018). The results confirm this expectation: among males, roughly 91 percent (= (0.4867+0.2089) / 0.7679) of DI organ donors are in the 18 to 49 age range, and roughly 90 percent (= (0.0051+0.0031) / 0.0091) of the overall marginal effect of deaths on male DI donors is accounted for by donors in the 18 to 49 age range. Among females, the analogous fractions are 85 percent (= (0.3063+0.1993) / 0.5974) and 90 percent (= (0.0051+0.0031) / 0.0091), respectively. For both sexes, DI organ donations are relatively uncommon (and relatively unaffected by opioid overdoses) among those younger than 18 and older than 49.

3.4.1 The Effects of Opioid Overdoses on Transplants

We turn next to assessing the effects of opioid overdoses on the number of organ transplants. Column (2) of Table C.5 shows the estimated effect of opioid overdose deaths on total transplants from DI donors. The estimate implies that an increase of 100 overdose deaths results in an average

of 5.3 more organs transplanted. Note that the number of additional transplants is roughly 2.8 times the number of donors (1.9), which is roughly consistent with the descriptive statistics presented in Table 2.

The remaining estimates in column (2) show organ-specific estimates. The estimate for kidneys implies that an increase of one additional overdose death increases the number of kidneys transplanted by 0.029, or roughly 1.2 percent of the mean number of DI kidneys transplanted per million persons [2.044]. DI liver transplants increase by 0.017 per million persons (1.6 percent relative to the sample mean of 1.066), heart transplants increase by 0.006 (1.3 percent), and lung transplants increase by 0.005 (1.9 percent). The estimates are also positive for pancreatic and intestinal transplants but are small in magnitude in comparison to the other organs.

Columns (3) and (4) show analogous results for non-DI donors and transplants as a falsification test; all estimates in these columns are very small relative to their sample means (and negative in all cases except for intestines).

3.4.2 Discussion

Although it is likely that this increase in donors and number of transplants is largely mechanical because more deaths means there are more potential donors, there may also be some behavioral responses to the opioid crisis. For example, transplant centers may be more willing to recover DI organs as they learn more about their usefulness. That is, as more DI organs are transplanted over time, transplant centers may realize that the risks of using such organs (e.g., HIV/HBV transmission) are not as substantial as they previously believed. Figure C.5 lends support to this theory; over time the organ recovery rates for young, drug-related death donors increases over time much faster than the organ recovery rate for other young, non-opioid-related deaths.[19] If transplant centers are

[19] In the future, we will explore this theory in more detail. Additional future work might put this further into context by considering the correlation between other mechanisms of death rates and their corresponding donation rates, including gunshot/stab wounds, asphyxiation, blunt injury, cardiovascular, drowning, electrical, intracranial hemorrhage/stroke, natural causes, seizure, and SIDS.

becoming increasingly more willing to recover opioid related organs over time, then the effects that we find are not purely mechanical.

Transplant candidates may also respond to the opioid crisis. Ultimately, in order for a transplant to take place, candidates must approve an organ offer. If candidates do not wish to receive DI organs, they can refuse those offers. If candidates frequently refuse DI organs, it could counteract the mechanical increase in transplants from the increase in deaths. Organ discard rates may reflect such a behavioral response; if the opioid crisis increases candidates' beliefs that DI organs carry an increased risk of infection, they may be increasingly likely to refuse DI organs offered to them. The more an organ is refused, the more likely it is to be discarded eventually. However, Figure C.6 suggests that this is not the case: the discard rate for young DI organs remains steady over time, and DI organs are discarded at a similar rate to organs from donors who died from other mechanisms of death.[20] Note that these are not the only possible behavioral responses. In the following sections, we explore how the opioid epidemic has affected candidates' waitlist behavior and living organ donations.

3.5 Behavioral Responses to the Change in the Supply of Organs

3.5.1 Effects of Supply Shocks on Waitlist Additions

In this section, we examine how a shock to the supply of deceased donor organs via drug overdose affects whether and where candidates register for a deceased organ transplant. As Dickert-Conlin et al. (forthcoming) show, more candidates are induced to join a DSA's waitlist following a positive supply shock because the shock reduces expected waiting time and increases expected transplant quality. However, because of this influx of additional candidates, the net effect on expected waiting time is theoretically ambiguous. Moreover, they show that this influx generates a positive externality to neighboring DSAs, since candidates who are induced to register in multiple areas exit all waitlists once they receive a transplant.

We test the predictions of Dickert-Conlin et al. (forthcoming) in the context of the opioid

[20]This lack of a response is also supported by regressions. Results are available upon request.

epidemic using SRTR and NVSS data from 1999 to 2017. We estimate the following model:

$$Additions_{st} = \alpha_s + \delta_t + \gamma(Deaths)_{st} + \epsilon_{st}, \tag{3.2}$$

where $Additions_{st}$ is a measure of the number of waitlist additions per capita, s indexes the DSA, t indexes the year, and $Deaths_{st}$ is the number of opioid overdose deaths per capita in that DSA and year. All specifications include a full set of DSA and year indicators (α_s and δ_t, respectively). We weight each observation by the DSA's population in that year using U.S. Census Bureau estimates. Estimates of γ based on (3.2) capture the association between waitlist registrations and opioid overdose deaths over time within DSAs.

In Table C.6, we present estimates of the effect of opioid overdose deaths on total waitlist additions and separately by organ, including kidneys, livers, hearts, lungs, and pancreases (for brevity, we exclude results for intestines hereafter, as intestines represent a very small segment of the transplant market). In column (1) of the top row, the estimate implies that 100 additional opioid overdose deaths results in an average of 15.4 more waitlist additions, with a standard error of 6.7. This is a 9.3 percent increase relative to the mean of 165.881. The organ-specific estimates suggest that increases in opioid overdoses mainly generate inflows onto waitlists for livers (21.6 percent), lungs (17.5 percent), and kidneys (6.3 percent, though this is not statistically significant at conventional levels). The estimated magnitudes of the wait list responses are large, especially compared the increase in transplants that we estimated earlier: the increase in registrations are 2.9 (=15.4/5.3) times as large as the increase in transplants. Note that these estimates capture how waitlist additions respond to differential changes in opioid overdoses across DSAs. However, as Dickert-Conlin et al.'s (forthcoming) conceptual framework implies, there may exist spillover effects between DSAs. As a result, the estimates in Table C.6 may understate the true effects because relatively large shocks in one DSA may induce additional waitlist registrations in another DSA that experiences a relatively small supply shock.

Columns (2) and (3) of Table C.6 provide insight on which candidates respond to supply shocks. Using zip code data for candidates and transplant centers, we generate separate counts of waitlist additions for those who live inside and outside of the DSA's boundaries. Waitlist inflows induced

by opioid overdoses are disproportionately concentrated among out-of-DSA candidates, relative to the overall sample means. The organ-specific estimates suggest that most of the out-of-DSA inflows primarily come from kidney and liver candidates, but the coefficient for kidneys is not statistically significant at conventional levels. Additionally, liver candidates drive the increase in in-DSA registrations, but lung and kidney candidates also see an increase in in-DSA registrations in response to the increased opioid deaths.

The waitlist inflows presented in Table C.6 represent new registrations in the DSA, but not necessarily new transplant candidates. This is because candidates may simultaneously register on waitlists across multiple DSAs. Table C.7 differentiates the effects of opioid overdose deaths on waitlist inflows separately for candidates who only list at one transplant center and those who ever multilist. From columns (1) and (4), we can see that most of the increase in waitlist registrations come from single listers (10.8 per 100 vs 4.5 per 100 for multilisters). Among single listers, most of the increase in registrations is from an increase in within-DSA listings, but the increase in out-of-DSA listings is proportionally larger. Among listings by multilisters, most come from out-of-DSA listings, but estimates are either marginally statistically significant or not significant at conventional levels.

3.5.2 Living Donor Crowd-Out

Previous literature documents significant substitution away from living donor transplants in response to deceased donor supply shocks, especially among kidney candidates (Dickert-Conlin et al., forthcoming; Fernandez et al., 2013; Lemont, 2019; Choi, 2019). While earlier work shows evidence of crowd-out, we find no such evidence. Specifically, in Table C.8 we present estimates from models of living-donor transplants as a function of opioid overdose deaths, finding small and statistically insignificant estimates for all organs, kidneys, and "all organs except kidneys" (kidneys account for nearly all living-donor transplants).

3.5.3 Discussion

Overall, we find some evidence of candidates responding to the increase in supply of DI organs, but the response is much smaller than that shown in other settings. Notably, the wait list response from kidney candidates is smaller and we do not find any crowd out of living kidney donors. One reason this might be that the quality of the DI organs is lower than that of the supply shocks used to measure responses in earlier papers, such as shocks due to increased deaths of helmetless motorcyclists. In addition, there may be stigma associated with DI organs.

Additionally, we primarily see a response in wait listing by single listers. This increase in single listings is likely driven by candidates choosing to list at a different DSA than they otherwise would have, rather than an increase in new candidates who wouldn't have otherwise listed. This is because an increase in opioid deaths is unlikely to induce new candidates to want or need a transplant.[21] This is further supported by our lack of evidence of living donor crowd out, which would have led to new candidates joining the waitlist.

Given that we see very little behavioral response by candidates, we expected that this should improve patient survival. If more transplants are taking place, and no/few additional wait list candidates, candidates should have shorter wait times and should have better survival rates. However, we find little evidence of improved wait times or survival.

3.6 Conclusion

This study highlights the existence of unexpected beneficiaries of the opioid crisis: those awaiting organ transplants. Organ donations due to drug intoxication (DI) have increased more than tenfold since 2000, and the rate of increase has accelerated in recent years as the opioid crisis has deepened. Our central estimates suggest that 5.3 additional organ transplants occur for every 100 additional opioid overdose deaths. These effects are concentrated among organ donors aged

[21] One exception to this might be liver candidates. Some centers are relaxing sobriety rules for listing candidates with liver failure due to alcoholism. (Source: `https://www.chicagotribune.com/business/ct-biz-liver-transplant-sober-policy-0304-story.html`) It is possible that the increase in the supply of livers from DI donors has had some effect on this decision.

18-49, who are disproportionately likely to die of opioid overdoses.

Surprisingly, we see little demand-side response. In contrast to previous papers that find that kidney candidates respond strongly to supply shocks, we find a relatively small and statistically insignificant increase in waitlist registrations by these candidates. Additionally, they do not appear to substitute away from living donors. Rather, we find that liver and lung candidates drive most of the additional waitlist registrations. It is possible that, due to lower life expectancies of liver and lung candidates, they cannot be as selective about their organ source. The limited demand-side response to the opioid supply shock is especially puzzling when contrasted with our evidence that transplant centers are becoming increasingly willing to recover DI organs for transplant.

Based on our estimates, the number of transplant candidates who died while awaiting an organ in 2015 would have been significantly higher in the absence of the opioid epidemic. While the crisis has undoubtedly been a tragedy, it has profoundly affected the lives of thousands of transplant recipients.

APPENDICES

APPENDIX A

TABLES AND FIGURES FOR CHAPTER 1

Table A.1: Characteristics of Pediatric, Young Adult, and Adult Kidney Candidates Before Share 35

	Pediatric	Young Adult	Adult
Age	10.67	19.64	48.07
Male =1	0.58	0.56	0.60
White =1	0.55	0.51	0.55
Black =1	0.21	0.25	0.25
Hispanic =1	0.20	0.17	0.13
Other Race =1	0.05	0.06	0.07
Type A blood =1	0.35	0.37	0.36
Type B blood =1	0.13	0.12	0.13
Type AB blood =1	0.04	0.03	0.04
Type O blood =1	0.48	0.48	0.46
Does not have diabetes	0.97	0.96	0.69
Has diabetes	0.01	0.01	0.29
Unknown diabetes status	0.02	0.02	0.02
Private Insurance =1	0.50	0.47	0.51
Public Insurance =1	0.45	0.49	0.46
Other Insurance =1	0.05	0.04	0.03
$0 \leq$ PRA < 20	0.55	0.61	0.68
$20 \leq$ PRA < 80	0.03	0.06	0.09
$80 \leq$ PRA ≤ 100	0.01	0.03	0.05
Unknown PRA	0.41	0.31	0.18
Pre-Transplant Dialysis =1	0.24	0.42	0.47
Died while still on the wait list =1	0.01	0.02	0.05
Received a transplant =1	0.95	0.90	0.87
Observations	5,586	2,762	97,776

Notes:
This table contains pediatric (age 0 to 17), young adult (age 18 to 21), and adult (age 22+) kidney-only transplant candidates who started waiting for a kidney transplant between 1998 and 2005 who have not had any previous kidney transplants. The age of the candidate is how old they were at their HLA typing test. Public insurance is either Medicare, Medicaid, CHIP, Department of VA, or "other government". PRA score represents what percentage of the potential donor pool a candidate has antibodies against that would cause them to reject an organ. High PRA scores are typically a result of previous transplants or pregnancies. Other outcomes besides death on the wait list or transplant from the wait list are patient removed due to improved or deteriorated health, candidate refused transplant, unable to contact candidate, or candidate still waiting.

Table A.2: Estimates of Overall Share 35 Effect on Wait Time and Quality

	Wait Time Before Transplant				Quality
	< 3 Months	< 6 Months	< 12 Months	< 18 Months	
	[0.16]	[0.37]	[0.62]	[0.75]	[14.2]
Share*Pediatric	0.04**	0.09***	0.10***	0.11***	-1.7*
	(0.01)	(0.02)	(0.02)	(0.02)	(1.0)
Observations	17,329	17,329	17,329	17,329	16,806

Robust Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
This table contains the estimated coefficients of equation 1.1 where $y_i = KDPI_i$ or $y_i = 1$ if recipient i was transplanted within 3, 6, 12, or 18 months using my entire sample of pediatric and young adult kidney transplant recipients. The model include indicators for transplant year, age, and transplant center. Standard errors of estimates, listed in parentheses, are robust to clustering within DSA over time. Pre Share 35 pediatric sample mean is listed in brackets.

Table A.3: Estimates of Coefficients for Living Donor Use at First Transplant

	All Living Donors
	[0.56]
Share*Pediatric	-0.17***
	(0.02)
Observations	17,355

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
This table contains the estimated coefficients of equation 1.1 where $y_i = LivingDonor_i$ using my entire sample of pediatric and young adult kidney transplant recipients. The model includes indicators for years, age, and transplant center. Standard errors of estimates, listed in parentheses, are robust to clustering within DSA over time. Pre Share 35 pediatric sample mean is listed in brackets.

Table A.4: Characteristics of Pediatric and Young Adult Deceased Donor Kidney Recipients Before and After Share 35

	Pediatric		Young Adult	
	Pre Share 35	Post Share 35	Pre Share 35	Post Share 35
Male =1	0.57	0.57	0.55	0.58
White =1	0.42	0.37	0.39	0.35
Black =1	0.30	0.25	0.36	0.33
Hispanic =1	0.21	0.31	0.18	0.24
Other Race =1	0.07	0.06	0.07	0.08
Type A blood=1	0.31	0.30	0.37	0.37
Type B blood=1	0.14	0.13	0.10	0.12
Type AB blood=1	0.03	0.03	0.04	0.04
Type O blood=1	0.52	0.53	0.49	0.47
Does not have Diabetes	0.97	0.98	0.96	0.97
Has Diabetes	0.01	0.00	0.01	0.03
Unknown Diabetes Status	0.02	0.01	0.03	0.01
Private Insurance =1	0.34	0.31	0.23	0.20
Public Insurance =1	0.63	0.68	0.75	0.79
Other Insurance =1	0.04	0.01	0.02	0.00
Pre-Transplant Dialysis =1	0.83	0.78	0.93	0.93
$0 \leq$ PRA < 20	0.85	0.50	0.76	0.60
$20 \leq$ PRA < 80	0.05	0.04	0.11	0.12
$80 \leq$ PRA ≤ 100	0.01	0.01	0.05	0.03
Unknown PRA	0.08	0.45	0.08	0.25
Transplanted in less than a year	0.44	0.58	0.22	0.19
Mean KDPI	27.9	18.9	35.6	35.7
Mean Donor Age	26.2	21.0	29.9	29.2
Observations	2,481	4,175	1,018	978

Notes:
This table contains pediatric and young adult deceased donor kidney transplant recipients who had no previous kidney transplants, and who were transplanted between 1998 and 2013. Public insurance is either Medicare, Medicaid, CHIP, Department of VA, or "other government". PRA score represents what percentage of the potential donor pool a candidate has antibodies against that would cause them to reject an organ. High PRA scores are typically a result of previous transplants or pregnancies.

Table A.5: Characteristics of Pediatric and Young Adult Living Donor Kidney Recipients Before and After Share 35

	Pediatric		Young Adult	
	Pre Share 35	Post Share 35	Pre Share 35	Post Share 35
Male =1	0.59	0.60	0.57	0.57
White =1	0.67	0.67	0.62	0.59
Black =1	0.13	0.10	0.16	0.13
Hispanic =1	0.16	0.19	0.16	0.23
Other Race =1	0.03	0.05	0.05	0.05
Type A blood=1	0.38	0.37	0.37	0.38
Type B blood=1	0.12	0.12	0.13	0.12
Type AB blood=1	0.04	0.04	0.03	0.04
Type O blood=1	0.46	0.47	0.46	0.47
Does not have Diabetes	0.97	0.98	0.96	0.97
Has Diabetes	0.00	0.00	0.02	0.01
Unknown Diabetes Status	0.03	0.01	0.02	0.02
Private Insurance =1	0.60	0.58	0.54	0.55
Public Insurance =1	0.36	0.41	0.44	0.45
Other Insurance =1	0.04	0.01	0.02	0.01
Pre-Transplant Dialysis =1	0.63	0.60	0.73	0.71
$0 \leq$ PRA < 20	0.28	0.24	0.46	0.40
$20 \leq$ PRA < 80	0.01	0.01	0.03	0.04
$80 \leq$ PRA ≤ 100	0.00	0.00	0.01	0.01
Unknown PRA	0.71	0.74	0.51	0.55
Transplanted in less than a year	0.77	0.74	0.72	0.64
Mean KDPI	2.2	3.9	6.8	7.8
Mean Donor Age	37.0	37.0	38.4	38.5
Parent was Donor =1	0.75	0.65	0.52	0.43
Other Relative was Donor =1	0.18	0.19	0.36	0.34
Non-Relative was Donor =1	0.08	0.16	0.12	0.24
Observations	3,157	2,479	1,605	1,475

Notes:
This table contains pediatric and young adult living donor kidney transplant recipients who had no previous kidney transplants, and who were transplanted between 1998 and 2013. Public insurance is either Medicare, Medicaid, CHIP, Department of VA, or "other government". PRA score represents what percentage of the potential donor pool a candidate has antibodies against that would cause them to reject an organ. High PRA scores are typically a result of previous transplants or pregnancies. "Other Relative" is a child, identical twin, sibling, spouse, or "other relative". "Non-Relative" is any unrelated donor.

Table A.6: Estimates of Share 35 Effect on Deceased Donor Stayers

	Wait Time Before Transplant				Quality
	< 3 Months	< 6 Months	< 12 Months	< 18 Months	
	[0.10]	[0.22]	[0.44]	[0.61]	[27.8]
Share*Pediatric	0.06***	0.15***	0.20***	0.22***	-8.4***
	(0.02)	(0.03)	(0.03)	(0.03)	(1.4)
Observations	8,634	8,634	8,634	8,634	8,634

Robust Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes:
This table contains the estimated coefficients of equation 1.1 with $y_i = KDPI_i$ or $y_i = 1$ if recipient i was transplanted within 3, 6, 12, or 18 months where each observation is weighted using the weights described in Section 1.5.4 using only deceased donor recipients in my sample of pediatric and young adult kidney transplant recipients. All models include indicators for years, age, and transplant center. Standard errors of estimates, listed in parentheses, are robust to clustering within DSA over time. Standard errors are bootstrapped over both steps of estimation. Pre Share 35 pediatric deceased donor sample mean is listed in brackets.

Table A.7: Estimates of Switching Effect on Wait Time and Quality

	Wait Time Before Transplant				Quality
	< 3 Months	< 6 Months	< 12 Months	< 18 Months	
	[0.21]	[0.49]	[0.74]	[0.87]	[2.7]
$\hat{\beta}_{Switcher}$	0.03	0.15	0.10	0.11	11.8***
	(0.08)	(0.11)	(0.08)	(0.09)	(4.0)
Observations	17,336	17,336	17,336	17,336	17,336

Bootstrapped Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
This table contains the estimates of $\beta_{Switcher}$ derived using the method described in Section 1.5.5. Pre Share 35 pediatric living donor recipient sample mean is listed in brackets

Table A.8: Characteristics of Deceased Donor Recipients at Their Second Transplant

	Pediatric at First Transplant		Young Adult at First Transplant	
	First Transplant Before Share 35	First Transplant After Share 35	First Transplant Before Share 35	First Transplant After Share 35
Age	19.46	17.38	28.91	26.87
Received EPTS Priority	0.28	0.60	0.12	0.52
Used a Living Donor	0.19	0.20	0.18	0.10
White=1	0.43	0.39	0.41	0.40
Black=1	0.30	0.26	0.34	0.39
Hispanic=1	0.22	0.29	0.18	0.18
Other Race=1	0.05	0.06	0.07	0.03
KDPI of First Transplant	30.60	19.95	36.83	41.71
Observations	758	514	309	105

Note:
This table includes the characteristics of recipients at their second transplant if they were pediatric or a young adult when they received their first deceased donor kidney transplant between 1998 and 2013.

Table A.9: Estimates of Coefficients for Living Donor Use at Second Transplant

	OLS	Heckman
ShareFirst	-0.15***	-0.22
	(0.05)	(0.26)
PediatricFirst	0.05	0.03
	(0.04)	(0.03)
ShareFirst*PediatricFirst	0.07	0.04
	(0.04)	(0.05)
Observations	1,690	
Censored Observations		6,573
Uncensored Observations		1,562

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
This table contains the estimated coefficients of equation 1.7 using the second transplant observations of pediatric and young adult first transplant deceased donor kidney recipients in my sample. Both models include indicators for year of first transplant and second transplant DSA. Standard errors of estimates, listed in parentheses, are robust to clustering within DSA over time.

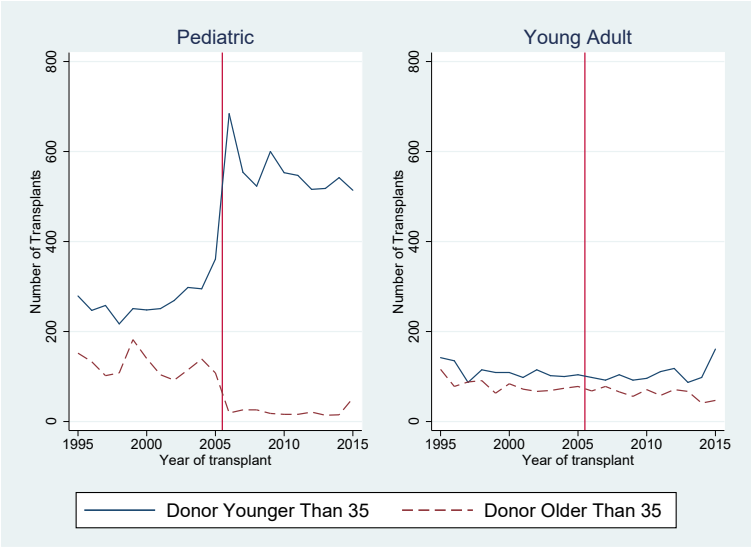
Table A.10: Robustness: Coefficient on $Share * Pediatric$

	Original	Exclude Age 17 & 18	Exclude 2005 & 2006
All Pediatric Recipients (Section 1.5.1):			
Quality	-1.7*	-1.9**	-1.5*
Wait Time			
< 3 Months	0.04**	0.04**	0.05***
< 6 Months	0.09***	0.09***	0.11***
< 12 Months	0.10***	0.09***	0.12***
< 18 Months	0.11***	0.11***	0.13***
Crowd out in Living Donors (Section 1.5.2):	-0.17***	-0.16***	-0.17***
Stayers (Section 1.5.4):			
Quality	-8.4***	-8.7***	-8.8***
Wait Time			
< 3 Months	0.06***	0.05**	0.07***
< 6 Months	0.15***	0.14***	0.17***
< 12 Months	0.20***	0.18***	0.22***
< 18 Months	0.22***	0.21***	0.24***

*** p<0.01, ** p<0.05, * p<0.1

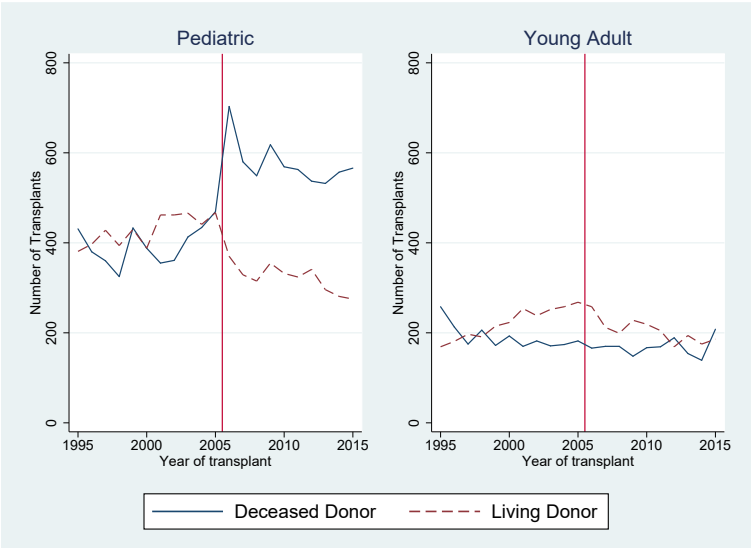
Note:
This table replicates existing estimations listed in the table by excluding candidates who are age 17 or 18 in column 2 or by excluding candidates who were transplanted within one year on either side of Share 35 in column 3.

Figure A.1: Deceased Donor Kidney Transplants by Donor Age



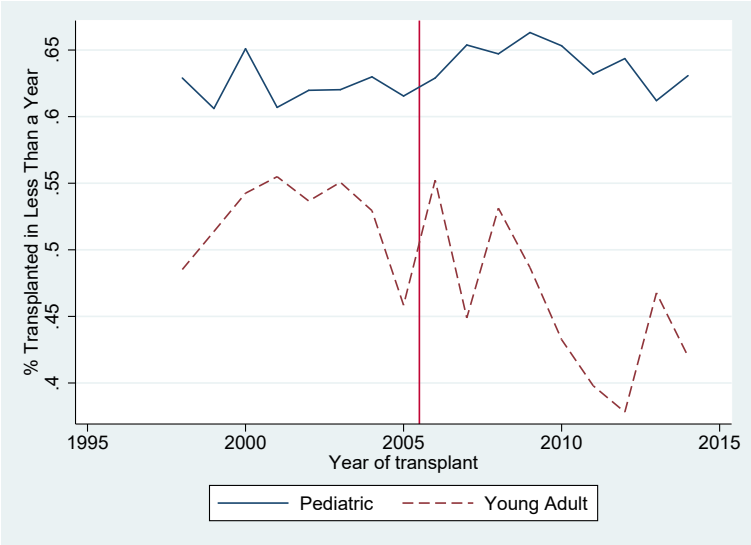
Notes:
Author's calculations from SRTR data. Candidates are considered pediatric if they are less than 18 years old at the start of their wait time. Candidates are considered young adult if they are 18 to 21 years old at the start of their wait time.

Figure A.2: Kidney Transplants by Donor Type



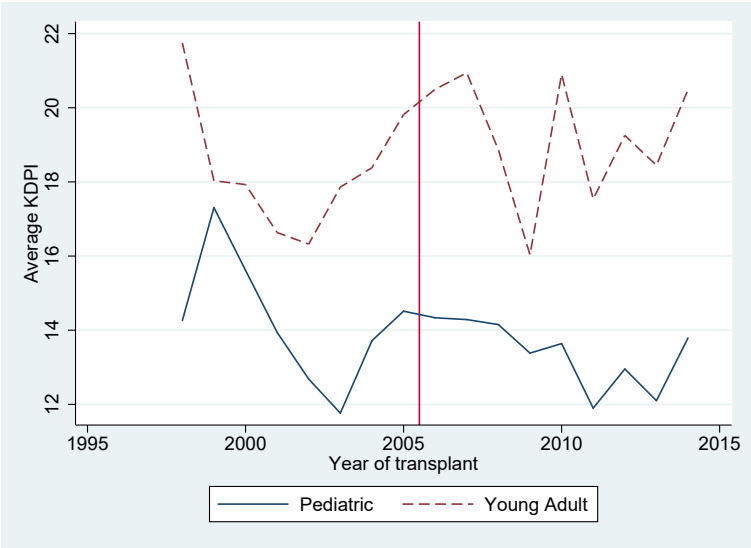
Notes:
Author's calculations from SRTR data. Candidates are considered pediatric if they are less than 18 years old at the start of their wait time. Candidates are considered young adult if they are 18 to 21 years old at the start of their wait time.

Figure A.3: Transplant Wait Time Less than a Year Among All Donor Types



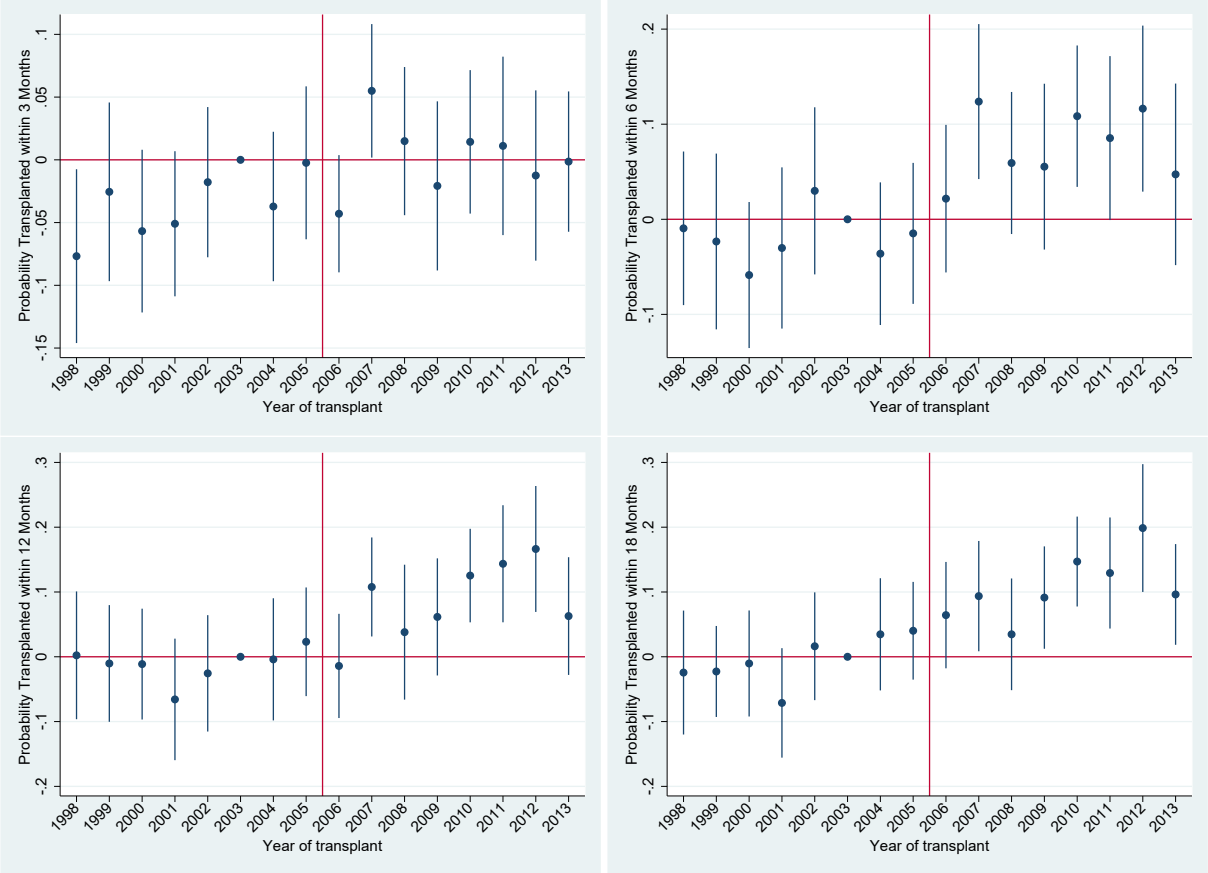
Notes:
Author's calculations from SRTR data. Candidates are considered pediatric if they are less than 18 years old at the start of their wait time. Candidates are considered young adult if they are 18 to 21 years old at the start of their wait time.

Figure A.4: Average KDPI Among All Donor Types



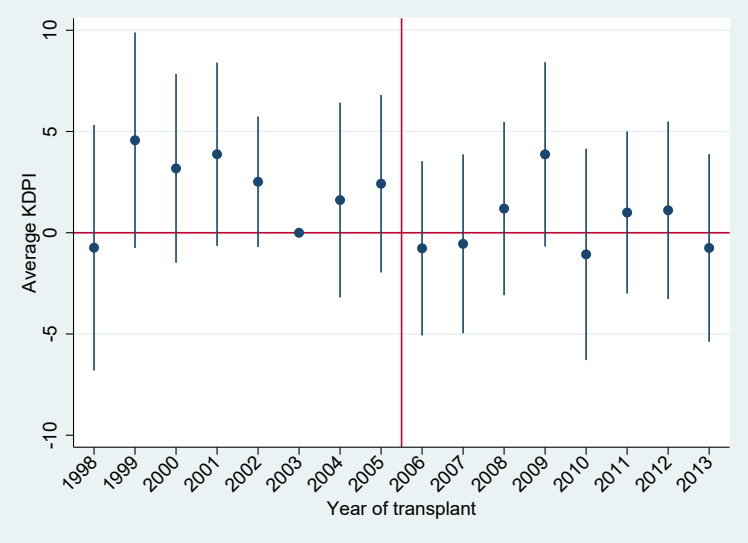
Notes:
Author's calculations from SRTR data. Candidates are considered pediatric if they are less than 18 years old at the start of their wait time. Candidates are considered young adult if they are 18 to 21 years old at the start of their wait time.

Figure A.5: Event Study Estimates: Wait Time Among All Donor Types



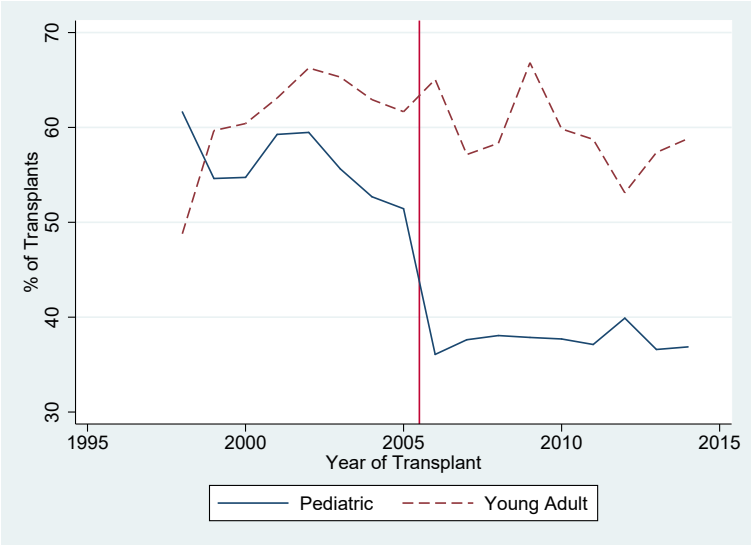
Notes:
Author's calculations from SRTR data. This figure plots the estimated β_τ's from equation 1.2 where $y_i = 1$ if recipient i was transplanted within 3, 6, 12, or 18 months using the entire sample of pediatric and young adult deceased and living donor recipients. β_{2003} is omitted and therefore equal to zero.

Figure A.6: Event Study Estimates: Average KDPI Among All Donor Types



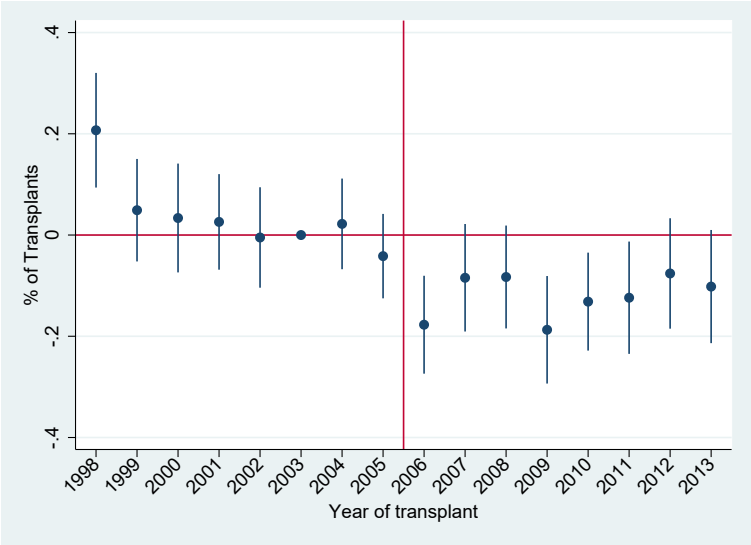
Notes:
Author's calculations from SRTR data. This figure plots the estimated β_τ's from equation 1.2 where $y_i = KDPI_i$ using the entire sample of pediatric and young adult deceased and living donor recipients. β_{2003} is omitted and therefore equal to zero.

Figure A.7: Percent of First Transplants That Use a Living Donor



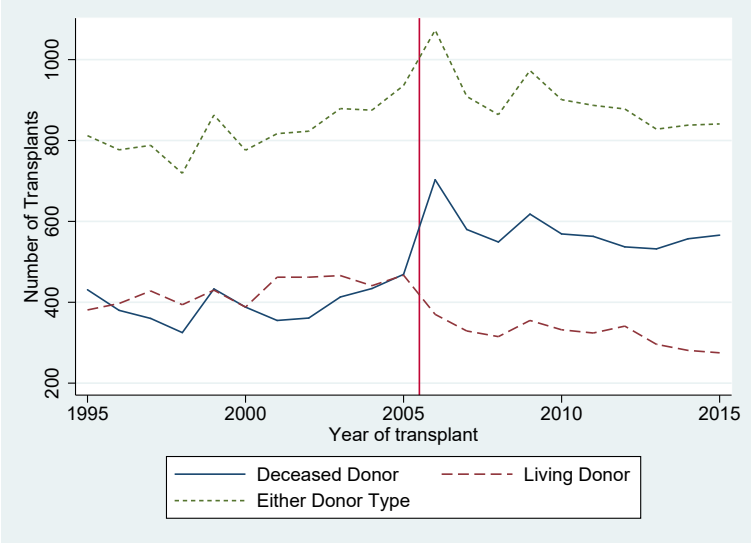
Notes:
Author's calculations from SRTR data. The percent of transplants in this figure is calculated as the total number of living donor transplants divided by the total number of deceased and living donor transplants in a given year. Candidates are considered pediatric if they are less than 18 years old at the start of their wait time. Candidates are considered young adult if they are 18 to 21 years old at the start of their wait time.

Figure A.8: Event Study Estimates: First Transplant Uses Living Donor



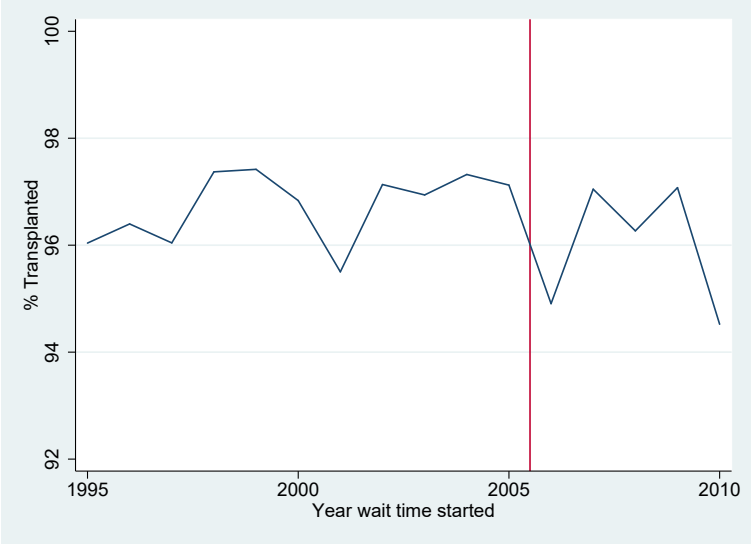
Notes:
Author's calculations from SRTR data. This figure plots the estimated β_τ's from equation 1.2 where $y_i = LivingDonor_i$ using the entire sample of pediatric and young adult deceased and living donor recipients. β_{2003} is omitted and therefore equal to zero.

Figure A.9: Pediatric Kidney Transplants



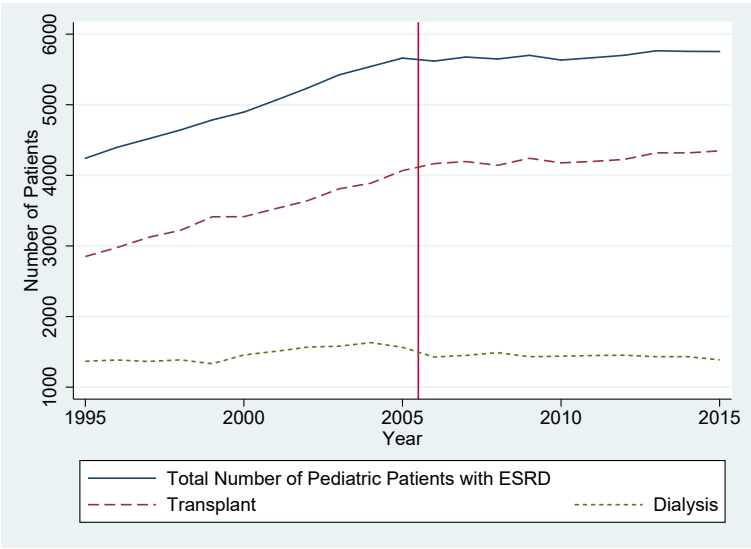
Notes:
Author's calculations from SRTR data. Candidates are considered pediatric if they are less than 18 years old at the start of their wait time.

Figure A.10: Percent of Pediatric Candidates who Receive a Transplant



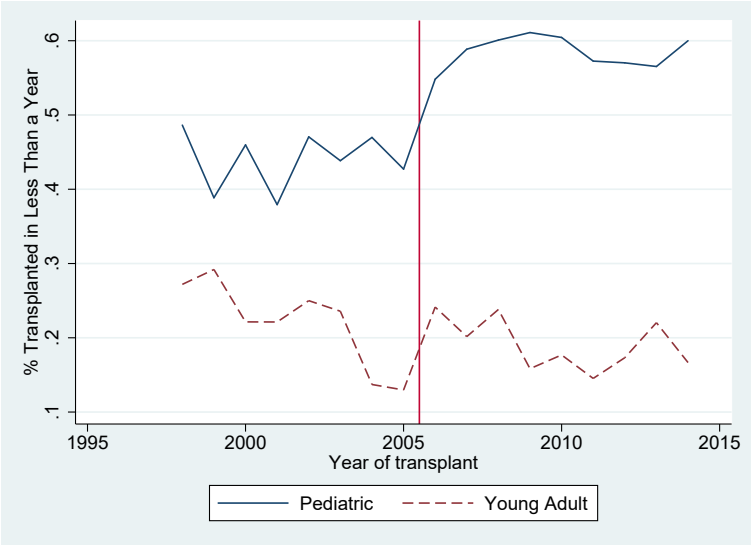
Notes:
Author's calculations from SRTR data. The percent of candidates who receive a transplant in this figure is calculated as conditional on starting waiting in a given year, the total number of candidates who eventually receive a transplant divided by the total number of wait list registrations and living donor transplants from candidates who did not register. Candidates are considered pediatric if they are less than 18 years old at the start of their wait time.

Figure A.11: Treatment Choice by Year



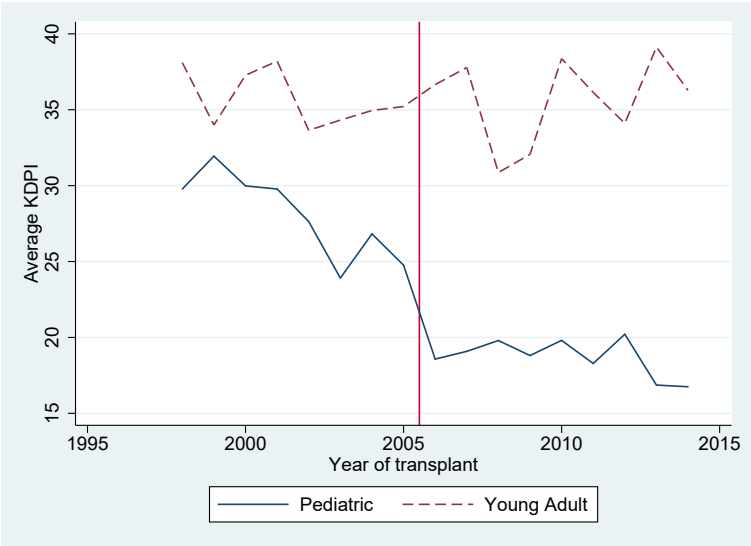
Notes:
Author's calculations from the United States Renal Data System, 2017 Annual Data Report: Epidemiology of Kidney Disease in the United States. National Institutes of Health, National Institute of Diabetes and Digestive and Kidney Diseases, Bethesda, MD, 2017. This figure shows the treatment choice of all current ESRD patients who are 0 to 17 years old. Transplant is counted as a "treatment" for ESRD so the total number of children with ESRD contains both children who are using dialysis and those who have a functioning kidney transplant.

Figure A.12: Wait Time Less than a Year Among Deceased Donor Recipients



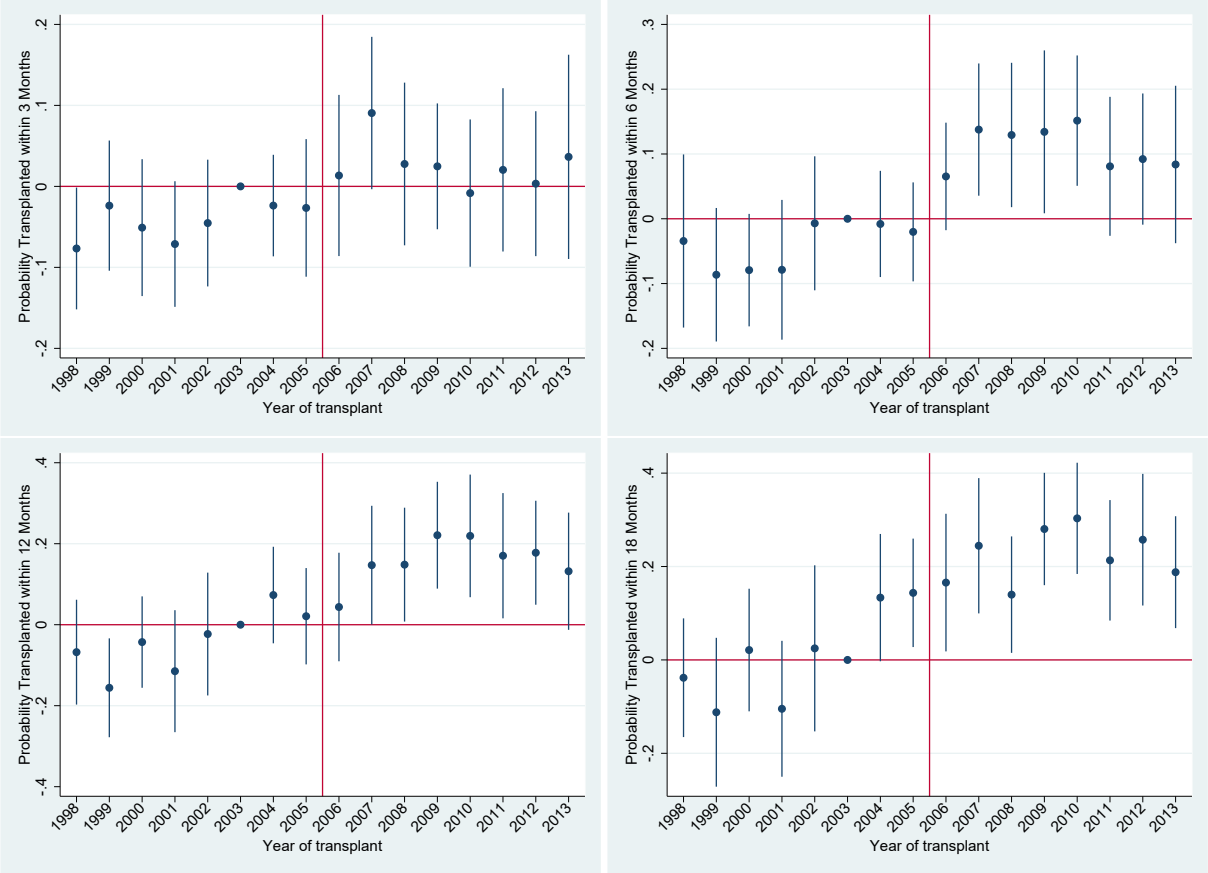
Notes:
Author's calculations from SRTR data. Candidates are considered pediatric if they are less than 18 years old at the start of their wait time. Candidates are considered young adult if they are 18 to 21 years old at the start of their wait time.

Figure A.13: Average KDPI Among Deceased Donor Recipients



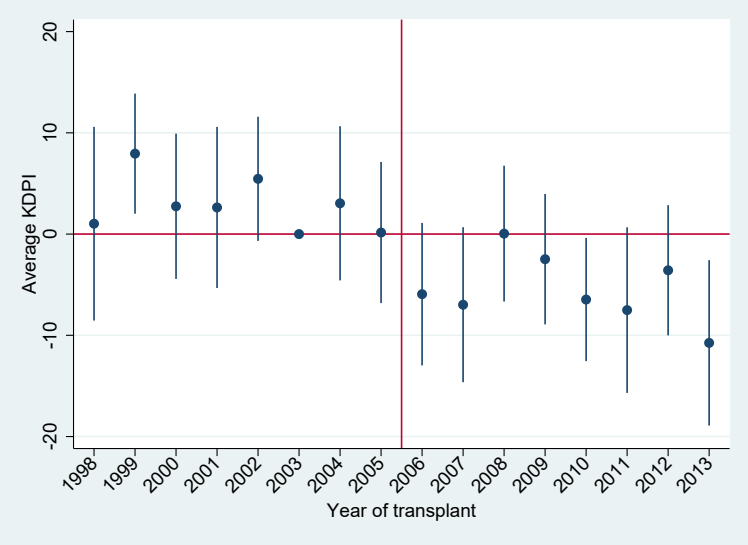
Notes:
Author's calculations from SRTR data. Candidates are considered pediatric if they are less than 18 years old at the start of their wait time. Candidates are considered young adult if they are 18 to 21 years old at the start of their wait time.

Figure A.14: Event Study Estimates: Wait Time Among Deceased Donor Stayers



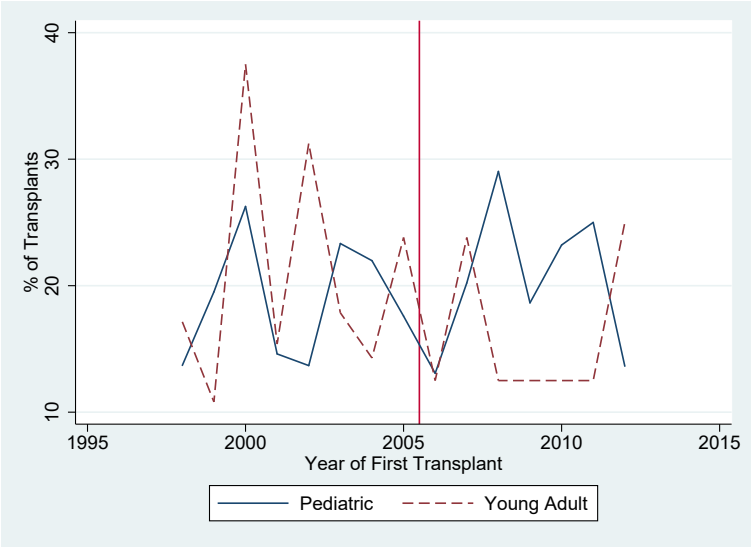
Notes:
Author's calculations from SRTR data. This figure plots the estimated β_τ's from equation 1.2 where $y_i = 1$ if recipient i was transplanted within 3, 6, 12, or 18 months using the sample of pediatric and young adult deceased recipients, weighted as described in Seciton 1.5.4. β_{2003} is omitted and therefore equal to zero.

Figure A.15: Event Study Estimates: Average KDPI Among Deceased Donor Stayers



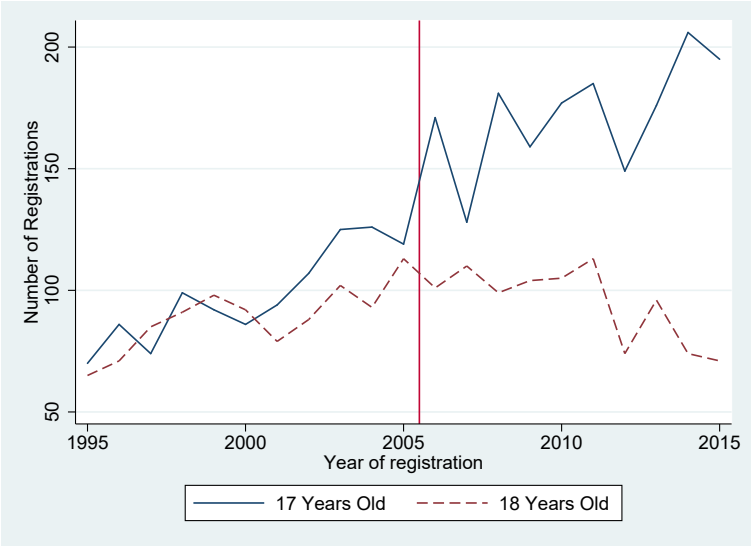
Notes:
Author's calculations from SRTR data. This figure plots the estimated β_τ's from equation 1.2 where $y_i = KDPI_i$ using the sample of pediatric and young adult deceased recipients, weighted as described in Seciton 1.5.4. β_{2003} is omitted and therefore equal to zero.

Figure A.16: Percent of Second Transplants That Use a Living Donor That Used a Deceased Donor for the First Transplant



Notes:
Author's calculations from SRTR data through March 2019. The percent of transplants in this figure is calculated as the total number of living donor second transplants divided by the total number of deceased and living donor second transplants in a given year. Candidates are considered pediatric if they were less than 18 years old at the start of their wait time for their first transplant. Candidates are considered young adult if they were 18 to 21 years old at the start of their wait time for their first transplant.

Figure A.17: Number of Wait List Additions by Age



Notes:
Author's calculations from SRTR data. Age is determined at the date of the candidate's wait list registration.

APPENDIX B

TABLES AND FIGURES FOR CHAPTER 2

Table B.1: State Decisions to Expand Medicaid or Include Transplants as an EHB

State	EHB in 2017	Medicaid Expansion Date
Alabama	Yes	
Alaska	Yes	9/1/2015
Arizona		1/1/2014
Arkansas		1/1/2014
California		1/1/2014
Colorado		1/1/2014
Connecticut		1/1/2014
Delaware		1/1/2014
District of Columbia		1/1/2014
Florida		
Georgia		
Hawaii		1/1/2014
Idaho		TBD
Illinois		1/1/2014
Indiana		2/1/2015
Iowa		1/1/2014
Kansas		
Kentucky		1/1/2014
Louisiana		7/1/2016
Maine		1/10/2019
Maryland		1/1/2014
Massachusetts	Yes	1/1/2014
Michigan		4/1/2014
Minnesota	Yes	1/1/2014
Mississippi		
Missouri		
Montana		1/1/2016
Nebraska		TBD
Nevada		1/1/2014
New Hampshire	Yes	8/8/2014
New Jersey		1/1/2014
New Mexico	Yes	1/1/2014
New York		1/1/2014
North Carolina		
North Dakota		1/1/2014
Ohio		1/1/2014

Table B.1 (Cont'd)

Oklahoma		
Oregon		1/1/2014
Pennsylvania	Yes	1/1/2015
Rhode Island		1/1/2014
South Dakota	Yes	
South Carolina		
Tennessee		
Texas		
Utah		TBD
Vermont		1/1/2014
Virginia		1/1/2019
Washington		1/1/2014
West Virginia		1/1/2014
Wisconsin		
Wyoming		

Notes:
State that did not choose to include transplants as an EHB in 2017 already chose to include them in 2014. States without a Medicaid Expansion date did not choose to expand Medicaid. States with "TBD" as their Medicaid Expansion date have not yet determined when their Medicaid expansion will take effect.
Sources:
Medicaid Expansion Dates: `https://www.kff.org/health-reform/state-indicator/state-activity-around-expanding-medicaid-under-the-affordable-care-act/`
Essential Health Benefits: `https://www.cms.gov/cciio/resources/data-resources/ehb.html`

Table B.2: Transplant Candidate Characteristics

	Kidney		**Heart**	
	Before ACA	After ACA	Before ACA	After ACA
Age $<$ 18	0.03	0.03	0.15	0.14
18 $\leq$ Age $\leq$ 64	0.82	0.79	0.72	0.70
65 $\leq$ Age	0.16	0.18	0.13	0.16
White	0.46	0.44	0.65	0.61
Black	0.29	0.29	0.21	0.23
Hispanic	0.17	0.18	0.09	0.10
Other Race	0.08	0.09	0.04	0.05
Medicaid	0.07	0.09	0.17	0.18
Private	0.43	0.43	0.52	0.49

Table B.2 (Cont'd)

Other Insurance	0.50	0.48	0.31	0.33
Previously transplanted	0.14	0.13	0.05	0.04
Died within ...				
6 months of listing	0.02	0.02	0.10	0.10
1 year of listing	0.04	0.03	0.14	0.13
2 years of listing	0.07	0.07	0.18	0.19
3 years of listing	0.11	0.11	0.22	0.24
Received a transplant within a year of listing	0.20	0.24	0.56	0.54
Observations	218,031	192,154	21,841	22,694

	Lung		**Liver**	
	Before ACA	After ACA	Before ACA	After ACA
Age $<$ 18	0.04	0.02	0.06	0.06
18 $\leq$ Age $\leq$ 64	0.74	0.69	0.81	0.75
65 $\leq$ Age	0.22	0.29	0.12	0.19
White	0.82	0.78	0.69	0.69
Black	0.09	0.10	0.10	0.09
Hispanic	0.07	0.09	0.15	0.16
Other Race	0.03	0.03	0.06	0.06
Medicaid	0.09	0.09	0.17	0.19
Private	0.56	0.48	0.57	0.51
Other Insurance	0.35	0.43	0.26	0.30
Previously transplanted	0.06	0.04	0.07	0.05
Died within ...				
6 months of listing	0.12	0.11	0.10	0.10
1 year of listing	0.18	0.16	0.15	0.15
2 years of listing	0.26	0.25	0.21	0.22
3 years of listing	0.34	0.33	0.25	0.27
Received a transplant within a year of listing	0.64	0.71	0.45	0.49
Observations	14,416	14,485	70,003	62,799

Table B.2 (Cont'd)

Note:
Sample includes transplant candidates registered between 2008 and 2018.

Table B.3: Monthly Wait List Additions per 1 Million Population

	Kidney		Heart	
	Medicaid [0.49]	Private [3.35]	Medicaid [0.15]	Private [0.44]
Transplant is EHB	0.049 (0.081)	0.12 (0.23)	-0.037 (0.034)	0.018 (0.032)
Post Medicaid expansion	0.29*** (0.093)	-0.23 (0.20)	0.028* (0.016)	-0.085** (0.033)
Observations	6,732	6,732	6,732	6,732
R-squared	0.307	0.330	0.090	0.104
	Lung		Liver	
	Medicaid [0.04]	Private [0.30]	Medicaid [0.41]	Private [1.43]
Transplant is EHB	-0.0081 (0.016)	-0.032 (0.031)	-0.045 (0.045)	-0.063 (0.11)
Post Medicaid expansion	0.024** (0.0098)	-0.023 (0.019)	0.17*** (0.052)	-0.16** (0.074)
Observations	6,732	6,732	6,732	6,732
R-squared	0.055	0.123	0.175	0.183

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
Author's calculations from SRTR data. This table contains estimates of equation (2.1) where y_{st} is number of Medicaid insured or privately insured wait list additions per 1 million state population. Estimation sample includes 50 states and the District of Columbia from 2008 to 2018. The unit of observation is a state-month-year. Standard errors are clustered at the state level. Pre-ACA sample means are listed in brackets

Table B.4: Monthly Deceased Donor Transplants per 1 Million Population

	Kidney		Heart	
	Medicaid [0.12]	Private [0.71]	Medicaid [0.10]	Private [0.28]
Transplant is EHB	0.0012	-0.088	-0.0098	0.011
	(0.024)	(0.075)	(0.012)	(0.027)
Post Medicaid expansion	0.034	-0.037	0.0071	-0.025
	(0.021)	(0.051)	(0.012)	(0.023)
Observations	6,732	6,732	6,732	6,732
R-squared	0.150	0.139	0.065	0.083
	Lung		Liver	
	Medicaid [0.03]	Private [0.21]	Medicaid [0.22]	Private [0.77]
Transplant is EHB	-0.0070	-0.064**	-0.033	-0.059
	(0.010)	(0.031)	(0.046)	(0.044)
Post Medicaid expansion	0.014**	-0.0092	0.091***	-0.093***
	(0.0059)	(0.017)	(0.028)	(0.032)
Observations	6,732	6,732	6,732	6,732
R-squared	0.053	0.078	0.107	0.151

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes:
Author's calculations from SRTR data. This table contains estimates of equation (2.1) where y_{st} is number of Medicaid insured or privately insured deceased donor transplants per 1 million state population. Estimation sample includes 50 states and the District of Columbia from 2008 to 2017. The unit of observation is a state-month-year. Standard errors are clustered at the state level. Pre-ACA sample means are listed in brackets

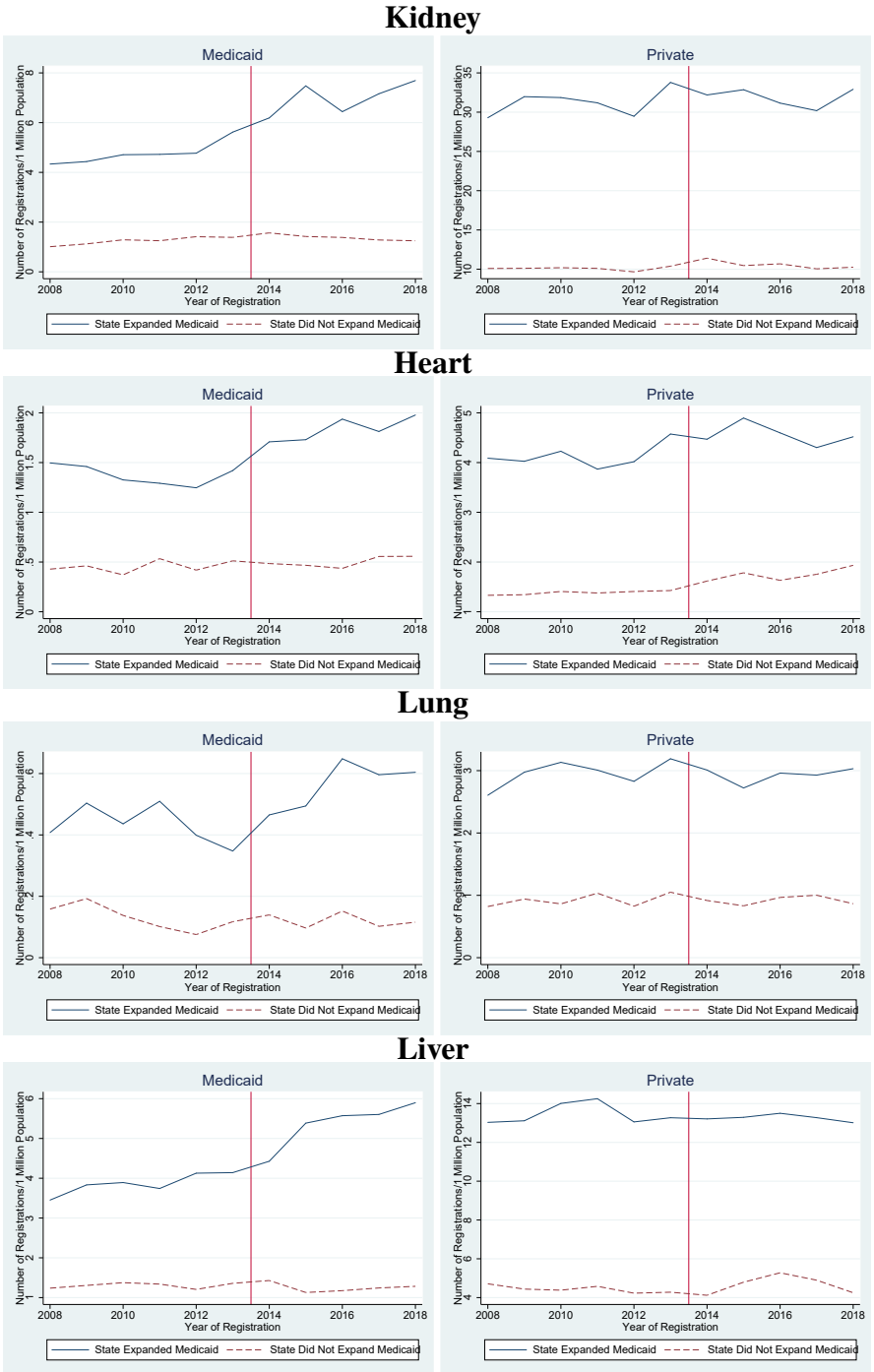
Table B.5: Monthly Living Donor Transplants per 1 Million Population

	Kidney		Liver	
	Medicaid [0.04]	Private [0.80]	Medicaid [0.005]	Private [0.03]
Transplant is EHB	-0.013 (0.011)	-0.032 (0.038)	0.00020 (0.0026)	0.0071 (0.011)
Post Medicaid expansion	0.014 (0.0095)	-0.13*** (0.040)	0.0067*** (0.0022)	0.0064 (0.0084)
Observations	6,732	6,732	6,732	6,732
R-squared	0.077	0.197	0.084	0.169

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

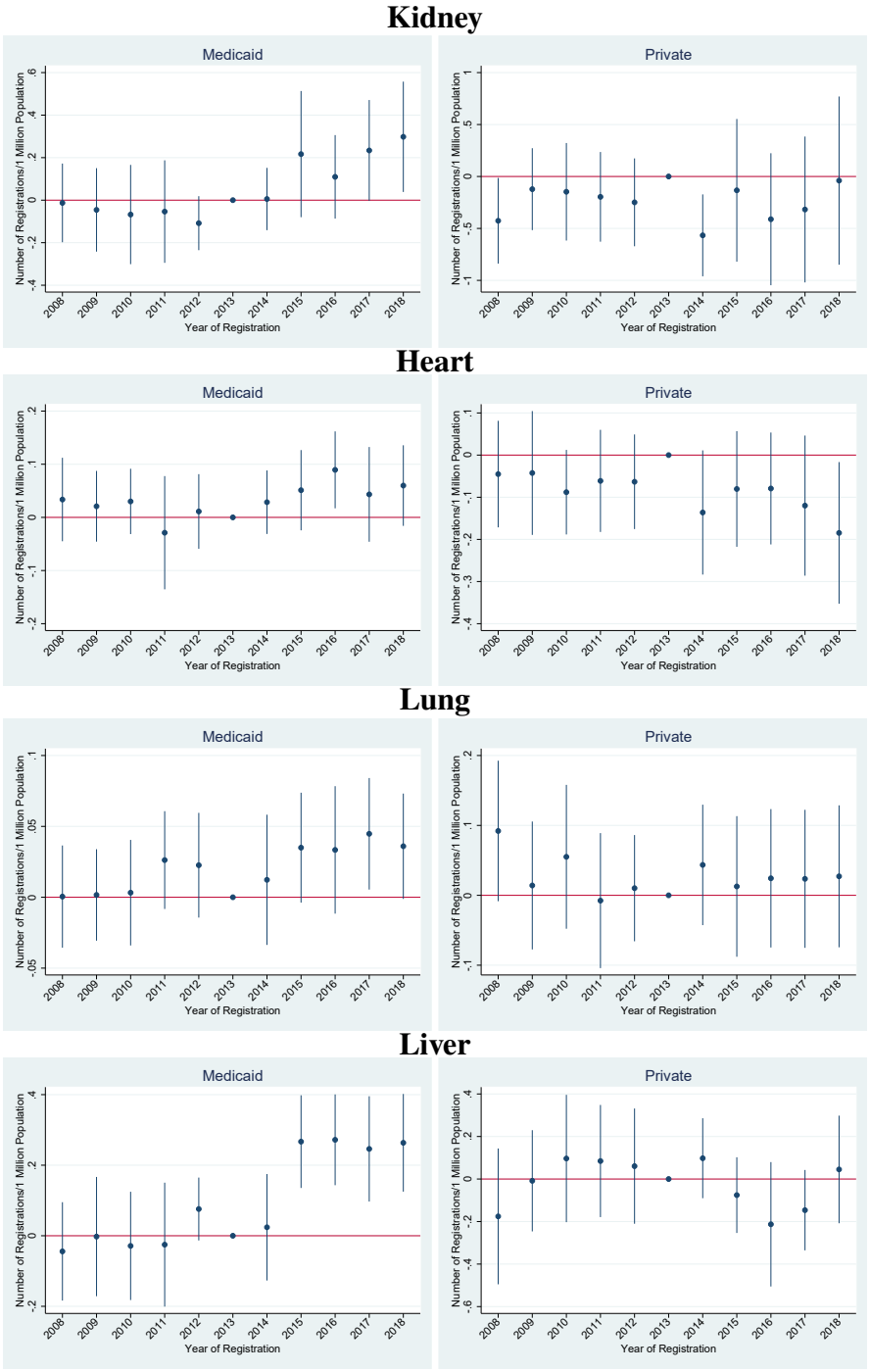
Notes:
Author's calculations from SRTR data. This table contains estimates of equation (2.1) where y_{st} is number of Medicaid insured or privately insured living donor transplants per 1 million state population. Estimation sample includes 50 states and the District of Columbia from 2008 to 2018. The unit of observation is a state-month-year. Standard errors are clustered at the state level. Pre-ACA sample means are listed in brackets

Figure B.1: Registrations by Medicaid Expansion Status



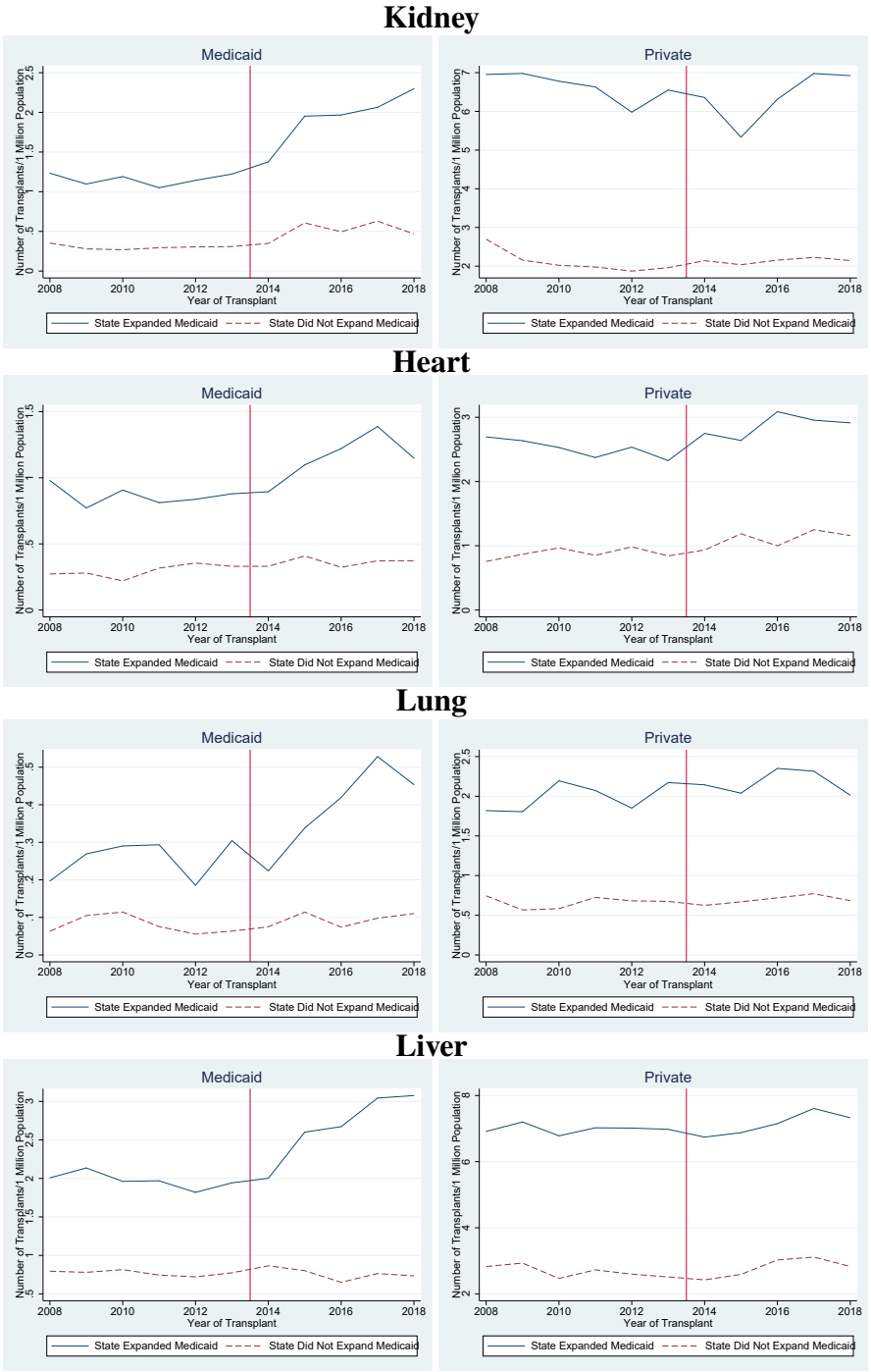
Note:
This figure plots the number of registrations per million population, averaged across all states who either expanded Medicaid or did not.

Figure B.2: Wait List Addition Trends by Organ



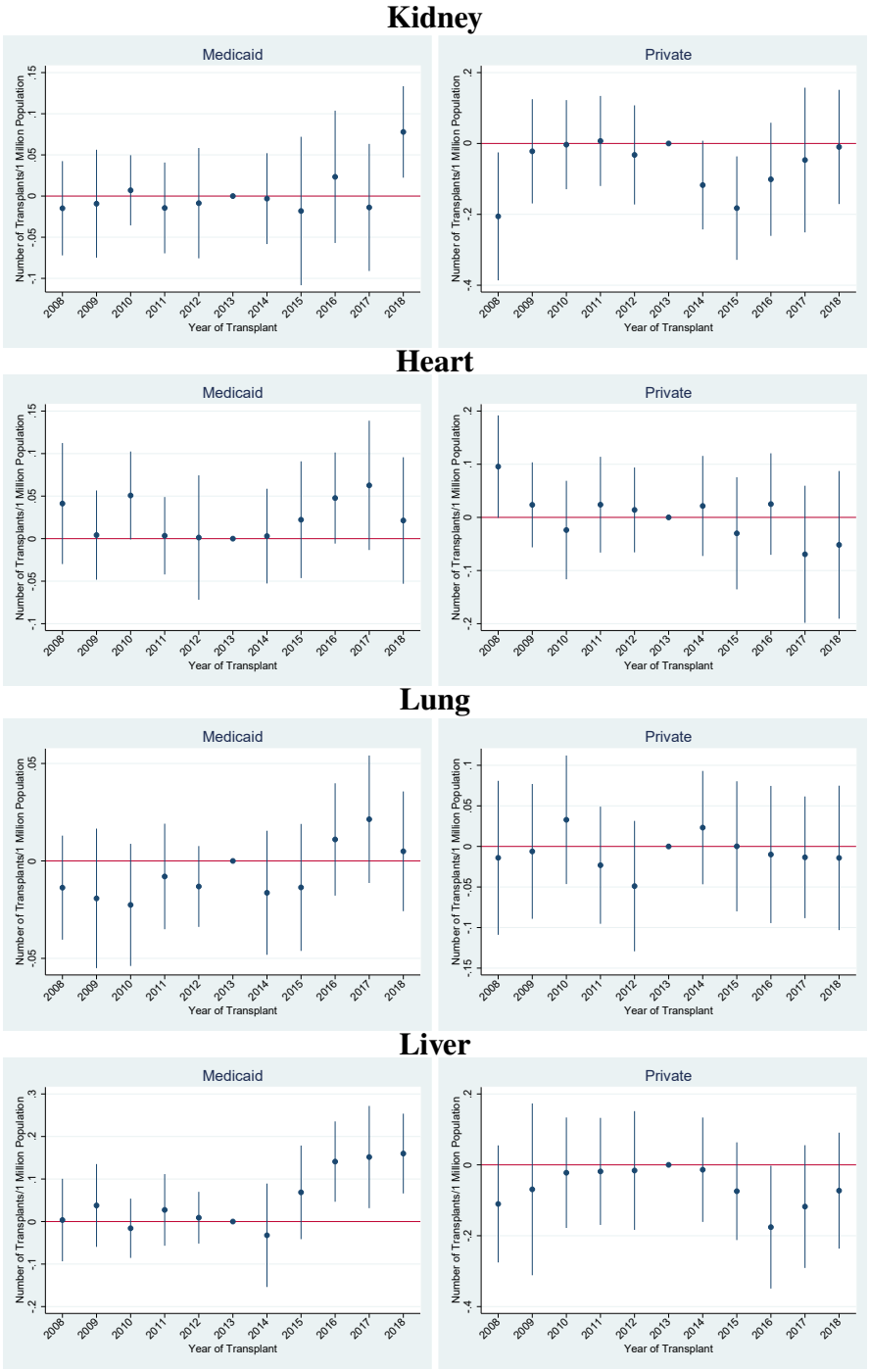
Notes:
Author's calculations from SRTR data. This figure plots the estimated β_y's from equation (2.2) where y_{st} is number of Medicaid insured or privately insured wait list additions per 1 million state population. Estimation sample includes 50 states and the District of Columbia from 2008 to 2018. The unit of observation is a state-month-year. Standard errors are clustered at the state level.

Figure B.3: Deceased Donor Transplants by Medicaid Expansion Status



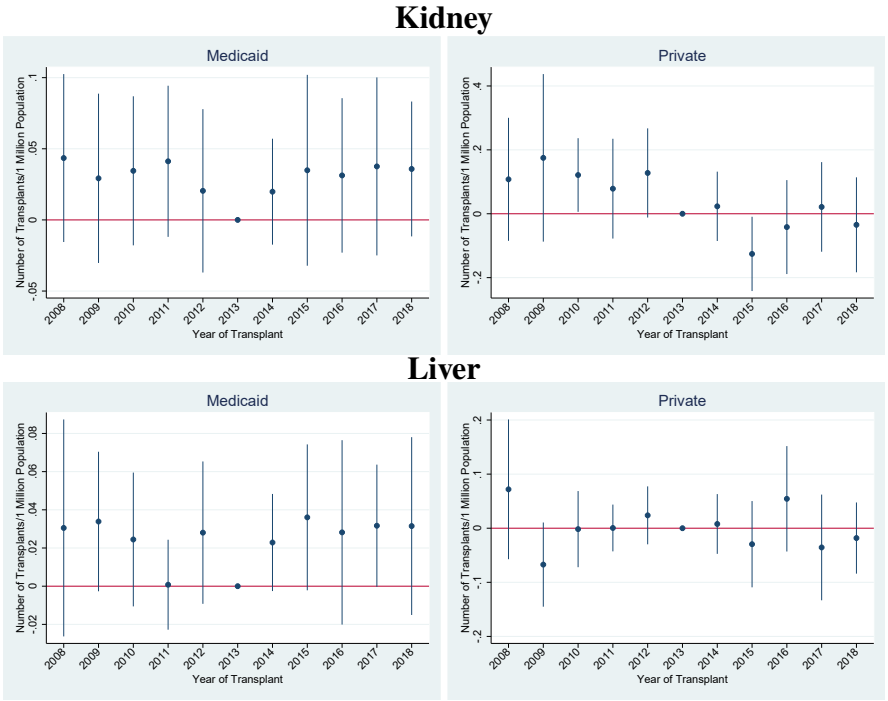
Note:
This figure plots the number of deceased donor transplants per million population, averaged across all states who either expanded Medicaid or did not.

Figure B.4: Deceased Donor Transplant Trends by Organ



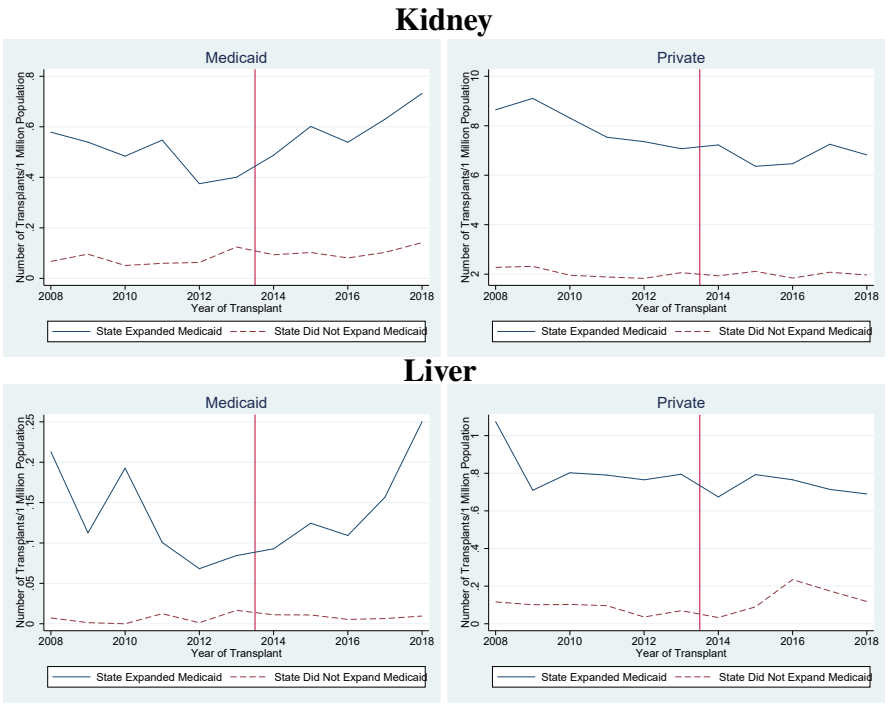
Notes:
Author's calculations from SRTR data. This figure plots the estimated β_y's from equation (2.2) where y_{st} is number of Medicaid insured or privately insured deceased donor transplants per 1 million state population. Estimation sample includes 50 states and the District of Columbia from 2008 to 2018. The unit of observation is a state-month-year. Standard errors are clustered at the state level.

Figure B.5: Living Donor Transplant Trends by Organ



Notes:
Author's calculations from SRTR data. This figure plots the estimated β_y's from equation (2.2) where y_{st} is number of Medicaid insured or privately insured living donor transplants per 1 million state population. Estimation sample includes 50 states and the District of Columbia from 2008 to 2018. The unit of observation is a state-month-year. Standard errors are clustered at the state level.

Figure B.6: Living Donor Transplants by Medicaid Expansion Status



Note:
This figure plots the number of living donor transplants per million population, averaged across all states who either expanded Medicaid or did not.

APPENDIX C

TABLES AND FIGURES FOR CHAPTER 3

Table C.1: Average Number of Organs Transplanted per Donor, by Mechanism of Death

Mechanism	Kidney	Liver	Heart	Lung	Pancreas	Intestine	Total
Gunshot	1.775	0.892	0.582	0.713	0.354	0.023	4.340
Blunt Injury	1.738	0.812	0.465	0.388	0.256	0.029	3.687
Stab	1.735	0.769	0.388	0.399	0.224	0.004	3.519
Asphyxiation	1.698	0.758	0.376	0.334	0.198	0.029	3.394
Seizure	1.575	0.714	0.356	0.415	0.150	0.036	3.247
Drowning	1.767	0.756	0.415	0.117	0.128	0.058	3.231
Electrical	1.756	0.711	0.356	0.211	0.144	0.022	3.200
Drug Intoxication	**1.529**	**0.784**	**0.360**	**0.356**	**0.102**	**0.006**	**3.138**
Other	1.500	0.713	0.344	0.288	0.137	0.040	3.022
Natural Causes	1.418	0.668	0.236	0.255	0.079	0.012	2.668
Stroke	1.282	0.751	0.182	0.315	0.078	0.008	2.616
SIDS	0.704	0.604	0.734	0.036	0.118	0.213	2.408
Cardiovascular	1.286	0.664	0.155	0.168	0.055	0.009	2.336

Note:
Authors' calculations using 2000-2018 SRTR data.

Table C.2: Average Number of Organs Transplanted per Donor, by Mechanism of Death

	Drug Deaths Measured as:			
	Opioid Deaths	Opioid Overdoses	Drug Overdoses	Sample Mean
Donor Mechanism	(1)	(2)	(3)	(per million)
Drug Intoxication	0.019	0.019	0.021	1.365
	(0.002)	(0.002)	(0.003)	
All Others	-0.017	-0.018	-0.010	24.141
	(0.007)	(0.007)	(0.005)	

Notes:
All estimation samples consist of 57 DSAs from 1999 to 2017. The unit of observation is a DSA-year. All models include indicators for years and DSAs. Standard errors, listed in parentheses, are robust to clustering with DSA over time. All variables are measured per million DSA residents.

Table C.3: Organ Donors by Year, Gender, and Mechanism

	Mechanism: Drug Intoxication			Mechanism: All Others		
	All	Male	Female	All	Male	Female
2000	66	35	31	5924	3451	2472
2001	84	47	37	5999	3531	2468
2002	107	57	50	6089	3640	2449
2003	138	75	63	6324	3721	2603
2004	188	91	97	6964	4019	2945
2005	158	79	79	7437	4345	3092
2006	230	135	95	7793	4649	3144
2007	268	148	120	7826	4734	3092
2008	285	153	132	7708	4583	3125
2009	322	168	154	7701	4560	3141
2010	342	179	163	7604	4506	3098
2011	473	238	235	7657	4528	3129
2012	441	231	210	7707	4592	3115
2013	560	309	251	7714	4601	3113
2014	625	374	251	7977	4793	3184
2015	848	501	347	8236	4987	3249
2016	1262	763	499	8717	5197	3520
2017	1384	798	586	8907	5403	3504
2018	1401	834	567	9322	5662	3660

Note:
Authors' calculations using 2000-2018 SRTR data.

Table C.4: Estimates of the Effect of Opioid Overdose Deaths on Organ Donations Due to Drug Intoxication, by Gender and Age

	Males	Females	Pooled
	DI Organ Donors (1)	DI Organ Donors (2)	DI Organ Donors (3)
Overall	0.0097	0.0091	0.0188
	(0.0014)	(0.0009)	(0.0021)
	[0.7679]	[0.5974]	[1.3652]
Age Categories:			
<18	0.0002	0.0001	0.0002
	(0.0001)	(0.0001)	(0.0001)
	[0.0253]	[0.0211]	[0.0464]
18-34	0.0050	0.0051	0.0102
	(0.0009)	(0.0005)	(0.0012)
	[0.4867]	[0.3063]	[0.7930]
35-49	0.0038	0.0031	0.0069
	(0.0006)	(0.0005)	(0.0010)
	[0.2089]	[0.1993]	[0.4082]
50-64	0.0006	0.0008	0.0014
	(0.0002)	(0.0001)	(0.0002)
	[0.0459]	[0.0686]	[0.1145]
65+	0.0001	0.0000	0.0001
	(0.0000)	(0.0001)	(0.0001)
	[0.0010]	[0.0021]	[0.0031]

Notes:
All estimation samples consist of 57 DSAs from 1999 to 2017. The unit of observation is a DSA-year. All models include indicators for years and DSAs. Standard errors, listed in parentheses, are robust to clustering with DSA over time. Sample means for relevant dependent variables are listed in brackets, with all variables measured per million DSA residents.

Table C.5: Estimates of the Effect of Opioid Overdose Deaths on Organ Transplants, by Organ

	DI Organ Donors (1)	DI Organ Transplants (2)	Non-DI Organ Donors (3)	Non-DI Organ Transplants (4)
Overall	0.019	0.053	-0.017	-0.045
	(0.002)	(0.007)	(0.007)	(0.020)
	[1.365]	[4.001]	[24.141]	[70.281]
By Organ				
Kidney		0.029		-0.021
		(0.005)		(0.009)
		[2.044]		[34.935]
Liver		0.017		-0.002
		(0.002)		(0.004)
		[1.066]		[18.527]
Heart		0.006		-0.006
		(0.001)		(0.002)
		[0.471]		[7.508]
Lung		0.005		-0.003
		(0.001)		(0.003)
		[0.269]		[4.991]
Pancreas		0.001		-0.001
		(0.001)		(0.002)
		[0.142]		[3.888]
Intestine		0.000		0.000
		(0.000)		(0.001)
		[0.009]		[0.431]

Notes:
All estimation samples consist of 57 DSAs from 1999 to 2017. The unit of observation is a DSA-year. All models include indicators for years and DSAs. Standard errors, listed in parentheses, are robust to clustering with DSA over time. Sample means for relevant dependent variables are listed in brackets, with all variables measured per million DSA residents.

Table C.6: Estimates of the Effect of Opioid Overdose Deaths on Waiting List Additions by In- Versus Out-of-Area

	All Additions (1)	In-DSA (2)	Out-of-DSA (3)
Overall	0.154	0.089	0.065
	(0.067)	(0.047)	(0.032)
	[165.881]	[128.980]	[36.901]
By Organ			
Kidney	0.063	0.029	0.034
	(0.049)	(0.037)	(0.024)
	[100.242]	[81.173]	[19.069]
Liver	0.076	0.054	0.021
	(0.027)	(0.017)	(0.012)
	[35.237]	[26.029]	[9.209]
Heart	0.000	0.000	0.000
	(0.006)	(0.005)	(0.003)
	[10.844]	[8.390]	[2.455]
Lung	0.012	0.008	0.004
	(0.006)	(0.003)	(0.003)
	[6.850]	[4.249]	[2.601]
Pancreas	-0.003	-0.002	-0.001
	(0.004)	(0.002)	(0.002)
	[1.999]	[1.362]	[0.637]

Notes:
All estimation samples consist of 57 DSAs from 1999 to 2017. The unit of observation is a DSA-year. All models include indicators for years and DSAs. Standard errors, listed in parentheses, are robust to clustering with DSA over time. Sample means for relevant dependent variables are listed in brackets, with all variables measured per million DSA residents.

Table C.7: Estimates of the Effect of Opioid Overdose Deaths on Waiting List Additions by In- Versus Out-of-Area and by Multilisting Status

	No Multilistings			Multilistings		
	All Additions (1)	In-DSA (2)	Out-of-DSA (3)	All Additions (4)	In-DSA (5)	Out-of-DSA (6)
Overall	0.108	0.070	0.039	0.045	0.019	0.026
	(0.051)	(0.039)	(0.022)	(0.025)	(0.016)	(0.014)
	[122.559]	[101.038]	[21.521]	[43.322]	[27.942]	[15.380]
By Organ						
Kidney	0.036	0.018	0.018	0.027	0.011	0.016
	(0.036)	(0.029)	(0.016)	(0.019)	(0.012)	(0.010)
	[70.710]	[61.917]	[8.794]	[29.532]	[19.256]	[10.275]
Liver	0.066	0.049	0.017	0.010	0.005	0.005
	(0.024)	(0.016)	(0.010)	(0.007)	(0.004)	(0.004)
	[29.198]	[22.431]	[6.767]	[6.040]	[3.598]	[2.442]
Heart	-0.001	-0.001	0.000	0.001	0.001	0.000
	(0.005)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)
	[9.695]	[7.606]	[2.089]	[1.149]	[0.784]	[0.365]
Lung	0.013	0.008	0.005	0.000	0.000	-0.001
	(0.006)	(0.003)	(0.003)	(0.001)	(0.000)	(0.001)
	[5.894]	[3.779]	[2.115]	[0.957]	[0.471]	[0.486]
Pancreas	-0.003	-0.002	-0.001	-0.001	-0.001	0.000
	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
	[1.248]	[0.859]	[0.389]	[0.751]	[0.503]	[0.248]

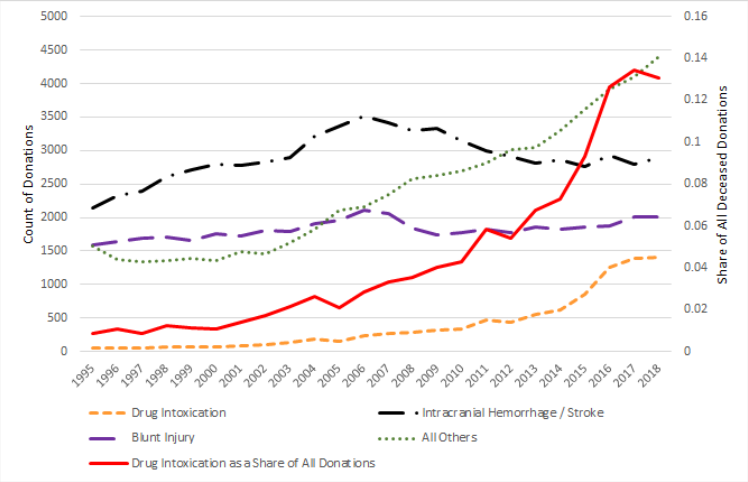
Notes:
All estimation samples consist of 57 DSAs from 1999 to 2017. The unit of observation is a DSA-year. All models include indicators for years and DSAs. Standard errors, listed in parentheses, are robust to clustering with DSA over time. Sample means for relevant dependent variables are listed in brackets, with all variables measured per million DSA residents.

Table C.8: Estimates of the Effect of Opioid Overdose Deaths on Living-Donor Transplants

	All Organs	Kidneys	All Except Kidneys
Overall	0.002	0.000	0.002
	(0.009)	(0.009)	(0.003)
	[19.385]	[18.563]	[0.823]

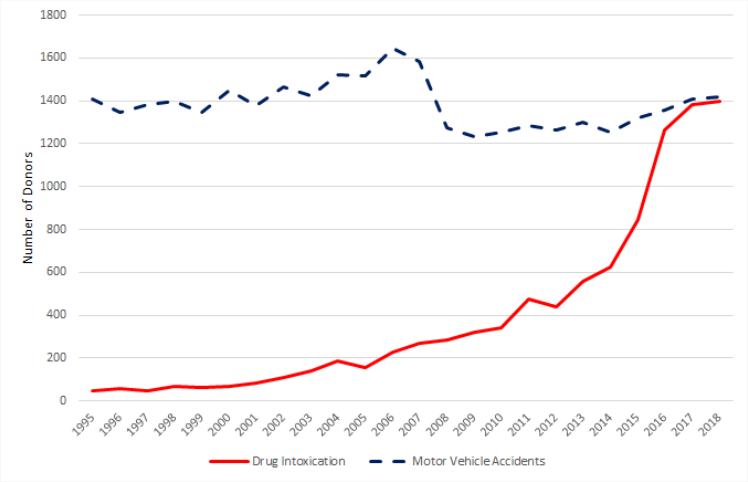
Notes:
All estimation samples consist of 57 DSAs from 1999 to 2017. The unit of observation is a DSA-year. All models include indicators for years and DSAs. Standard errors, listed in parentheses, are robust to clustering with DSA over time. Sample means for relevant dependent variables are listed in brackets, with all variables measured per million DSA residents.

Figure C.1: Donations by Mechanism of Death



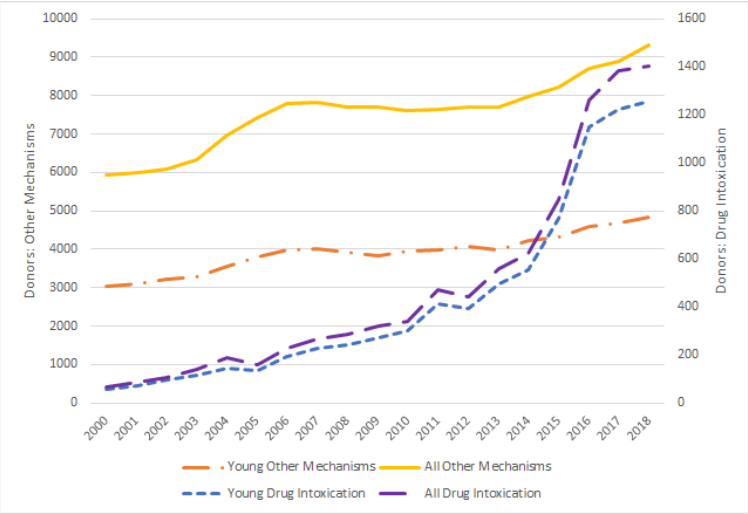
Notes:
Authors' calculations from the SRTR data. "All others" include Gunshot/Stab wound, Asphyxiation, Cardiovascular, Drowning, Electrical, Natural Causes, None of the above.

Figure C.2: Number of Donors by Source



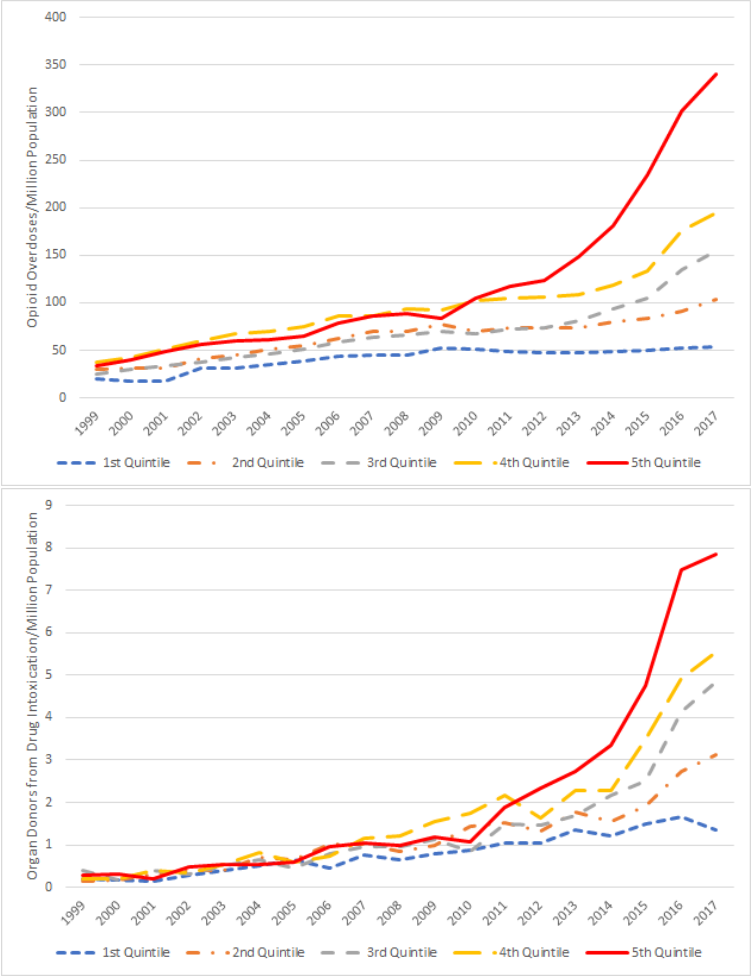
Notes:
Authors' calculations from the SRTR data. In the SRTR data, Motor Vehicle Accidents are coded as a circumstance of death and Drug Intoxications are a mechanism of death, but there is almost no overlap in the two in the data.

Figure C.3: Organ Donors by Year, Age, and Mechanism



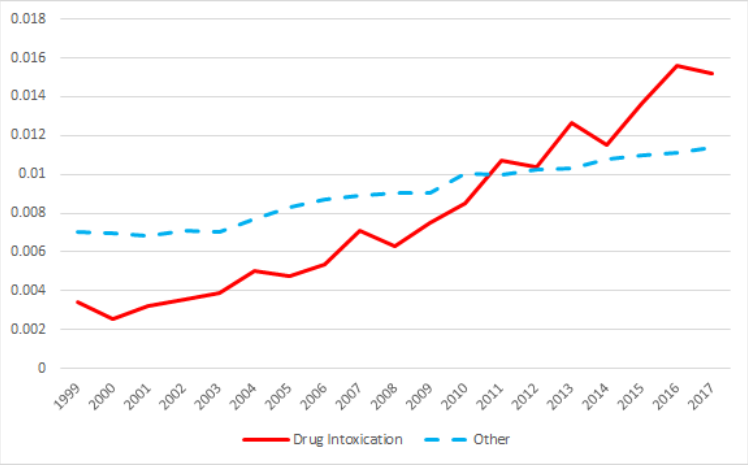
Notes:
Authors' calculations from the SRTR data. "Other Mechanisms" include Gunshot/Stab wound, Blunt Injury, Stab, Seizure, Stroke, SIDS, Asphyxiation, Cardiovascular, Drowning, Electrical, Natural Causes, None of the above. Donors are "young" if they are 19-49 years old.

Figure C.4: Opioid Overdoses and Organ Donors by 2016 Quintile of Opioid Overdose Levels



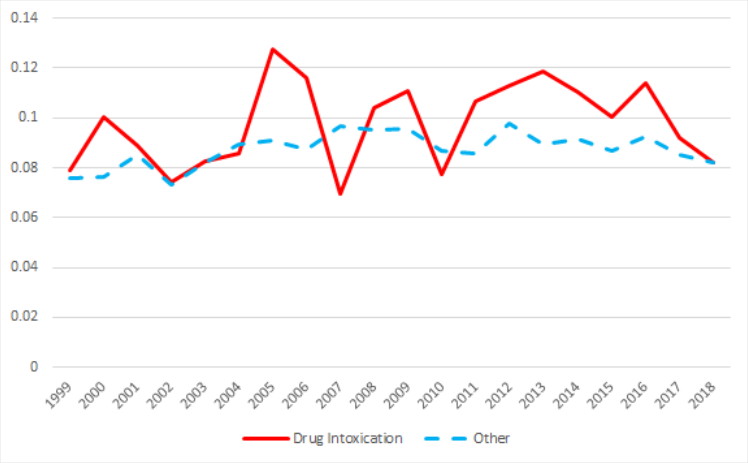
Notes:
Authors' calculations from the Vital Statistics Mortality Data and SRTR data. The 1st quintile contains the following DSAs: AROR, CADN, CAGS, CAOP, HIOP, IAOP, MSOP, MWOB, NEOR, TXGC, TXSA, and TXSB. The 2nd quintile contains the following DSAs: ALOB, AZOB, CASD, CORS, GALL, INOP, LAOP, MNOP, OKOP, ORUO, and WALC. The 3rd quintile contains the following DSAs: DCTC, FLFH, NCCM, NCNC, NYAP, NYRT, PADV, SCOP, TNMS, UTOP, VATB, and WIUW. The 4th quintile contains the following DSAs: FLMP, FLUF, FLWC, ILIP, MIOP, MOMA, NJTO, NMOP, NVLV, NYFL, and TNDS. The 5th quintile contains the following DSAs: KYDA, MAOB, MDPC, NYWN, OHLB, OHLC, OHLP, OHOV, PATF, CTOP, and WIDN. See appendix Table F.1 for the full names of the OPOs that oversee the DSAs and the state that their headquarter is located in.

Figure C.5: Young Donor Recovery Rates



Notes:
Authors' calculations from the SRTR data. Young donor drug intoxication rate is calculated using donors 18 to 49 years old whose mechanism of death was drug intoxication and using 18 to 49-year-old deaths whose death was classified as "opioid-related" as previously defined in this paper. Other young donor rate is calculated using donors 18 to 49 years old whose mechanism of death was not drug intoxication and using 18 to 49-year-old deaths whose death was not classified as "opioid-related" as previously defined in this paper. Recovery rate is calculated as the total number of organs recovered that are intended for transplant divided by 8 times the number of deaths.

Figure C.6: Young Donor Discard Rates



Notes:
Authors' calculations from the SRTR data. Young donor drug intoxication rate is calculated using donors 18 to 49 years old whose mechanism of death was drug intoxication. Other young donor rate is calculated using donors 18 to 49 years old whose mechanism of death was not drug intoxication. Discard rate is calculated as the total number of organs recovered that are intended for transplant, but not ultimately transplanted divided by the total number of organs recovered that are intended for transplant.

APPENDIX D

APPENDICES FOR CHAPTER 1

Table D.1: Wait Time Differences

	Deceased Donor	Registered Living Donor
Average Wait Time	464	365
(test date)	(435)	(384)
Average Wait Time	347	264
(registration date)	(392)	(334)
Average Δ Wait Time	117	101
	(299)	(253)
Observations	6,645	2,428

Notes:
This table contains pediatric kidney recipients who registered on the waiting list and received a deceased or living donor kidney between 1995 and 2013.
Wait Time (test date)= Transplant date - HLA test date
Wait Time (Registration date)= Transplant date - Registration date
Δ Wait Time = Wait Time (test date) - Wait Time (Registration date)

Table D.2: Estimates of Share 35 Effect on Deceased Donor Stayers

	Wait Time Before Transplant								Quality	
	< 3 Months		< 6 Months		< 12 Months		< 18 Months			
Weighted?	Y	N	Y	N	Y	N	Y	N	Y	N
Share*Pediatric	0.06***	0.04**	0.15***	0.12***	0.20***	0.16***	0.22***	0.21***	-8.4***	-8.9***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(1.4)	(1.2)
Observations	8,634	8,602	8,634	8,602	8,634	8,602	8,634	8,602	8,634	8,540

Robust Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

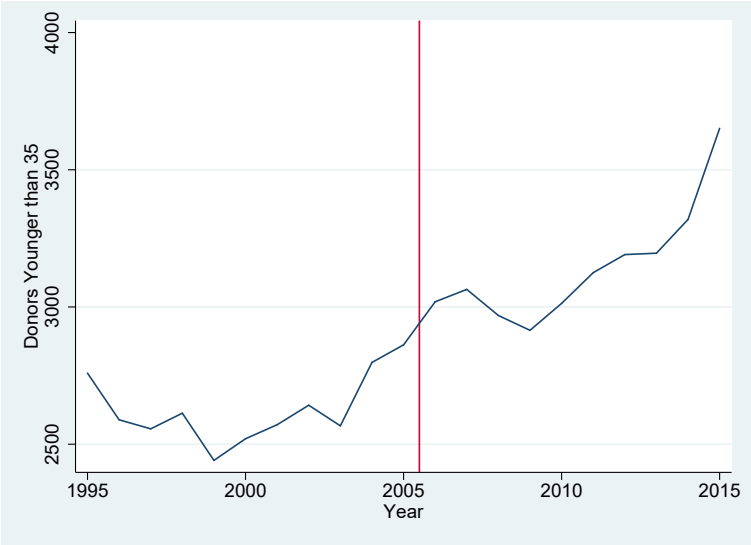
Notes:
This table contains the estimated coefficients of equation 1.1 with $y_i = KDPI_i$ or $y_i = 1$ if recipient i was transplanted within 3, 6, 12, or 18 months where each observation is weighted using the weights described in Section 1.5.4 or where observations have not been re-weighted, using only deceased donor recipients in my sample of pediatric and young adult kidney transplant recipients. All models include indicators for years, age, and transplant center. Standard errors of estimates, listed in parentheses, are robust to clustering within DSA over time. Standard errors for weighted estimates are bootstrapped over both steps of estimation.

Figure D.1: Hypothetical Wait List Change for a Kidney from a Donor Younger than 35

Wait List Before Share 35	**Wait List After Share 35**
1: Adult	1: Pediatric up 7
2: Adult	2: Pediatric up 11
3: Adult	3: Adult
4: Adult	4: Adult
5: Adult	5: Adult
6: Adult	6: Adult
7: Adult	7: Adult
8: Pediatric *	8: Adult
9: Adult	9: Adult
10: Young Adult *	10: Adult
11: Adult	11: Young Adult down 1
12: Adult	12: Adult
13: Pediatric *	13: Adult
14: Adult	14: Adult
15: Adult	15: Adult

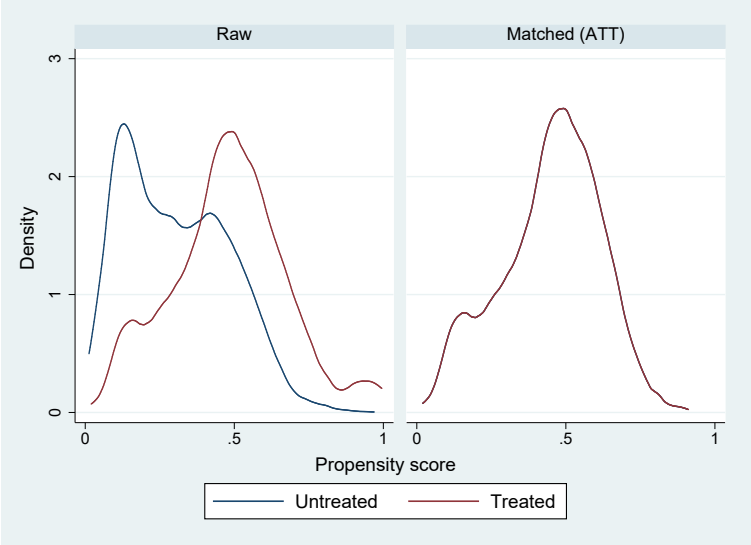
Note:
25,814 Adult, 456 Young adult, and 851 Pediatric candidates were added to the wait list in 2004

Figure D.2: Number of Deceased Donors Who Are Younger Than 35



Note:
Author's calculations from SRTR data.

Figure D.3: Density of Propensity Scores Before and After Matching



Note:
Author's calculations from SRTR data.

APPENDIX E

APPENDICES FOR CHAPTER 2

Table E.1: State Medicaid Childless Individual Income Eligibility Levels as a Percent of the Federal Poverty Level

State	2011	2012	2013	2014	2015	2016	2017	2018	2019
Alabama	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Alaska	0.00	0.00	0.00	0.00	0.00	1.38	1.38	1.38	1.38
Arizona	1.10	1.10	1.00	1.38	1.38	1.38	1.38	1.38	1.38
Arkansas	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
California	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
Colorado	0.00	0.00	0.20	1.38	1.38	1.38	1.38	1.38	1.38
Connecticut	0.73	0.72	0.70	1.38	1.38	1.38	1.38	1.38	1.38
Delaware	1.10	1.10	1.10	1.38	1.38	1.38	1.38	1.38	1.38
District of Columbia	2.11	2.11	2.11	2.15	2.15	2.15	2.15	2.15	2.15
Florida	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Georgia	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hawaii	1.00	1.00	1.00	1.38	1.38	1.38	1.38	1.38	1.38
Idaho	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Illinois	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
Indiana	0.00	0.00	0.00	0.00	0.00	1.39	1.39	1.39	1.39
Iowa	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
Kansas	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kentucky	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
Louisiana	0.00	0.00	0.00	0.00	0.00	0.00	1.38	1.38	1.38
Maine	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.38
Maryland	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
Massachusetts	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
Michigan	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
Minnesota	0.00	0.75	0.75	2.00	1.38	1.38	1.38	1.38	1.38
Mississippi	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Missouri	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Montana	0.00	0.00	0.00	0.00	0.00	1.38	1.38	1.38	1.38
Nebraska	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nevada	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
New Hampshire	0.00	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38
New Jersey	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
New Mexico	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
New York	1.00	1.00	1.00	1.38	1.38	1.38	1.38	1.38	1.38
North Carolina	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
North Dakota	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38

Table E.1 (Cont'd)

Ohio	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
Oklahoma	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Oregon	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
Pennsylvania	0.00	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38
Rhode Island	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
South Carolina	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
South Dakota	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tennessee	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Texas	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Utah	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Vermont	1.60	1.50	1.60	1.38	1.38	1.38	1.38	1.38	1.38
Virginia	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.38
Washington	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
West Virginia	0.00	0.00	0.00	1.38	1.38	1.38	1.38	1.38	1.38
Wisconsin	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00
Wyoming	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: https://www.kff.org/medicaid/state-indicator/medicaid-income-eligibility-limits-for-other-non-disabled-adults/

Table E.2: State Medicaid Family of Three Income Eligibility Levels as a Percent of the Federal Poverty Level

State	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Alabama	0.26	0.25	0.24	0.24	0.24	0.23	0.16	0.18	0.18	0.18	0.18	0.18
Alaska	0.81	0.85	0.81	0.81	0.81	0.78	1.28	1.46	1.43	1.41	1.39	1.38
Arizona	2.00	2.00	1.06	1.06	1.06	1.06	1.38	1.38	1.38	1.38	1.38	1.38
Arkansas	0.18	0.17	0.17	0.17	0.17	0.16	1.38	1.38	1.38	1.38	1.38	1.38
California	1.06	1.06	1.06	1.06	1.06	1.06	1.38	1.38	1.38	1.38	1.38	1.38
Colorado	0.66	0.66	0.66	1.06	1.06	1.06	1.38	1.38	1.38	1.38	1.38	1.38
Connecticut	1.91	1.91	1.91	1.91	1.91	1.91	2.01	2.01	1.55	1.55	1.38	1.55
Delaware	1.06	1.21	1.21	1.20	1.19	1.20	1.38	1.38	1.38	1.38	1.38	1.38
District of Columbia	2.07	2.07	2.07	2.07	2.06	2.06	2.21	2.21	2.21	2.21	2.21	2.21
Florida	0.56	0.55	0.53	0.59	0.58	0.56	0.35	0.34	0.34	0.33	0.33	0.32
Georgia	0.53	0.52	0.50	0.50	0.49	0.48	0.39	0.38	0.37	0.37	0.36	0.35
Hawaii	1.00	1.00	1.00	1.00	1.00	1.38	1.38	1.38	1.38	1.38	1.38	1.38
Idaho	0.42	0.28	0.27	0.39	0.39	0.37	0.27	0.27	0.26	0.26	0.26	0.25
Illinois	1.91	1.85	1.85	1.91	1.91	1.39	1.38	1.38	1.38	1.38	1.38	1.38
Indiana	0.26	0.26	0.25	0.36	0.24	0.24	0.24	0.24	1.39	1.39	1.39	1.39
Iowa	0.89	0.86	0.83	0.83	0.82	0.80	1.38	1.38	1.38	1.38	1.38	1.38
Kansas	0.34	0.34	0.32	0.32	0.32	0.31	0.38	0.38	0.38	0.38	0.38	0.38
Kentucky	0.64	0.62	0.62	0.62	0.59	0.57	1.38	1.38	1.38	1.38	1.38	1.38
Louisiana	0.20	0.26	0.25	0.25	0.25	0.24	0.24	0.24	0.24	1.38	1.38	1.38
Maine	2.06	2.06	2.06	2.00	2.00	2.00	1.05	1.05	1.05	1.05	1.05	1.38
Maryland	0.37	1.16	1.16	1.16	1.16	1.22	1.38	1.38	1.38	1.38	1.38	1.38
Massachusetts	1.33	1.33	1.33	1.33	1.33	1.33	1.38	1.38	1.38	1.38	1.38	1.38
Michigan	0.61	0.66	0.64	0.64	0.63	0.64	1.38	1.38	1.38	1.38	1.38	1.38
Minnesota	2.75	2.75	2.15	2.15	2.15	2.15	2.05	1.38	1.38	1.38	1.38	1.38
Mississippi	0.32	0.46	0.44	0.44	0.44	0.29	0.29	0.28	0.27	0.27	0.27	0.26
Missouri	0.39	0.26	0.25	0.37	0.36	0.35	0.24	0.23	0.22	0.22	0.22	0.21
Montana	0.60	0.58	0.56	0.56	0.55	0.54	0.52	0.51	1.38	1.38	1.38	1.38
Nebraska	0.59	0.58	0.58	0.58	0.57	0.58	0.55	0.55	0.63	0.63	0.63	0.63
Nevada	0.94	0.91	0.88	0.88	0.87	0.84	1.38	1.38	1.38	1.38	1.38	1.38

Table E.2 (Cont'd)

New Hampshire	0.55	0.51	0.49	0.49	0.49	0.47	0.75	1.38	1.38	1.38	1.38	1.38
New Jersey	1.33	2.00	2.00	2.00	2.00	2.00	1.38	1.38	1.38	1.38	1.38	1.38
New Mexico	0.63	0.69	0.67	0.67	0.85	0.85	1.38	1.38	1.38	1.38	1.38	1.38
New York	1.50	1.50	1.50	1.50	1.50	1.50	1.38	1.38	1.38	1.38	1.38	1.38
North Carolina	0.52	0.51	0.49	0.49	0.49	0.47	0.45	0.45	0.44	0.44	0.43	0.42
North Dakota	0.63	0.62	0.59	0.59	0.59	0.57	1.38	1.38	1.38	1.38	1.38	1.38
Ohio	0.90	0.90	0.90	0.90	0.90	0.96	1.38	1.38	1.38	1.38	1.38	1.38
Oklahoma	0.50	0.48	0.47	0.53	0.53	0.51	0.48	0.46	0.44	0.44	0.43	0.42
Oregon	1.00	1.00	0.40	0.40	0.40	0.39	1.38	1.38	1.38	1.38	1.38	1.38
Pennsylvania	0.59	0.36	0.34	0.46	0.46	0.58	0.38	1.38	1.38	1.38	1.38	1.38
Rhode Island	1.91	1.81	1.81	1.81	1.81	1.81	1.38	1.38	1.38	1.38	1.38	1.38
South Carolina	1.00	0.90	0.89	0.93	0.91	0.89	0.67	0.67	0.67	0.67	0.67	0.67
South Dakota	0.56	0.54	0.52	0.52	0.52	0.50	0.54	0.53	0.52	0.51	0.50	0.49
Tennessee	0.80	1.34	1.29	1.27	1.26	1.22	1.11	1.03	1.01	0.99	0.98	0.95
Texas	0.28	0.27	0.26	0.26	0.26	0.25	0.19	0.19	0.18	0.18	0.18	0.17
Utah	0.47	0.68	0.44	0.44	0.44	0.42	0.47	0.46	0.45	0.44	0.60	0.60
Vermont	1.91	1.91	1.91	1.91	1.91	1.91	1.38	1.38	1.38	1.38	1.38	1.38
Virginia	0.31	0.30	0.29	0.31	0.31	0.30	0.52	0.45	0.39	0.38	0.38	1.38
Washington	0.76	0.77	0.74	0.74	0.73	0.71	1.38	1.38	1.38	1.38	1.38	1.38
West Virginia	0.35	0.34	0.33	0.33	0.32	0.31	1.38	1.38	1.38	1.38	1.38	1.38
Wisconsin	1.91	2.00	2.00	2.00	2.00	2.00	1.00	1.00	1.00	1.00	1.00	1.00
Wyoming	0.55	0.54	0.52	0.52	0.51	0.50	0.59	0.58	0.57	0.56	0.55	0.54

Source: https://www.kff.org/medicaid/state-indicator/medicaid-income-eligibility-limits-for-parents/

APPENDIX F

APPENDICES FOR CHAPTER 3

Table F.1: Crosswalk of Organ Procurement Organizations and Abbreviations

OPO Abbreviation	OPO	OPO State
ALOB	Legacy of Hope	AL
AROR	Arkansas Regional Organ Recovery Agency	AR
AZOB	Donor Network of Arizona	AZ
CADN	Donor Network West	CA
CAGS	Sierra Donor Services	CA
CAOP	OneLegacy	CA
CASD	Lifesharing - A Donate Life Organization	CA
CORS	Donor Alliance	CO
DCTC	Washington Regional Transplant Community	VA
FLFH	TransLife	FL
FLMP	Life Alliance Organ Recovery Agency	FL
FLUF	LifeQuest Organ Recovery Services	FL
FLWC	LifeLink of Florida	FL
GALL	LifeLink of Georgia	GA
HIOP	Legacy of Life Hawaii	HI
IAOP	Iowa Donor Network	IA
ILIP	Gift of Hope Organ & Tissue Donor Network	IL
INOP	Indiana Donor Network	IN
KYDA	Kentucky Organ Donor Affiliates	KY
LAOP	Louisiana Organ Procurement Agency	LA
MAOB	New England Organ Bank	MA
MDPC	The Living Legacy Foundation of Maryland	MD
MIOP	Gift of Life Michigan	MI
MNOP	LifeSource Upper Midwest Organ Procurement Organization	MN
MOMA	Mid-America Transplant Services	MO
MSOP	Mississippi Organ Recovery Agency	MS
MWOB	Midwest Transplant Network	KS
NCCM	LifeShare Carolinas	NC
NCNC	Carolina Donor Services	NC
NEOR	Live On Nebraska	NE
NJTO	New Jersey Organ and Tissue Sharing Network OPO	NJ
NMOP	New Mexico Donor Services	NM
NVLV	Nevada Donor Network	NV
NYAP	Center for Donation and Transplant	NY
NYFL	Finger Lakes Donor Recovery Network	NY

Table F.1 (Cont'd)

NYRT	LiveOnNY	NY
NYWN	Upstate New York Transplant Services Inc	NY
OHLB	Lifebanc	OH
OHLC	Life Connection of Ohio	OH
OHLP	Lifeline of Ohio	OH
OHOV	LifeCenter Organ Donor Network	OH
OKOP	LifeShare Transplant Donor Services of Oklahoma	OK
ORUO	Pacific Northwest Transplant Bank	OR
PADV	Gift of Life Donor Program	PA
PATF	Center for Organ Recovery and Education	PA
PRLL*	LifeLink of Puerto Rico	PR
SCOP	We Are Sharing Hope SC	SC
TNDS	Tennessee Donor Services	TN
TNMS	Mid-South Transplant Foundation	TN
TXGC	LifeGift Organ Donation Center	TX
TXSA	Texas Organ Sharing Alliance	TX
TXSB	Southwest Transplant Alliance	TX
UTOP	DonorConnect	UT
VATB	LifeNet Health	VA
WALC	LifeCenter Northwest	WA
WIUW	UW Health Organ and Tissue Donation	WI
CTOP	LIfeChoice Donor Services	MA
WIDN	Versiti Wisconsin, Inc	WI

Note:
We have no mortality data for Puerto Rico so it is not included in our sample.

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