Sharing is Caring: Does Organ Allocation Policy Work?

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Abstract

I evaluate recent changes in the allocation policies governing four solid organs—kidneys, livers, lungs, and hearts—designed to increase the sharing of donated organs across the country. These policies are intended to save lives by transferring organs to the "sickest" patients, regardless of where they reside. I find evidence that the policies increase the flow of organs across the country. Some evidence also suggests that relatively "sicker" patients receive organs. However, I find no evidence that these policies save lives among those waitlisted for organs, those who have received a transplant, or those who could benefit from a transplant.

Keywords: Organ Transplant, Organ Allocation, Healthcare Policy

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1 Introduction

Since the advent of immunosuppresive drugs in the 1980s, organ transplantation has become a viable (and for many conditions, the only) treatment option for many otherwise fatal conditions. Living donors provide some kidneys and liver segments for transplantation, but most transplantation surgeries rely on cadaveric organs donated by those who consent to and die in ways consistent with organ donation. However, the number of individuals needing a life-saving organ transplant far exceeds the number of donated organs each year. In 2021, for example, over 6,000 people died while waiting for an organ transplant. Because the demand for cadaveric organs exceeds the supply of these organs and because Congress banned the sale of organs with the passage of the National Organ Transplant Act of 1984 (NOTA), the laws, rules, and policies governing organ allocation are critically important in what has been described as a "functionally . . . zero-sum rationing process" by the organization responsible for developing and implementing these rules. (UNOS, 2018, 1).

Historically, donated organs were first offered to transplant candidates in the same geographic area where the organ was donated. Locally focused allocation policies that favored patients in the same geographic area were initially necessary, as transporting cadaveric organs long distances was not medically feasible. As technology developed and longer transportation became possible, organ allocation policy became more focused on the broader sharing of cadaveric organs across the country. Over the past two decades in particular, organ allocation policy has moved away from local preferences to broader organ sharing. For example, in 2016, the allocation policies for kidneys, livers, lungs, and hearts required that patients within a defined geographic boundary be offered an organ in descending order of medical urgency before the organ was offered to other transplant candidates across the country. By 2023, none of the allocation policies for these four solid organs included such local preferences.

Given the scarcity of cadaveric organs, the fact that organ allocation policy determines who receives life-saving access to those organs, and the trend towards greater organ sharing across the country, it is unsurprising that contentious debates over organ allocation policy have erupted over the last few years. On one side, organ transplant centers and their patients in the South and Midwest argue that new policies unfairly require these regions to "export" more and more of the organs they recover to the West Coast and Northeast. Transplant centers and their patients in the areas that have increased the number of organs they "import" argue that this increase is necessary because patients in those areas are sicker, are more likely to die on waitlists, and have less access to locally donated organs. Southern and Midwestern transplant centers and patients respond that patients in other areas are not actually sicker, are more likely to die on waitlists because of the way waitlists are constructed, and bene-

fit from manipulation of the metrics that govern organ allocation policy. The fundamental disagreement over organ allocation policy has resulted in multiple lawsuits, congressional inquiries, and exposés in major newspapers.

The primary impetus behind recent policy changes mandating the broader sharing of organs is the desire to save more lives and ensure that organs go to those patients who need them most. By removing geographic boundaries, the argument goes, donated organs can go to the most medically urgent patients, regardless of where those patients reside. And the governing federal law is consistent with these desires and arguments that organs go to those most in need. However, critics of these new allocation policies have argued that these policies require organs to be transported over longer distances making them less viable for transplant, are based on inaccurate (and potentially manipulated) measures of "need," and generally funnel organs away from rural and poorer areas of the country to richer and more urban areas. In other words, transporting organs over longer distances based on inaccurate measures of medical need will not result in more lives saved. Instead of saving lives, they argue, new allocation policies mandating more sharing simply shift organ transplants from certain parts of the country (primarily the Midwest and South) to other parts of the country (primarily the Northeast and California).

Across the four major solid organs—kidneys, livers, lungs, and hearts—seven major policy changes to allocation rules have been implemented to increase the sharing of cadaveric organs across the country since 2010.[1] Each organ is subject to its own set of allocation rules, and these rules are developed and implemented by the Organ Procurement and Transplantation Network (OPTN). Though different rules govern different organs, the OPTN has steadily implemented major changes to these rules over the last decade to increase the rate at which organs recovered in one area of the country are transplanted in a different part of the country.

Before each rule change, the OPTN typically models the effect of the change prospectively. Given the importance of these policies, however, post-implementation evaluations are relatively rare (Rohan et al., 2022). For example, Massie et al. (2015) evaluated the impact of one early policy change designed to increase organ sharing, Giorgakis et al. (2023) evaluated a later change in liver allocation policy, Egan and Edwards (2016) focused on the implementation of a new model for lung allocation, and Patzer et al. (2022) concentrated on a change in kidney allocation policy. While this work provides important information about the impact of different rule changes, these individual studies generally focus on very specific rule changes for a specific organ using organ-specific metrics and sometimes include

[1]These are not the only solid organs that can be transplanted. Pancreases, for example, can be transplanted. And non-solid-organ transplantations can also take place. However, the four solid organs highlighted here make up most of the solid organ transplantations, and the rules governing them have been subject to the strongest debate.

only data from one or a few transplant centers.

The absence of a comprehensive analysis evaluating rule changes designed to increase organ sharing has left an important gap in the literature. No work has sought to evaluate the overall impact of different allocation policies designed to increase organ sharing across the country, despite the fact that all these policies stem from the same underlying (and highly litigated) legal mandate. Additionally, by focusing on highly specific metrics and different models and definitions of mortality, the literature has become somewhat fragmented and does not provide a general answer to the question of whether broader national organ sharing has accomplished its goals. This paper fills that important gap in the literature and provides more general and more comprehensive evidence on the impact of major policies designed to increase organ sharing across the country.

Specifically, I evaluate seven major policies across all four organs by analyzing comprehensive data from the Scientific Registry of Transplant Recipients (SRTR). Additionally, because prior work has criticized organ transplant data for being manipulated and incomplete based on who reports the relevant information (McMichael, 2022; Kizer, English and Hackmann, 2022; Scanlon et al., 2004; Snyder, 2010), I separately develop a novel measure of transplant amenable deaths. Relying on the more general metric of healthcare amenable deaths, which prior work has defined as those deaths which could have been avoided by timely access to healthcare (Nolte and McKee, 2011), I develop a crosswalk from the diagnosis codes available for transplant candidates in the SRTR dataset to ICD-10 codes in mortality data maintained by the National Vital Statistics System. Using this crosswalk, I develop a measure of transplant amenable deaths, which are those deaths that could have potentially been avoided had the individual received an organ transplant. While not perfect, this new measure allows me to evaluate the impact of various policies designed to reduce deaths via organ transplantation without relying on potentially incomplete or manipulated data from the transplantation system itself.

Because the NOTA effectively federalized organ transplantation, I cannot rely on models typically used to evaluate state-level legal changes, such as two-way fixed models. However, changes in organ allocation rules are implemented on specific, known dates across the country.[2] Additionally, because the federalized organ allocation system is the only source of cadaveric organs and because organ transplantation is the only cure for many diseases, changes in organ allocation rules should have immediate effects with little to no phase-in periods. For some metrics, these rule changes can have an impact hours after they are implemented because they immediately change who will receive cadaveric organs. Based on

[2]In fact, the transplant community generally knows the exact time the old rule will end and the new rule will begin.

these features of organ allocation rules, I estimate a series of regression discontinuity in time (RDIT) models along the lines of Hausman and Rapson (2018). This approach has recently been implemented in different healthcare contexts where researchers were interested in the impact of a federal policy and where no untreated group was available (Gupta et al., 2023; Brodeur et al., 2021). This and similar approaches have also been applied in non-healthcare contexts when the relevant policy was applied to the entire population simultaneously (Anderson, 2014; Chen and Whalley, 2012; Burger, Kaffine and Yu, 2014; Moeeni and Tanaka, 2023; Clark, 2023). To confirm the validity of these results, I also follow a time-shifting approach to create a valid control group and estimate difference-in-differences models similar to the approaches of Brodeur et al. (2021) and Leder-Luis (2023).

Estimating a series of RDIT models, I find consistent evidence that policies designed to increase organ sharing accomplish that goal. With the exception of one policy designed to increase the sharing of cadaveric hearts, the proportion of transplant surgeries completed using organs from local donors decreases, consistent with greater organ sharing. I also find some evidence that some policies designed to increase organ sharing lead to more organs going to the sickest patients as measured by the organ-specific metrics that purportedly capture medical urgency. For example, the median end-stage liver disease (MELD) score is supposed to represent mortality risk in liver transplant candidates. Following the implementation of a new liver allocation policy, the MELD score at transplant increased, suggesting that measurably sicker patients gained greater access to donated livers. However, other rule changes did not lead to sicker patients gaining better access to organs. Despite this improved access from some rule changes, I find no statistically significant evidence that deaths on the waitlist declined, suggesting that these rule changes may not facilitate the more efficient use of organs—a key goal in allocation policy. I similarly find no statistically significant evidence of an improvement in one-year post-transplant survival rates, again suggesting that these rule changes may not lead to the more efficient use of organs.

Because the SRTR dataset contains information produced by the allocation and transplantation system itself, it may suffer from incompleteness or bias as a result of manipulation (Kizer, English and Hackmann, 2022; McMichael, 2022; Murken et al., 2017; Snyder, 2010; Scanlon et al., 2004). In fact, the federal government recently announced a complete overhaul of the regulatory system governing organ procurement organizations because of concerns over self-reported data. To address this important potential problem, I develop a novel measure of transplant amenable deaths using data external to the allocation and transplantation system. By relying on individual death certificates, which are much less likely to be manipulated or incomplete, I am better able to measure the impact of policy changes on deaths that could be avoided through transplantation. In general, I find little evidence that trans-

plant amenable deaths decline, and some evidence suggests that transplant amenable deaths increase following the implementation of rule changes designed to increase organ sharing. Collectively, the evidence developed in this paper suggests that, while organ allocation rule changes designed to increase organ sharing achieve this goal, the increased organ sharing does not appear to reduce the number of deaths on waitlists, the number of deaths less than a year after transplant, or the number of transplant amenable deaths.

Beyond providing new evidence on one of the most important legal and policy debates in organ transplantation and filling gaps in the existing literature, the analysis reported here contributes to multiple components of the economic literature on organ transplantation. Prior work has examined the role of allocation policy in encouraging individuals to register as organ donors and increase the supply of available organs (Kessler and Roth, 2012). The results below demonstrate how current trends in allocation policy have affected the effectiveness of the organ transplantation system, which is germane to many individuals' decision to donate (O'Dell et al., 2019). The results on the impacts of current allocation policy also provide context for the various papers that have investigated the effects of different policies designed to increase the supply of cadaveric organs. My analysis evaluates how well any increase in supply is used by the current system, which offers insight into the downstream effects that have been the subject of past economic investigations. The results here also contribute to the healthcare policy literature on the impact of specific organ allocation rules on transplant-relevant outcomes.

2 Background and Institutional Context

Organ transplantation requires careful clinical matching between the organ donor and transplant recipient to minimize the risk of organ rejection and other adverse clinical outcomes. The clinical matching that must take place is responsible for much of the complexity and difficulty present in organ allocation. Prior to the passage of the NOTA in 1984, individual transplant centers largely located and recovered cadaveric organs for transplantation from local patient populations. Some centers, particularly those in the southeastern United States, had arrangements that allowed the sharing of organs that were recovered but not clinically suitable for their own transplant candidates. The NOTA replaced informal organ-sharing networks with a federal legal framework governing the allocation of cadaveric organs for transplant. The NOTA also banned the sale of human organs, leaving the federalized allocation scheme as the only legal means by which patients could obtain a cadaveric organ.

Within this framework, organ procurement organizations (OPOs) are responsible for identifying and recovering cadaveric organs within their designated donor service areas (DSAs).

DSAs include collections of counties that often span multiple states and are determined by the Department of Health and Human Services (HHS). Historically, transplant candidates within the same DSA as the organ donor received some degree of priority for the organ. For example, prior to 2013, cadaveric livers were offered to clinically appropriate transplant candidates in the same DSA where the liver was recovered in descending order of MELD scores, *i.e.*, in descending order of medical urgency to the extent the MELD score captures medical urgency.[3] If no clinically appropriate candidate within the same DSA could be located, the cadaveric liver would be offered to regional transplant candidates—regions are larger collections of states and include multiple DSAs. In the absence of any appropriate regional candidate, the organ would be offered to candidates nationally.

Local preferences may have originally stemmed from the lack of technology necessary to transport organs long distances, but improvements in technology have enabled organs to traverse greater distances. Commensurate with the technological feasibility of transporting organs further, transplant centers with less access to local supplies of donated organs have increasingly pushed for greater national organ sharing. This sharing is arguably mandated by the 1999 "Final Rule," which HHS passed under NOTA to provide additional legal framework for the rules governing organ allocation. The Final Rule establishes the framework for "policies for the equitable allocation of cadaveric organs among potential recipients" and directs that those policies "[s]hall be based on sound medical judgment . . . [s]hall seek to achieve the best use of donated organs . . . [and] [s]hall be designed to avoid wasting organs, to avoid futile transplants, to promote patient access to transplantation, and to promote the efficient management of organ placement."[4] Additionally, the Final Rule provides that "allocation policies . . . [s]hall not be based on the candidate's place of residence or place of listing" and requires "[d]istributing organs over as broad a geographic area as feasible. . . and in order of decreasing medical urgency"[5] While those in favor of recent changes mandating broader organ sharing emphasize the latter of these provisions, those who favor continued local preferences in allocation policies emphasize the former provisions and other provisions that direct the development of "[p]olicies that reduce inequities resulting from socioeconomic status."[6]

While the Final Rule sets the overall goals and framework of organ allocation policy, a private body ultimately develops the specific rules. Under the NOTA, the OPTN formulates the allocation policies that govern organ allocation on a day-to-day basis. The OPTN

[3]This is a somewhat simplified example, since many clinical factors play a role, but it illustrates the basic point of preferences for local candidates.

[4]42 C.F.R. §121.8(a).

[5]42 C.F.R. §121.8(a)–(b).

[6]42 C.F.R. §121.4(a).

is operated, in turn, by a private body—the United Network for Organ Sharing (UNOS). UNOS, via the OPTN, develops new allocation rules under the NOTA and Final Rule by gathering information from interested parties, proposing rules, receiving feedback, and ultimately implementing new policies. Over the decade, the OPTN has stepped up its efforts to move toward greater national organ sharing. These efforts have produced multiple new rules across all four major solid organs designed to increase organ sharing. Given the importance of transplants to patients and the high reimbursements transplant centers receive for transplant surgeries, it is not surprising that patients and transplant centers have filed multiple federal lawsuits challenging new allocation rules.

Typically, transplant centers that stand to suffer substantial losses in their transplant volumes challenge the legal validity of new allocation rules. The details of these lawsuits are beyond the scope of this paper, but the unique legal structure of organ allocation policies makes them difficult to challenge in court.[7] The difficulty of challenging these rules in court adds to the urgency of getting these rules right in the first place, particularly given their life and death implications. Proponents of local preferences have highlighted that greater national organ sharing exacerbates socioeconomic inequalities; shifts organs from poorer, more rural areas of the country to richer, more urban areas of the country; and are based on erroneous and manipulated measures of medical urgency (Cascino et al., 2022; Parker et al., 2020, 2018; Pullen, 2019; Godfrey et al., 2019; Karp, Segal and Patil, 2020; McMichael, 2022). Even if proponents of local preferences are correct about the harms associated with broader national organ sharing, however, rules implementing that sharing may be justified if they facilitate greater efficiency in the use of a scarce lifesaving resource. Thus, a key question in the ongoing debate over organ allocation policy is the efficacy of rules mandating greater national organ sharing.

While the OPTN has implemented many policies over the last decade, not all of them are aimed at changing the degree of organ sharing across the country. Table 1 reports the seven policies that were aimed most directly at increasing national organ sharing. The most common approach to greater national sharing is the elimination of the DSA as a relevant geographic unit for allocation. Instead of offering organs first to clinically appropriate trans-

[7]For example the Eleventh Circuit explained in a case about liver allocation policy that HHS has discretion to intervene into the rulemaking process implemented by the OPTN. When it received complaints from those favoring broader national organ sharing, it intervened to require a new rule to that effect. When similar complaints were made by those in favor of maintaining more local preferences in allocation, it declined to do so. The Eleventh Circuit held that its decision was allowable under the current legal framework despite the fact that this meant those in favor of local allocation policy never had the opportunity to pursue those policies through a governmental organization. Callahan v. United States Dep't of Health & Hum. Servs. through Alex Azar II, 939 F.3d 1251 (11th Cir. 2019). The Eighth Circuit reached a similar conclusion in the context of kidney allocation rules. Adventist Health Sys./SunBelt, Inc. v. United States Dep't of Health & Hum. Servs., 17 F.4th 793 (8th Cir. 2021).

plant candidates within the same DSA as the organ donor, organs are offered to clinically appropriate candidates within larger and larger circles around the hospital where the organ is recovered. The details are somewhat different for different organs, and this approach does not completely eliminate local preferences. However, it clearly advantages coastal areas of the country (since oceans are rarely home to transplant candidates), and it may eliminate positive network effects that transplant centers may generate when working with their local OPOs.

Beyond the elimination of DSAs as a geographic unit of allocation, policies specific to individual organs have also targeted organ sharing. The kidney allocation scheme prioritized candidates with the longest predicted survival, which may advantage candidates in richer areas of the country with better access to healthcare. For livers, the share 35 policy required that cadaveric livers first be offered to patients in the same region with MELD scores of 35 or higher. While not the same as eliminating DSAs, this policy was intended to increase the transfer of livers across longer distances. However, it offers an obvious point of manipulation since patients receive higher priority for donated livers upon reaching a MELD score of 35 (McMichael, 2022). For hearts, the 6 tier system replaced the existing three statuses with six statuses that offered more granularity. One key feature of this 6 six tier system is the role of treatment intensity in determining medical urgency. For example, patients receiving extra-corporeal membrane oxygenation (ECMO) or having an intra-aortic balloon pump (IABP) are placed in higher tiers. This offers an obvious point of waitlist manipulation, as ordering these therapies allows physicians to increase the statuses of their patients regardless of whether these treatments are medically necessary (Cascino et al., 2022).

Despite the importance of allocation policy to the organ transplantation system, only a patchwork of narrowly focused studies have evaluated allocation rule changes. For example, two studies evaluated the kidney allocation scheme, and one was based on pre-implementation simulations (Israni et al., 2014; Massie et al., 2014). Several studies also examined the elimination of DSAs in kidney allocation, but they reached somewhat conflicting conclusions about the positive and negative impacts of this rule change (Rohan et al., 2022; Tandukar and Tandukar, 2022; Rausch, Niederhaus and Forbes, 2022). In particular, Rohan et al. (2022) questioned the continued reliance on predictive modeling when implementing large-scale changes to allocation rules.

The policies governing livers seem to have attracted more attention, and several studies have evaluated their impacts. For example, multiple studies have evaluated the share 35 program and found that it generally increased transplants among patients with a MELD score of 35 or higher (Washburn et al., 2016; Murken et al., 2017). However, this has not necessarily led to improvements in patient outcomes, particularly those that are relevant

under the Final Rule. Nicolas et al. (2017) found that the share 35 policy did not reduce mortality significantly, Zhang (2017) found that the policy failed to improve access to liver transplants among minority populations (though it did reduce wait time discrepancies among populations), Brock, Washburn and Marvin (2019) found that the share 35 policy was associated with discrepancies in wait list dropouts among patients with high MELD scores, and Croome et al. (2017) found that patients with hepatocelluar carcinoma (a type of liver cancer that requires a liver transplant to treat) had higher waitlist mortality following the implementation of the share 35 policy.

Several studies have examined potential explanations for the failure of the share 35 policy to improve relevant outcomes. Washburn et al. (2016) concluded that centers were less likely to accept livers for patients with MELD scores over 34, which could ultimately undermine access to transplants. Goldberg et al. (2019) similarly evaluated the behavioral changes associated with the adoption of the share 35 policy and found that fewer transplants may be performed as physicians and patients rejected more offers of cadaveric livers. Murken et al. (2017) also noted that the share 35 policy asymmetrically impacted transplant centers (with some increasing their transplant volume and others decreasing), suggesting that different transplant centers responded to the policy differently. Murken et al. (2017) also found evidence that MELD scores used for liver allocation may not have accurately represented patients' mortality risk following the share 35 program.[8] McMichael (2022) examined the possibility that transplant centers manipulated waitlist metrics, particularly MELD scores, to increase the number of livers they received, and found consistent evidence of such manipulation.

While fewer studies have evaluated the elimination of DSAs as a unit of geography in the allocation of livers, the evidence that has been developed has proven equally mixed. For example, Mogul et al. (2020) examined projections of how the new policy would affect various outcomes and concluded that the policy would likely address disparities for pediatric transplant candidates by increasing transplants and decreasing waitlist mortality. They also flatly stated that this new paradigm was more consistent with the Final Rule than the older approach. On the other hand, Nagai et al. (2022) found that while the new policy may improve waitlist outcomes, substantial variation exists among how transplant centers in different parts of the country are affected.

Fewer studies have examined changes in lung allocation policy, and this may be explained by the fact that fewer transplant centers perform lung transplants, leading to less disagree-

[8]More specifically, liver transplant candidates receive two different MELD scores. The laboratory MELD score is based on a known formula that involves four laboratory values as inputs. The allocation MELD score, however, actually determines transplant priority.

ment over allocation. Drolen et al. (2020) conducted one of the most throughgoing analyses of the 2017 change to lung allocation policy. They examined the impact of this new policy on the characteristics of those allocated a cadaveric lung, receipt of pre-transplant ECMO, length of hospitalization, and post-transplant complications across transplant centers facing high and low levels of competition. They found that waitlist time decreased and the lung allocation score (LAS) of transplant recipients increased. They also concluded that the new policy increased length of stay in the hospital but found no differences in pre-transplant treatment or post-transplant outcomes. Benvenuto et al. (2022) examined the impact of the elimination of DSAs from lung allocation and found that it reduced some geographic disparities but failed to eliminate all such disparities.

Finally, heart policy changes have generated more interest among researchers than lung allocation changes, and the older 6 tiers policy has generated more analysis so far. For example, Ashraf et al. (2022), Elde et al. (2023), and Bradbrook et al. (2023) find that this policy reduced wait times and waitlist mortality while post-transplant outcomes changed little. Golbus et al. (2023) similarly found that this policy improved waitlist outcomes as well as resulted in more uniform access to heart transplants. On the other hand, Cogswell et al. (2022) found evidence that the new policy did little to address racial disparities in access to transplants, and Kelty et al. (2023) found that the new policy undermined the ability of low socioeconomic status individuals to obtain a transplant. Cascino et al. (2022) found that individual transplant centers varied substantially in how they responded to the new policy. Because the receipt of intensive treatments like IABPs and ECMO increased the chances that a patient would receive a transplant (regardless of whether such treatment was medically necessary), some transplant centers substantially increased their use of these treatments. This would undermine the ability of the organ allocation and transplant system to funnel organs to the most medically urgent patients. Corroborating this evidence, Hess et al. (2023) noted that ECMO bridging increased the probability of transplant.

Collectively, these studies provide important insight into the effects of individual policies on a variety of outcomes. Some of these outcomes are relevant to whether these policies accomplish their legally mandated goals, but some are only indirectly relevant to these goals. Substantial variation exists in the methods employed by the various studies. To address this patchwork of evidence in the existing literature, I estimate a series of models for all policy changes designed to increase national organ sharing across all four organs.

The more comprehensive approach employed in this paper directly addresses two important gaps in the current literature. First, the studies discussed above targeted single policy interventions. While useful, these singularly focused studies do not address the more general policy trend of broader national organ sharing. This trend, which stems from the

Final Rule, has motivated all of these recent policy changes. To evaluate the effectiveness of this more general impetus, it is necessary to evaluate the various policies attributable to it together, using similar methods and examining common outcomes. Second, the existing literature has limited itself to only transplant-related outcomes available in datasets generated by the allocation and transplantation system. While this is an obvious and important starting point, those datasets are incomplete and do not provide a comprehensive picture of the role of allocation policy in affecting transplant-related outcomes. Despite vaguely (at best) supported claims to the contrary, the Final Rule does not categorically ban considering the impact of organ and transplantation policy on individuals not yet connected with the allocation and transplantation system (Glazier, 2018; Nagai et al., 2022).[9] Accordingly, this paper fills a large gap in the literature by examining a new measure of transplant-related outcomes that captures individuals who could benefit from a transplant even if they are not yet on a waitlist.

Filling these holes in the literature is particularly warranted now, as the next phase of allocation policies involves "continuous distribution." These policies are designed to replace existing policies with more measures of medical urgency and organ compatibility and to reduce even further the role of geography. While some aspects of these policies may be desireable, it is important to examine how reducing the role of geography affects outcomes before moving further down this path. This paper provides evidence directly relevant to the impact of de-emphasizing geography in organ allocation by examining seven policies implemented over the last decade designed to do exactly that.

Beyond contributing to the literature concerned with the impacts of various organ allocation policies and healthcare policies more generally, the evidence developed in this paper contributes to several strands of the economic literature that focus on issues related to organ transplantation. One strand of the economic literature has focused on the role of different incentives in encouraging individuals to donate their organs (Abadie and Gay, 2006; Becker and Elías, 2007; Bilgel, 2012; Callison and Levin, 2016; Lacetera, Macis and Stith, 2014; Li, Hawley and Schnier, 2013; Wellington and Sayre, 2011; Fernandez, Howard and Stohr Kroese, 2013). Studies within this strand are primarily concerned with increasing the supply of cadaveric organs (or living donations). The results in this paper offer greater context for previous work in this area by elucidating what happens with any increase in the supply of organs. One of the key goals under the Final Rule is the efficient use of donated

[9]This is one interpretation of the Final Rule's requirement that geography not factor into whether a candidate receive a transplant. Another, and equally valid, interpretation is that the Final Rule bans any role for geography, requiring the allocation and transplantation system to ensure that everyone have equal access to clinicians and care that can result in access to an organ waitlist if necessary. No court has ever interpreted this provision of the Final Rule.

organs, and this paper evaluates the extent to which that goal has been achieved with new policies. Kessler and Roth (2012) and Li, Hawley and Schnier (2013) are the most relevant papers to the instant analysis. They show that organ allocation policy can directly influence the decision of whether to donate. O'Dell et al. (2019) find similar results. These studies establish a direct connection between the allocation policies examined here and the supply of donated organs, which has been a key focus in the economic literature.

A second strand of research has focused on the impact of various state-level policies on the number of waitlist registrations and other transplant-related outcomes (Dickert-Conlin, Elder and Teltser, 2019; Dickert-Conlin et al., 2023). Once a patient accesses the waitlist, the allocation policies examined here become relevant, so the results of my analysis provide greater context for other work focused on how state-level laws affect waitlisting. A third strand considers the effectiveness of the transplant system overall, and the results reported below are directly germane to this issue (Deffains and Mercier Ythier, 2010; Howard, 2011).

3 Data

The data analyzed here come from two primary sources. First, I rely on the Scientific Registry of Transplant Recipients (SRTR) for information on organ waitlisting, allocation, and transplantation between 2010 and 2022.[10] Gathering data from OPOs, the OPTN, and other sources, the SRTR has created a comprehensive series of datasets on donors, transplant candidates, waitlist registrations, transplant surgeries, and post-transplant outcomes. With respect to donors, the SRTR datasets include information on every organ donor's medical history, location of donation, harvested organs, and the OPO that harvested the organs. For transplant candidates, the SRTR datasets include detailed information on medical histories, which organ(s) were transplanted, the transplant center that listed the candidate for a transplant, the DSA in which the transplant center is located, and the date of transplant.

From the information included in the SRTR dataset, I calculate a number of different outcomes that are relevant to organ allocation policy. First, I calculate the number of organs that a given DSA "exports" and "imports." An organ is counted as an export for a given DSA if it was recovered in that DSA but transplanted in a different DSA. An organ is counted as an import for a given DSA if it was recovered in a different DSA but transplanted in the given DSA. An organ is counted as a "local" organ if it was recovered and transplanted

[10]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 and in no way should be seen as an official policy of or interpretation by the SRTR or the U.S. Government.

within the same DSA.[11] Using these definitions of "export" and "import," I calculate the net imports and exports associated with each DSA to examine overall trends in the flow of organs across the country. However, because net imports and exports across the country will always amount to zero given the nature of the transplant system, I examine the percentage of local organs used in transplants to obtain a clearer picture of national organ-sharing trends. Examining these metrics does not directly bear on outcomes relevant to the the Final Rule, but these outcomes are relevant to the Final Rule's dictat that a candidate's geography should not matter for the purposes of allocation policy.

Next, I construct a measure of deaths on organ waitlists. Deaths include removals from the waitlist for actual deaths as well as removals because the candidate became too sick to receive a transplant (which functionally means the patient will die). To account for varying sizes of waitlists, I count the number of deaths per 10,000 patient days on the waitlist at the transplant center level. I focus on transplant centers instead of larger units, such as DSAs, because individual transplant centers have their own policies regarding waitlist access. By counting total patient days and waitlist deaths, I create a comparable measure of waitlist deaths across the country. In general, waitlist deaths are germane to the Final Rule's requirement that organs be used efficiently and not be wasted. A decline in waitlist deaths following the implementation of a specific policy is evidence that the policy may be facilitating the more efficient use of organs.

Turning to the next relevant stage of the transplantation process—transplantation itself—I examine multiple metrics relevant to transplant outcomes. First, I examine organ-specific metrics at the time of transplant. For kidneys, waitlist priority turns heavily on total waiting time, so for policies governing kidneys, I examine this metric. For livers, I examine allocation MELD scores. These scores are based on laboratory MELD scores, which are derived from a formula taking four blood test values as inputs. MELD scores are designed to predict mortality and vary from 6 to 40, with higher scores indicating a higher risk of mortality. Many allocation MELD scores are equal to the underlying laboratory MELD score, but allocation MELD scores may be higher because of the addition of exception points. These points are designed to account for higher mortality risks that the laboratory MELD score may not accurately capture. For example, the laboratory MELD scores of patients with hepatocellular carcinoma may not accurately reflect their risk of death, so these patients receive additional exception points in their allocation MELD scores to correct for this.

With respect to lungs, I focus on the (LAS), which takes various lab values, clinical test

[11] I count an organ as being recovered in a given DSA if the OPO assigned to that DSA is listed as the recovering OPO. I count an organ as being transplanted within a DSA if the transplant occurs in a transplant center located in that DSA. It is possible for either the donor or transplant recipient to reside outside the DSA where the recovery or transplant occurred.

results, and disease diagnoses as inputs to arrive at a score from 0 to 100. The LAS estimates the severity of a candidate's illness and their chance of success following a lung transplant. In general, candidates with a higher LAS receive higher priority for lungs available in the relevant geographic area. With respect to hearts, I focus on two different metrics. For the 6 tiers policy, I examine whether transplant recipients had received either an IABP or ECMO. Because the receipt of these treatments increased the medical urgency of patients following the implementation of the 6 tiers policy, they are the natural point of focus. For the elimination of DSAs as a unit of geography, I focus on the six statuses implemented by the 6 tiers policy. Higher tiers represent greater need for an organ transplant, and they include more information about priority than receipt of treatment alone. Therefore, I switch to this measure for the elimination of DSAs.[12] While I do not necessarily vouch for the validity of the various organ-specific measures of sickness and/or medical urgency, I nevertheless focus on these measures because they are directly relevant to the transplantation system. To the extent they accurately capture sickness or medical urgency, they are also germane to the Final Rule's mandate that organs be allocated first to those candidates most in need. If these measures of urgency increase (*i.e.*, change to indicate that more medically urgent patients are receiving transplants), this may be evidence that a specific policy is both facilitating the efficient use of cadaveric organs and ensuring the neediest patients receive organs faster.

In addition to organ-specific metrics at the time of transplant, I also consider ischemia times. First, I examine donor warm ischemia time, which is the time from the withdrawal of life support to the *in situ* aortic cold perfusion. Second, I examine cold ischemia time, which is the time the the organ is preserved in a hypothermic state prior to transplantation. Neither of these measures are directly relevant to the Final Rule. However, increases in ischemia time generally make the organ less viable for transplantation and may indicate that organs are being used less efficiently. Additionally, while I do not directly examine monetary costs associated with allocation policy, cold ischemia time may roughly correlate with distance traveled, so that longer cold ischemia times imply higher costs of transporting the organ.

Turning to the final step in the transplantation process—post-transplant success—I evaluate post-transplant survival. Specifically, I focus on whether a given patient survives more than one year after transplant. While this may not be the most relevant clinical outcome, it is the focus of various regulations relevant to the evaluation of transplant programs. Because of this, transplant programs likely care about this metric and will seek to manage it as best as possible. Additionally, the fact that it matters for regulatory purposes makes it directly

[12]Ideally, I would also use this metric for the implementation of the six tiers system, but patients were not placed into tiers until after the implementation of this policy.

relevant to this paper. In general, lower post-transplant survival may indicate a less efficient use of organs.

Overall, this collection of metrics allows me to examine the US organ allocation and transplantation system from start to finish. Collectively, they provide important insight into the outcomes that matter under the Final Rule and therefore represent the best available information for current regulatory approaches. However, the fact that they matter most under the current regulatory system does not necessarily imply that they accurately capture the performance of the organ allocation and transplantation system from society's perspective. Indeed, a recent report by the National Academies highlights the absence of individuals who could benefit from a transplant but are unable to access a waitlist for various reasons, including poverty, geography, and racial inequity (Kizer, English and Hackmann, 2022). While these individuals are irrelevant under the current regulatory approach, any meaningful evaluation of access to organ transplants would include them (as opposed to only measuring access for those on waitlists).

The SRTR dataset does not include individuals who may benefit from a transplant but have not accessed a waitlist. And no such dataset exists because transplant candidacy involves clinical evaluations and judgment. Only one study has attempted to use non-SRTR data to evaluate off-waitlist patients, and that study only included Medicaid paitnets in five states (Goldberg et al., 2016). To address this important gap in the available data, I define the new metric of "transplant amenable deaths." This metric is based on the same idea that underlies the concept of healthcare amenable deaths. A healthcare amenable death is "defined as [a] premature death from causes that should not occur in the presence of timely and effective health care" (Nolte and McKee, 2011). Recent research has used this definition when examining the impact of healthcare reforms, such as Medicaid expansion and the relaxation of scope of practice laws (Sommers, Long and Baicker, 2014; Miller, Johnson and Wherry, 2021; McMichael, 2023). I extend this concept to the more narrow class of deaths that could have potentially been avoided by timely receipt of a transplant. Healthcare amenable deaths are defined based on specific ICD-10 codes that represent underlying causes of death on individual death certificates. To obtain a list of deaths that could have been avoided by organ transplantation, I created a crosswalk from the diagnoses listed in the SRTR dataset to ICD-10 diagnosis codes available from death certificates. Unfortunately, the diagnosis codes available in the SRTR dataset are not ICD-10 codes, so a crosswalk was necessary to obtain a list of transplant amenable deaths.[13] That crosswalk is available in the appendix.

[13]I confirmed with very helpful SRTR staff that ICD-10 diagnosis codes are not available in any SRTR dataset.

In general, my definition of transplant amenable deaths is over-inclusive. Medical evaluations of everyone who died of what I define as a transplant amenable death would almost certainly lead to some exclusions from organ waitlists for valid clinical reasons, and I do not claim otherwise.[14] Transplant amenable deaths, however, represent the best available metric to examine access to organ transplants. The alternative is to simply ignore the large segment of the population that could benefit from a transplant but cannot access a waitlist. Despite the position of some advocates that this is the correct approach, ignoring these individuals would prevent me from fully evaluating various allocation policies.

To construct a measure of transplant amenable deaths, I start with data on every death that occurred in the United States between 2010 and 2020.[15] Data on these deaths comes from the United States' National Vital Statistics System, which is maintained by the National Center for Health Statistics (NCHS) and the Centers for Disease Control and Prevention (CDC). I analyze the restricted-use mortality files, which provide detailed information on all deaths at the county and month levels. Included in the dataset are the decedent's year of death, state and county of death, and cause of death as indexed by ICD-10 codes. I identify transplant amenable deaths with these ICD-10 codes. To obtain transplant amenable deaths per capita, I divide the number of organ-specific transplant amenable deaths at the county and month level by the county population from the the Surveillance, Epidemiology and End Results Program maintained by the National Cancer Institute.

[14]Importantly, federal regulators have already demonstrated a willingness to accept imperfect metrics derived from death certificates. Recently, the federal government overhauled the legal regime governing OPOs. The complexities of this overhaul are beyond the scope of this paper, but in general, the federal government replaced metrics reported by the OPOs themselves with cause, age, and location-consistent (CALC) deaths as the primary metric against which to judge OPO performance in recovering organs. Essentially, instead of relying on OPOs to report how many individuals died in ways such that their organs could be recovered, the federal government began relying on death certificates and underlying cause of death codes to obtain exogenous (to the organ procurement system) measures of deaths that could have resulted in organ recoveries (Lynch et al., 2022; Goldberg et al., 2019). It is certainly not the case that every CALC death could yield transplantable organs for many different reasons. Nevertheless, the importance of having a valid metric to judge OPO performance justifies the use of CALC deaths as an official metric. Similarly, the fact that not every death coded as transplant amenable could have actually been avoided with a transplant does not invalidate the use of transplant amenable deaths to examine organ allocation policy. Additionally, as with CALC deaths, the fact that transplant amenable deaths are counted using death certificates and not outcome measures reported by individuals associated with the transplant system means this measure is not manipulable in the same way as the measures of medical urgency are. Thus, transplant amenable deaths represent the best, if not perfect, outcome by which to examine the impact of organ allocation policies on individuals who have not been waitlisted for a transplant.

[15]Because of data availability issues, I am not able to examine transplant amenable deaths after 2020.

4 Conceptual Framework and Empirical Strategy

The goal of this paper is to evaluate the series of rule changes over the past decade to gain insight into whether the trend toward broader national organ sharing has achieved the goals legally mandated by the Final Rule. Namely, have rules designed to facilitate more organ sharing effectively increased sharing, and have they improved the efficiency of the organ allocation system in terms of reduced deaths (including waitlist deaths, post-transplant deaths, and transplant amenable deaths) and in terms of allocating organs to the most medically urgent patients? Because the goal of this paper is to answer the more general question about trends in allocation policies over time and across different organs, the conceptual framework is quite broad. Indeed, I remain relatively agnostic about the potential mechanisms of manipulation, error, or biases that may promote or hinder the ability of allocation rules to achieve the goals outlined in the Final Rule.

Given the level of generality of the analysis, my primary empirical strategy relies on regression discontinuity models, and I supplement these models with time-shifted difference-in-difference models. More specifically, I follow the lead of (Gupta et al., 2023) in implementing regression discontinuity in time (RDIT) models to estimate the effects of changes in policy that apply to the entire population simultaneously (Anderson, 2014; Chen and Whalley, 2012; Burger, Kaffine and Yu, 2014; Moeeni and Tanaka, 2023; Clark, 2023; Brodeur et al., 2021). Hausman and Rapson (2018) detail the differences in assumptions and interpretation in RDIT models relative to more traditional regression discontinuity models, where the running variable that determines treatment is something other than time.

In general, the legal and policy context of organ allocation policies is well suited for the estimation of RDIT models. First, time completely determines treatment, consistent with the RDIT approach. Until a new rule becomes effective, the old policy continues in place. Because of this, the estimates derived from RDIT models should be interpreted as discontinuities at a threshold and not local randomization as may be the case in other regression discontinuity models. The use of time as the running variable means that I cannot test or control for potential sorting. For example, I cannot test for discontinuity in the density of the treatment variable at the relevant cut point along the lines of McCrary (2008) because the density of time is uniform. Second, the lack of a valid control group makes other methods inappropriate.[16] Third, the fact that organ transplantation represents the only treatment for

[16]One potential control group for a given organ is the same or similar outcome for a different organ that did not undergo a rule change at the same time. Callison, Darden and Teltser (2023) employ this approach by using kidneys as a control group for livers. While they detected no violations of the parallel trends assumption in the context of their analysis, I find consistent violations when using other organs as control groups in the policy context I focus on. Additionally, the estimated effects are sensitive to which other

many diseases and the fact that the organ allocation and transplantation system represents the only legal source of organs minimizes concerns that other policies may bias the effect. Prior work has shown that some state laws may indirectly affect various organ allocation and transplantation intermediate outcomes, but only federal law affects the way organs are allocated and transplanted.[17]

Given that the policy context I examine is well suited to RDIT models, I estimate a series of local linear regression models to evaluate the impact of different allocation rule changes by comparing relevant outcomes adjacent to the cut point. My approach is equivalent to estimating the impacts of different rules on a subset of the data with a chosen bandwidth on either side of the cut point. I estimate the following regression model:

$$Y_{it} = \alpha + \beta_0 \cdot T_t + \beta_1 \cdot t + \beta_2 \cdot T_t \cdot t + \epsilon_{it}. \tag{1}$$

In this model, α is the average of the relevant outcome before the rule change, Y_{it} is the relevant outcome, and t is time in months. Because different outcomes are appropriately defined at different units of analysis, i indexes different units depending on the context. It may represent individual transplant candidates/recipients, transplant centers, DSAs, or counties depending on the outcome under consideration. To improve readability, the unit of analysis is defined in connection with the results of individual models below. T_t is an indicator variable for the period following the implementation of the new allocation rule. The coefficient β_2 represents the change in slope of the relevant outcome following the rule change, and β_0 represents the marginal impact of the rule change at the cut point. The latter coefficient, β_0, is the focus of my analysis, as it represents the discontinuity at the threshold. Throughout the analysis, I calculate clustered standard errors to address potential serial autocorrelation (Hausman and Rapson, 2018). For the models at the patient or transplant-center level, the standard errors are clustered at the transplant-center level. For the models at the DSA or county level, the standard errors are clustered at the DSA or county level, respectively. The bandwidths on either side of the cut point are determined by cross validation to reduce the

organs are used as control groups. Accordingly, I do not rely on these models. I similarly cannot implement synthetic control models where the other three organs form a donor pool to create a synthetic control for the remaining organ. With only three other organs, there is simply not enough untreated groups to reliably estimate synthetic control models.

[17] Additionally, the fact that state laws may indirectly impact organ transplantation outcomes does not necessarily mean that the estimates I derive are biased. Federal officials know (or should know) of relevant state laws. To the extent that state laws affect outcomes and federal laws do not account for those effects, this could be viewed as a failure of the relevant federal law and not necessarily as a source of bias. This viewpoint may not apply in settings where individuals act on their own behalf and different polices are designed to regulate their behavior, as is the case in most policy contexts. However, the fact that Congress federalized the organ allocation and transplantation system means that "biases" from state laws may not be biases but instead as the net effect of a federal approach that failed to account for all relevant factors.

mean square error following Calonico, Cattaneo and Titiunik (2014) and Calonico, Cattaneo and Farrell (2019). In the interest of readability, however, a full year is reported graphically on either side of the relevant cut point despite differences in the optimal bandwidth.

Beyond the primary RDIT models, I estimate a series of alternative models to probe the robustness of the primary results. First, I estimate the following quadratic specification:

$$Y_{it} = \alpha + \beta_0 \cdot T_t + \beta_1 \cdot t + \beta_2 \cdot T_t \cdot t + \beta_3 \cdot t^2 + \beta_4 \cdot t^2 \cdot T_t + \epsilon_{it}. \tag{2}$$

Higher order specifications like this one may be more appropriate in some empirical contexts, but the local linear regression implemented in the primary models can provide similar evidence without the higher risk of over-fitting (Cattaneo and Titiunik, 2021). If the higher order models provide similar estimates as the linear models, the linear models are preferred for this reason. In addition to estimating this higher order model, I also estimate a series of local linear regression models with additional control variables. Because prior work has highlighted potential inequities within the organ allocation system, I include control variables for different racial categories available in the SRTR, whether the candidate identifies as female, whether the candidate has completed any college education, and the age of the candidate.

Finally, I estimate a series of difference-in-differences models to test the sensitivity of the results from the RDIT models. Because allocation rules become effective across the country simultaneously, there is no clear control group that would not be treated by a new rule. To address this problem, I follow the lead of Brodeur et al. (2021) and construct a control group that is comprised of outcomes from the same organ under consideration but from a different time period.[18] Across all models, I define the treatment period as one year before and one year after the relevant allocation rule was implemented. I define the control period as three years before through one year before the relevant allocation rule was implemented. Essentially, I compare two two-year windows, with the treatment window experiencing the treatment at the halfway point. This allows me to include a series of lead and lag variables to estimate a series of event study models comparing outcomes from a given organ before and after treatment relative to the same outcomes two years prior. I include 12 lead variables and 12 lag variables, with the month immediately preceeding the implementation of the new policy as the baseline period. While these models are not traditional difference-in-differences models, they allow me to examine the impact of national policies with different models to probe the robustness of the primary RDIT models.

[18] Leder-Luis (2023) develops a similar time-shifting approach for synthetic control models. I am not able to estimate these models for the reasons given above—the lack of a sufficiently large donor pool to create a synthetic control.

5 Results

Because I examine a series of different outcomes related to organ allocation and transplantation and because the models for those outcomes differ somewhat, I report relevant summary information and model results for each outcome separately. The results are presented roughly in the order the relevant outcome occurs in the allocation and transplantation process. I begin with organ sharing before moving to waitlist deaths, transplant outcomes, and post-transplant survival. Models focused on transplant amenable deaths are presented last because, while clearly important from a policy perspective, they are not legally relevant under the Final Rule.

5.1 Organ Sharing

The purpose of the various policies considered in this paper is increased organ sharing. More specifically, the goal is to increase the flow of organs from one part of the country to others to ensure that organs are used efficiently and are allocated to patients with the greatest need for those organs. Before delving into the impact of different allocation policies on organ sharing, Figures 1 and 2 provide an overview of organ sharing across the country in 2021. Figure 1 reports the next imports and exports across all DSAs in 2021. Shades of red indicate that a DSA was a net importer of organs, with darker shades indicating a larger number of imports. Shades of blue indicate that a DSA was a net exporter of organs, with darker shades indicating more exports. Across all four organs, few DSAs are purely importers or exporters. For example, the DSA that includes most of Georgia is a net importer of kidneys and livers but a net exporter of lungs and hearts. However, Figure 1 suggests that parts of the country tend to be net exporters or importers of all four organs. The DSA containing New York City, for example, is in the highest category of net importers for all four organs. On the other hand, the DSAs containing Louisiana and most of Alabama are net exporters for all organs.

While Figure 1 is informative as to flows of organs across the country, net imports/exports is not necessarily the best way to measure organ flows over time because the total net import/export is zero and because some DSAs export all their organs for lack of a transplant center that performs the relevant organ transplantation. To address these shortcomings, Figure 2 reports the percentage of transplants within each DSA in 2021 that used organs recovered within the same DSA (*i.e.*, local organs). Darker shades of blue indicate higher percentages of local organs, with yellow indicating an absence of data because the relevant DSA does not include transplant centers performing transplants for the given organ. Unsur-

prisingly, the pattern largely tracks that seen in Figure 1. Net importers generally use lower percentages of local organs, and net exporters use higher percentages.

Examining local organ percentages as a measure of organ sharing in more depth, Table 2 reports a series of RDIT models with local organ percentage as the outcome. With the lone exception of the elimination of DSAs in heart allocation, there was a statistically significant decline in the percentage of transplants using local organs following the implementation of all new allocation rules. The Kidney Allocation Scheme and elimination of DSAs for kidney allocation reduced the use of local kidneys by approximately 12 and 18 percentage points, respectively. The share 35 policy and elimination of DSAs for livers reduced the use of local livers by approximately 14 and 28 percentage points, respectively. Local lung usage declined by about 25 percentage points following the elimination of DSAs as a geographic unit of allocation. Local heart usage declined by approximately 23 percentage points following the implementation of the 6 tiers system. Eliminating DSAs for heart allocation did not have a statistically significant impact on local heart usage, but this policy was implemented relatively shortly after the 6 tiers policy, which may explain the lack of impact.

To supplement the results in Table 2, Figure 3 presents the regression discontinuities graphically. Across all policy changes except the elimination of DSAs from heart allocation, a clear discontinuity is visible at the time the relevant policy was implemented. In general, the consistent evidence that the use of local organs declined following allocation rule changes suggests that these rule changes achieved their goal of increasing organ sharing across the country. A decrease in local organ usage necessarily means that more organs are being transplanted in DSAs other than the ones where the organs were recovered. To the extent organ sharing matters as an outcome under the Final Rule, six of the seven policies considered here meaningfully increased organ sharing. However, organ sharing is arguably an intermediate measure of the achievement of more important goals—such as saving lives.

5.2 Waitlist Deaths

Turning to the issue of lives saved, I begin with lives saved on organ waitlists. To measure waitlist deaths, I use the number of deaths on the waitlist (defined as removal for death or because the candidate became too sick to receive a transplant) per 10,000 patient days spent on the waitlist. I define this measure at the transplant-center level because individual transplant programs set their own rules for waitlisting patients. Figure 4 reports the number of waitlist deaths across the country in 2021, with darker shades indicating more deaths and yellow indicating the absence of a waitlist for the relevant organ.

Table 3 reports the results from a series of RDIT models with waitlist deaths per 10,000

patient days as the outcome. In general, I find little evidence that the policies considered here effectively reduced waitlist deaths. Indeed, the only evidence that is significant at the 10% level is that the implemenation of the 6 tiers system for heart allocation *increased* waitlist deaths. Otherwise, there is little evidence of a meaningful change in waitlist deaths following the implementation of changes to allocation rules. Figure 5 provides graphical evidence of this absence of a change in waitlist deaths. Large "blips" are evident in the various graphs of waitlist deaths, but the graphs nevertheless support the conclusion that the policy changes considered here did little to change waitlist deaths.

5.3 Transplant Outcomes

Next, I examine outcomes at transplant that may indicate whether allocation rule changes effectively funneled cadaveric organs to more medically urgent candidates. As detailed above, the allocation system relies on different metrics for different organs, so I examine wait time for kidneys,[19] MELD scores for livers, LAS for lungs, and either treatment intensity or status for hearts. Figure 6 reports various organ metrics across the country in 2021.[20]. Interestingly, there is some correlation with the geographic patterns evident in Figure 4 above, but the correlation is certainly not one-to-one.

Table 4 reports the results from a series of RDIT models with the various organ-specific metrics as the outcomes of interest. Beginning with kidneys, the Kidney Allocation Scheme reduced wait time by about 140 days, but the elimination of DSAs as a unit of allocation did not result in a statistically significant change in wait time. With respect to livers, the share 35 program did not result in patients having a higher MELD score at transplant. In other words, there is no statistically significant evidence that sicker patients were more likely to receive an organ under the share 35 program. On the other hand, the elimination of DSAs for liver allocation did increase the MELD score at transplant, indicating that sicker patients had better access to cadaveric organs. The elimination of DSAs for lung allocation, however, did not result in a statistically significant change. For hearts, the implementation of the 6 tiers system increased the number of patients who had undergone more intensive treatment (receiving either an IABP or ECMO) prior to transplant. This could indicate an increase in the ability of sicker patients to access transplants. The elimination of DSAs for heart allocation had no statistically significant impact on the status of candidates receiving heart transplants, indicating that it may not have increased access to transplants among sicker

[19]In terms of medical urgency, kidneys are somewhat different from the other organs. Unlike livers, lungs, and hearts, for which no viable long term medical intervention to prolong life exists, end stage kidney disease patients can undergo dialysis to prolong their lives. Because of this and because wait time factors more heavily into allocation decisions for kidneys than other organs, I focus on this measure for kidneys.

[20]Because status for heart transplants is available in 2021, I report that metric in Figure 6

patients. Figure 7 graphically reports the results that were reported in Table **??**.

In general, the evidence from the organ-specific metrics is somewhat mixed. Unlike waitlist deaths, where there was no evidence of a positive impact of new allocation rules, those rules seem to improve some organ-specific metrics but not others. These results, however, may be best interpreted with some skepticism. McMichael (2022) demonstrated that transplant centers may manipulate allocation MELD scores. And Cascino et al. (2022) suggested that the increase in treatment intensity among patients receiving heart transplants was a result of transplant clinicians attempting to inflate the status of their patients and not a result of cadaveric hearts being funneled to relatively sicker patients. While I focus on these metrics because they are the ones that matter under the current legal regime, the results for these measures should be interpreted with these limitations in mind. It is also relevant that waitlist deaths do not respond as strongly to changes in allocation policy as the organ-specific metrics. This may be the result of manipulation of the metrics or the fact that the metrics imperfectly represent mortality risk (Godfrey et al., 2019). In either case, the use of these metrics may inhibit the ability of the allocation and transplantation system to meet the requirements of the Final Rule.

Beyond the organ-specific metrics measured at the time of transplant, two other categories of metrics may be indirectly relevant to the ability of new allocation rules to accomplish their goal of improving the efficient use of organs. Panels B and C of Table 4 report RDIT results for organ cold ischemia time and donor warm ischemia time, respectively.[21] Because of anatomical differences and differences in allocability of right and left lungs, Panel B separately reports models for the left and right lungs (Ben Nachum et al., 2011). In general, there is some, but not overwhelming, evidence that the policies examined here increased cold ischemia time. The elimination of DSAs for livers and lungs and the 6 tiers system for hearts all were accompanied by statistically significant increases in cold ischemia time. On the other hand, there is no indication of a statistically significant increase in donor warm ischemia time in connection with any of the policies. This difference in discontinuities between warm and cold ischemia time is interesting because it implies that the policies had little effect on how long organs remained in donors but increased the time between removal and transplantation. In other words, by requiring more organ sharing and necessitating longer travel distances, some allocation policies increase the cold ischemia time of organs, which can result worse patient outcomes following transplant.

[21] In the interest of succinctness and because ischemia time is not directly relevant to the current legal regime, I omit a graphical presentation of the RDIT results.

5.4 Post-Transplant Survival

The final stage of organ transplantation is post-transplant survival. While there may be good reasons to measure this in various ways, the current regulatory approach focuses heavily on one-year survival, so that is the focus on this paper as well. More specifically, I examine the rate at which patients transplanted before and after the implementation of a policy died within one year of that transplant. Figure 8 reports the death rate within one year of transplant across the country, with darker shades of blue indicating higher death rates. Table 5 reports the results of RDIT models with an indicator for whether the patient died within one year of transplant as the outcome. Across all models, there is no statistically significant evidence that any of the policies either increased or decreased the one-year post-transplant death rate. Figure 9 reports the results graphically and largely confirms the results in Table 5. However, Panel B, which reports results for the elimination of DSAs in kidney allocation, indicates the possibility that this policy reduced deaths over time as opposed to immediately upon implementation. To address this possibility, I estimated a kinked regression discontinuity model, and the results indicate that the change was not statistically significant.

The lack of evidence of a change in post-transplant death rates suggests that, though the various policies increased organ sharing across the country, they do not result in improved post-transplant outcomes. This evidence, particularly when combined with earlier evidence on waitlist deaths, does not suggest that these policies result in the more efficient use of organs. While the definition of efficient use is not entirely clear under current law, one would expect that if the law were to mandate transporting organs across the country, this would result in more lives saved. My analysis reveals no evidence that any more lives are saved.

5.5 Transplant Amenable Deaths

Finally, I examine transplant amenable deaths. To be clear, these deaths are irrelevant under the current approach to evaluating the effectiveness of the organ allocation and transplantation system (Goldberg et al., 2016). A recent report by the National Academies clearly explains that individuals who have not been waitlisted are ignored in the current system (Kizer, English and Hackmann, 2022). And some advocates of greater national organ sharing have actively argued that individuals who may benefit from a transplant but have not accessed a waitlist are irrelevant from the perspective of the transplant system (Glazier, 2018). Despite this legal irrelevance, I examine transplant amenable deaths because evaluating access to transplantation comprehensively necessarily involves considering individuals

who may benefit from a transplant even if they cannot access the current transplantation system. There may be various reasons for this lack of access to the current system—poverty, a lack of access to healthcare generally, geography (*i.e.*, living too far away from a transplant center), a low supply of transplant clinicians, racial inequities, etc. Whatever the reasons for an inability to access the transplant system, it is important to consider individuals who may benefit from a transplant. To do so, I focus on transplant amenable deaths, with the understanding that this is not a perfect measure of individuals who died because they did not receive a transplant. Unlike the previous metrics, which were based on SRTR data, transplant amenable deaths are based on death certificate data. This data only extends through 2020, so I am not able to evaluate the elimination of DSAs as a unit of allocation for kidneys.

Figure 10 reports transplant amenable deaths per 100,000 individuals across the country in 2019.[22] I roll all county-level information on transplant amenable deaths up to the DSA level to make the information in Figure 10 more direcly comparable with previous figures. The South, Midwest, and Appalachia tend to suffer more transplant amenable deaths per capita than other areas of the country. Interestingly, comparing this pattern of deaths with earlier maps, particularly those on net imports/exports and local organ usage, suggests that the parts of the country suffering the highest number of transplant amenable deaths are also the parts of the country that are more likely to be net exporters of organs. Conversely, California and the northeastern states have some of the lowest levels of transplant amenable deaths. Earlier results suggest that these areas tend be some of the largest net importers of organs.

In other words, current allocation policy seems to funnel organs away from areas that have higher rates of transplant amenable deaths to areas with lower rates of transplant amenable deaths. From the perspective of geographic equity, this pattern may raise significant issues. If all areas of the country experience similar levels of transplant amenable deaths because organs from areas with organically lower death rates were transferred to those with higher organic death rates, the organ allocation system may be working effectively. Similarly, if areas of the country experiencing higher rates of transplant amenable deaths were routinely importing more organs from areas of the country with lower death rates, the organ allocation system may be working to effect more geographically equitable outcomes. However, the fact that areas with higher rates of transplant amenable deaths export more organs to areas with lower rates suggests that the organ allocation and transplantation system may not be working as intended, given that the Final Rule states that geography should not determine a patient's access to transplantation.

[22] I report 2019 deaths to avoid the potential confounding effects of the Covid-19 pandemic in 2020.

To examine transplant amenable deaths in more detail, Table 6 reports the results of a series of RDIT models with organ-specific transplant amenable deaths as the outcome, and Figure 11 reports the same results graphically.[23] I find statistically significant evidence that kidney-transplant amenable deaths increased following the implementation of the kidney allocation scheme. I also find evidence that lung-transplant amenable deaths incresaed following the elimiantion of DSAs as an allocation unit. However, inspection of Panel D in Figure 11 suggests that this simply due to seasonal variation in deaths that could be avoided by a lung transplant. In particular, more people tend to die of pneumonia and respiratory diseases in the winter, and it appears that the increase in lung-transplant amenable deaths is due to this seasonality as opposed to the new lung allocation policy. Conversely, eliminating DSAs in liver allocation led to an immediate decrease in liver-transplant amenable deaths but a longer term uptick in those deaths, as demonstrated by Panel C of Figure 11.

In general, the evidence does not suggest that allocation policies designed to increase organ sharing meaningfully reduced transplant amenable deaths among the general population. While this may not be relevant under the Final Rule, it nevertheless suggests that recent changes to organ allocation policy have not meaningfully improved access to transplants for individuals who need them. Taken together with the evidence developed so far, the results of my analysis suggest that organ allocation rules designed to increase organ sharing accomplish this limited goal and may improve access to waitlisted patients who appear sicker under current metrics. However, this increased sharing does little to avoid deaths on waitlists, after transplant, or among the general population.

6 Robustness

To test the robustness of the results from the primary models, I estimate a series of RDIT models with local quadratic regressions. I also estimate a series of RDIT models with local linear regressions with control variables included.[24] All of these models are reported in the appendix. In general, the results are substantially similar to those reported in the primary models.

Next, I estimate a series of event-study models as described above. Following the lead of Brodeur et al. (2021), I use a time-shifting approach to generate a control group.[25] Because

[23] I re-estimated all the RDIT models in Figure 11 using a kinked RDIT design, and the results do not meaningful differ—none of the policies have a statistically significant effect on transplant amenable deaths.

[24] Because of the different nature of the data used for the transplant amenable death models, I am not able to estimate these models with the same control variables.

[25] I am unable to reliably estimate these models for the elimination of DSAs for heart allocation because this policy occurs near the end of my study period and because the six tiers policy was enacted so close in time, making the generation of a control group impossible. While this model is reported in the interest of

I estimate event-study models, I can directly examine the parallel trends assumption that underlies such models and confirm that, in most cases, the time-shifted outcomes for the same organ form a valid control group. As with the alternative RDIT models, the event-study models are reported in the appendix. And, in general, they yield similar evidence as the primary models reported above. Based on this similar evidence derived from models with substantially different structures and assumptions, I can be more confident in the evidence derived from the RDIT models and the conclusions drawn from that evidence.

7 Discussion and Conclusion

In general, I find consistent evidence that recent changes to organ allocation policy designed to increase organ sharing across the country have largely succeeded in achieving that goal. I also find evidence that this increase in organ sharing may increase the availability of organs to the highest urgency patients as determined by current urgency metrics. However, not all policies result in more access for the most urgent patients, and I find no statistically significant evidence that this increased access saved more lives. In general, neither waitlist mortality, nor post-transplant death rates, declined following the implementation of new allocation policies. Collectively, this does not support the conclusion that greater national organ sharing results in the more efficient use of cadaveric organs.

The evidence of statistically significant increases in organ sharing accompanied by no improvement in mortality and inconsistent improvement in access to organs among medically urgent candidates has important implications for the continued development of organ allocation policy. Advocates of greater national organ sharing point to the Final Rule's requirement that geography not play a role in a candidate's access to organ transplantation. The Final Rule, however, also mandates the efficient use of cadaveric organs. The evidence provided here does not suggest that greater national organ sharing resulted in more efficient use of organs. Indeed, with no changes in mortality, recent changes in allocation policy have not saved lives.

Instead, these policies have done more to choose which lives are saved. Since the demand for organs far outstrips supply, any decision to save someone through national organ sharing may result in a local death. It is hard to justify such an outcome if this choice results in no efficiency gains in terms of lives saved. This is even harder to justify given existing evidence that greater national organ sharing fails to address racial disparities, exacerbates socioeconomic disparities, and may discourage organ donation (O'Dell et al., 2019; Nagai et al., 2022; Cascino et al., 2022; Parker et al., 2020, 2018; Pullen, 2019; Godfrey et al., 2019;

completeness, it should be largely ignored.

Karp, Segal and Patil, 2020). And previous evidence suggesting that transplant centers in parts of the country that tend to import more organs are more likely to manipulate their patients' urgency metrics to increase the number of transplant surgeries they perform further undermine the justification for greater national organ sharing if that sharing results in no efficiency gains in terms of mortality (Snyder, 2010; Scanlon et al., 2004; McMichael, 2022). In other words, taken together with existing evidence, the results reported here do not support continued national organ sharing. These results are particularly relevant given that policymakers are now focused on continuous distribution, which may result in even greater national organ sharing.

Beyond the direct policy implications, the evidence developed in this paper may bear on a larger underlying question in organ allocation policy—whether transplant centers in the Northeast and California have orchestrated new organ allocation policies to benefit their patients at the expense of patients in other parts of the country. A recent exposè suggested this was the real motivation behind some of the allocation policies examined here (Carollo and Tanen, 2023). Evidence that these policies substantially increased organ sharing with no statistically significant effect on either pre- or post-transplant mortality supports the conclusion that the stated motivation of saving lives was pretextual. While the evidence here cannot, standing alone, prove the manipulation of organ rules to the benefit of certain parts of the country, it is nevertheless consistent with such a hypothesis.

More generally on the issue of geography, the evidence developed through the examination of transplant amenable deaths demonstrates that the areas of the country suffering the highest rates of these deaths are not the areas of the country that generally import more organs. Additionally, the analysis demonstrates that changes to allocation rules do not meaningfully reduce transplant amenable deaths. This is not necessarily surprising, as the current legal regime does not contemplate harms to individuals who have not been able to access an organ waitlist when evaluating the effectiveness of different allocation policies. The failure to do so is sometimes attributed to the Final Rule, but no court has ever stated that this is the case, and policymakers are certainly not forbidden from considering such evidence. Overall, the evidence is not favorable to recent allocation rule changes designed to increase national organ sharing.

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Figures and Tables

Table 1: Major Organ Allocation Policies

Date Implemented	**Organ**	**Policy Name**
12/4/2014	Kidney	Kidney Allocation Scheme
3/15/2021	Kidney	DSA Elimination
6/18/2013	Liver	Share 35
2/4/2020	Liver	DSA Elimination
11/24/2017	Lung	DSA Elimination
10/18/2018	Heart	Six Tiers
1/9/2020	Heart	DSA Elimination

Table 2: Regression Discontinuity in Local Organ Usage

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim.	(6) 6 Tiers	(7) H. DSA Elim.
RD Estimate	-11.825	-17.736	-14.219	-27.877	-25.271	-22.525	-0.111
	(1.938)	(3.028)	(2.417)	(2.565)	(3.873)	(4.122)	(5.415)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.984]

Notes: The outcome of interest in all models is an indicator variable for whether the organ used in a transplant was recovered within the same DSA as where the transplant occurred. The unit of observation is the individual transplant recipient. Regression discontinuity estimates are reported for each of seven different allocation rule changes listed at the top of each column. Standard errors clustered at the transplant center level are reported in parentheses, and p values based on those standard errors are reported in brackets.

Table 3: Regression Discontinuity in Waitlist Deaths Per Day

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim.	(6) 6 Tiers	(7) H. DSA Elim.
RD Estimate	-0.961	0.401	0.923	3.013	9.440	14.847	26.834
	(1.983)	(1.580)	(1.385)	(3.545)	(8.798)	(7.871)	(19.243)
	[0.628]	[0.800]	[0.505]	[0.395]	[0.283]	[0.059]	[0.163]

Notes: The outcome of interest in all models is the rate of deaths on waitlists per 10,000 patient waitlist days. The unit of observation is the transplant center at the month level. Regression discontinuity estimates are reported for each of seven different allocation rule changes listed at the top of each column. Standard errors clustered at the transplant center level are reported in parentheses, and p values based on those standard errors are reported in brackets.

Table 4: Regression Discontinuity in Outcomes at Transplant

Panel A: Individual Organ Metrics

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim.	(6) 6 Tiers	(7) H. DSA Elim.
RD Estimate	-139.741	-42.586	0.323	1.169	-1.275	0.093	0.199
	(41.885)	(46.755)	(0.406)	(0.412)	(1.573)	(0.025)	(0.119)
	[0.001]	[0.362]	[0.426]	[0.005]	[0.418]	[0.000]	[0.094]

Panel B: Organ Cold Ischemia Time

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim. (L)	(6) Lu. DSA Elim. (R)	(7) 6 Tiers	(8) H. DSA Elim.
RD Estimate	0.813	0.610	0.323	1.169	30.945	11.383	16.195	-2.468
	(0.337)	(0.370)	(0.406)	(0.412)	(9.210)	(10.842)	(4.988)	(7.818)
	[0.016]	[0.100]	[0.426]	[0.005]	[0.001]	[0.294]	[0.001]	[0.752]

Panel C: Donor Warm Ischemia Time

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim.	(6) 6 Tiers	(7) H. DSA Elim.
RD Estimate	-0.980	1.143	1.719	0.083	1.271	0.009	-0.421
	(2.149)	(1.028)	(2.152)	(0.392)	(0.840)	(0.009)	(0.714)
	[0.648]	[0.266]	[0.424]	[0.832]	[0.130]	[0.317]	[0.556]

Notes: The outcome of interest in the models reported in Panel A is the relevant organ-specific metric. The metrics for each organ are as follows: kidneys – wait time, livers – allocation median end-stage liver disease score, lungs – lung allocation score, hearts (6 tiers) – reciept of either IABP or ECMO, and hearts (DSA elimination) – status. The outcome of interest in the models reported in Panel B is cold ischemia time. The outcome of interest in the models reported in Panel C is donor warm ischemia time. The unit of observation is the individual transplant. Regression discontinuity estimates are reported for each of seven different allocation rule changes listed at the top of each column. Standard errors clustered at the transplant center level are reported in parentheses, and p values based on those standard errors are reported in brackets.

Table 5: Regression Discontinuity in Deaths Less Than One Year Post-Transplant

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim.	(6) 6 Tiers	(7) H. DSA Elim.
RD Estimate	0.508	-1.181	0.263	0.039	0.326	-1.041	3.491
	(0.737)	(1.244)	(1.423)	(1.445)	(2.135)	(2.114)	(3.207)
	[0.490]	[0.343]	[0.853]	[0.978]	[0.879]	[0.622]	[0.276]

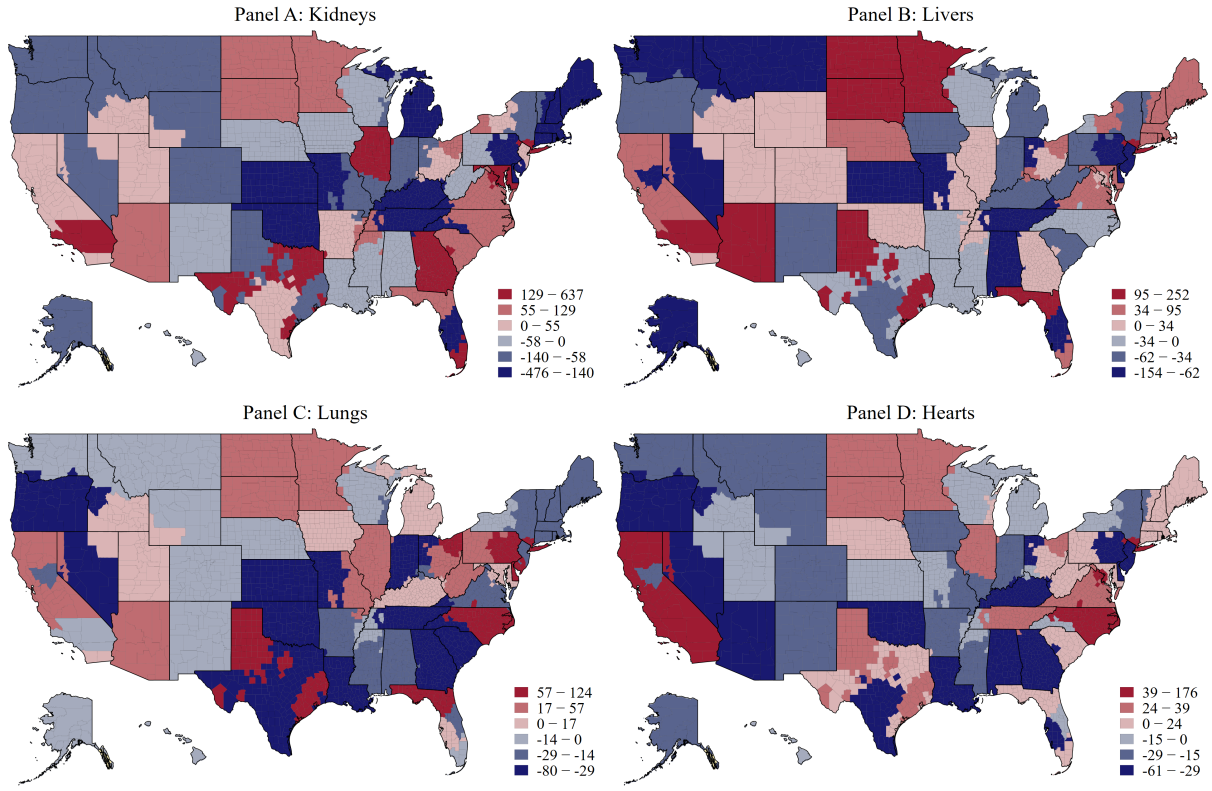
Notes: The outcome of interest in all models is the rate of deaths less than one year following transplant per 100 transplants. The unit of observation is the individual transplant recipient. For the purposes of assigning policy cut points, the date of transplantation is used. Regression discontinuity estimates are reported for each of seven different allocation rule changes listed at the top of each column. Standard errors clustered at the transplant center level are reported in parentheses, and p values based on those standard errors are reported in brackets.

Table 6: Regression Discontinuity in Transplant Ammenable Deaths

	(1) K. All. Scheme	(2) Share 35	(3) Li. DSA Elim.	(4) Lu. DSA Elim.	(5) 6 Tiers	(6) H. DSA Elim.
RD Estimate	0.216	-0.076	-0.516	0.058	-0.045	0.197
	(0.101)	(0.130)	(0.197)	(0.184)	(0.234)	(0.319)
	[0.032]	[0.557]	[0.009]	[0.750]	[0.848]	[0.537]

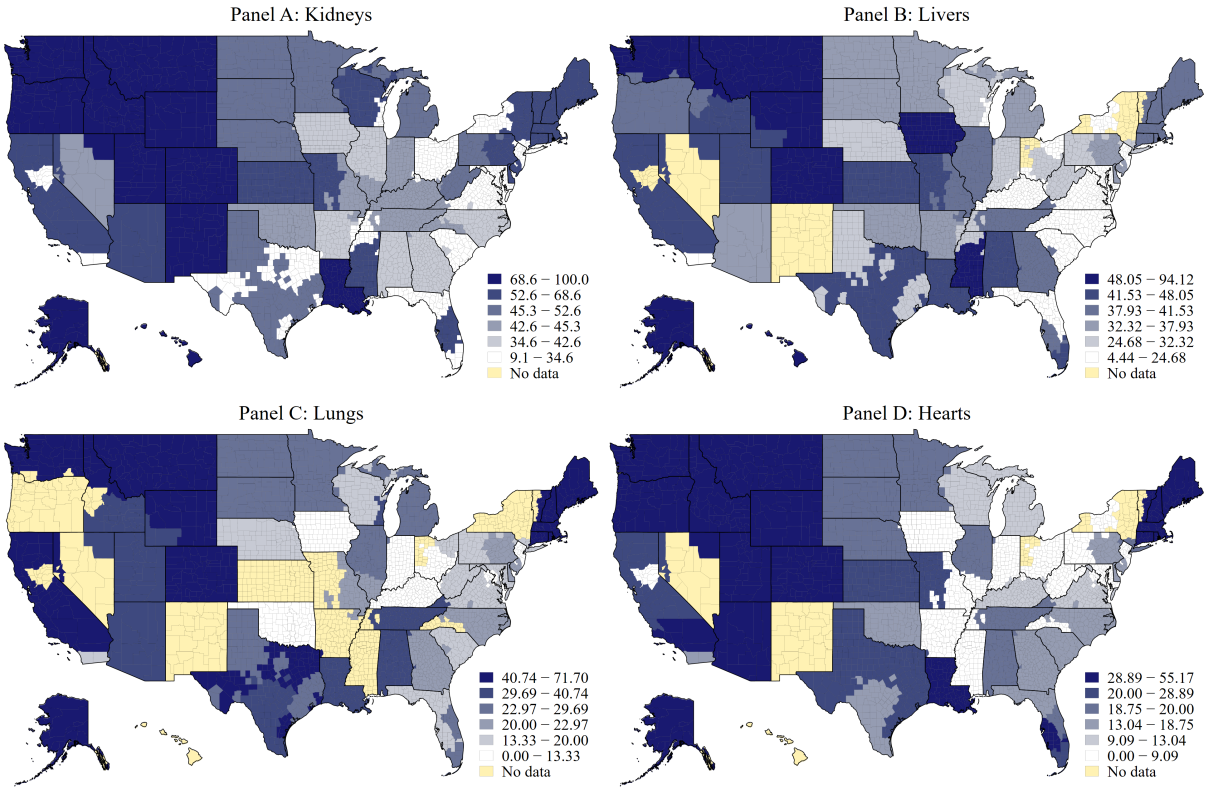
Notes: The outcome of interest in all models is the rate of transplant amenable deaths per 100,000 individuals. The unit of observation is the county at the month level. Regression discontinuity estimates are reported for each of seven different allocation rule changes listed at the top of each column. Standard errors clustered at the transplant center level are reported in parentheses, and p values based on those standard errors are reported in brackets.

Figure 1: Net Imports and Exports



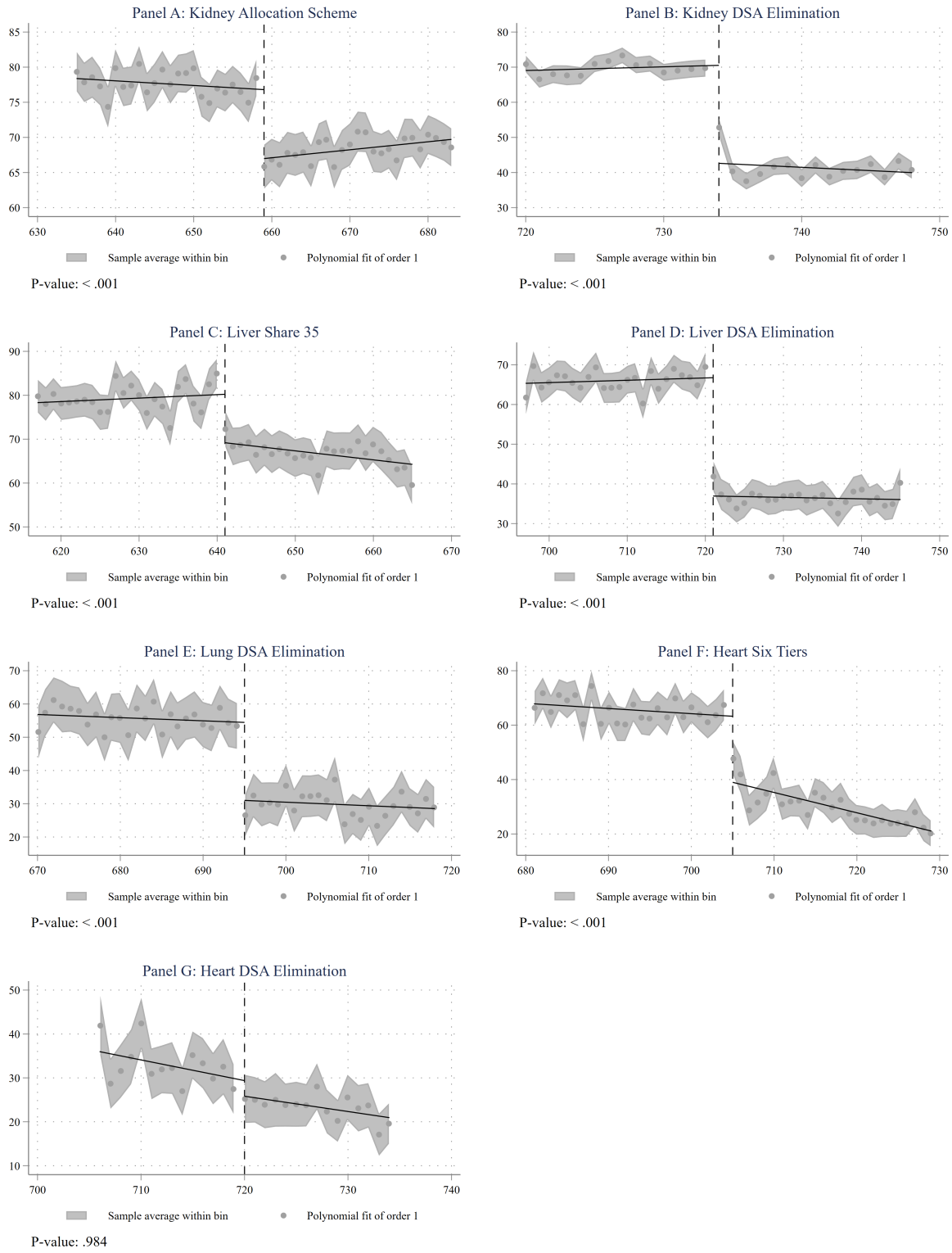
Notes: Imports include all organs transplanted in a given DSA that were recovered in another DSA. Exports include all organs recovered in a DSA but transplanted in another DSA. Net imports/exports are reported for each DSA for the entirety of 2021.

Figure 2: Local Organ Usage



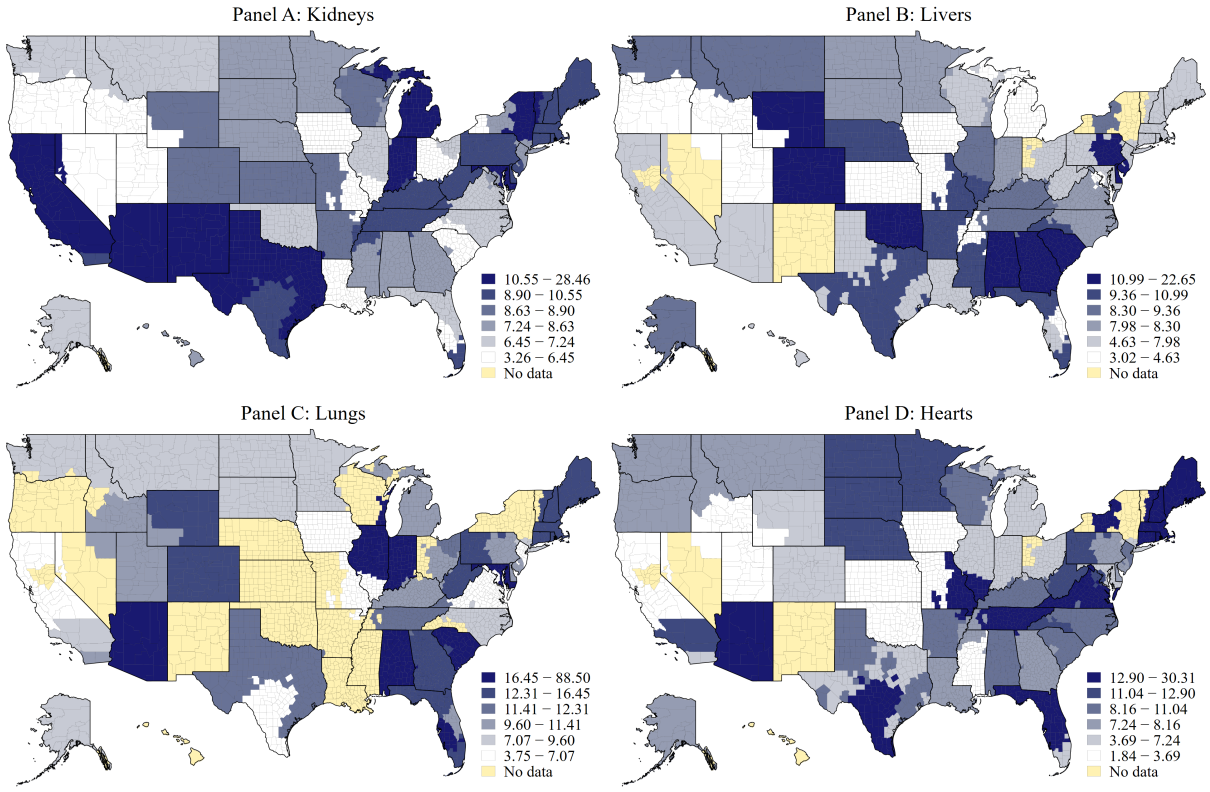
Notes: Local organs include all organs transplanted within the DSA of recovery. Local percentage is defined as the percent of local organs used across all transplants in each DSA for the entirety of 2021.

Figure 3: Regression Discontinuity in Local Organ Usage



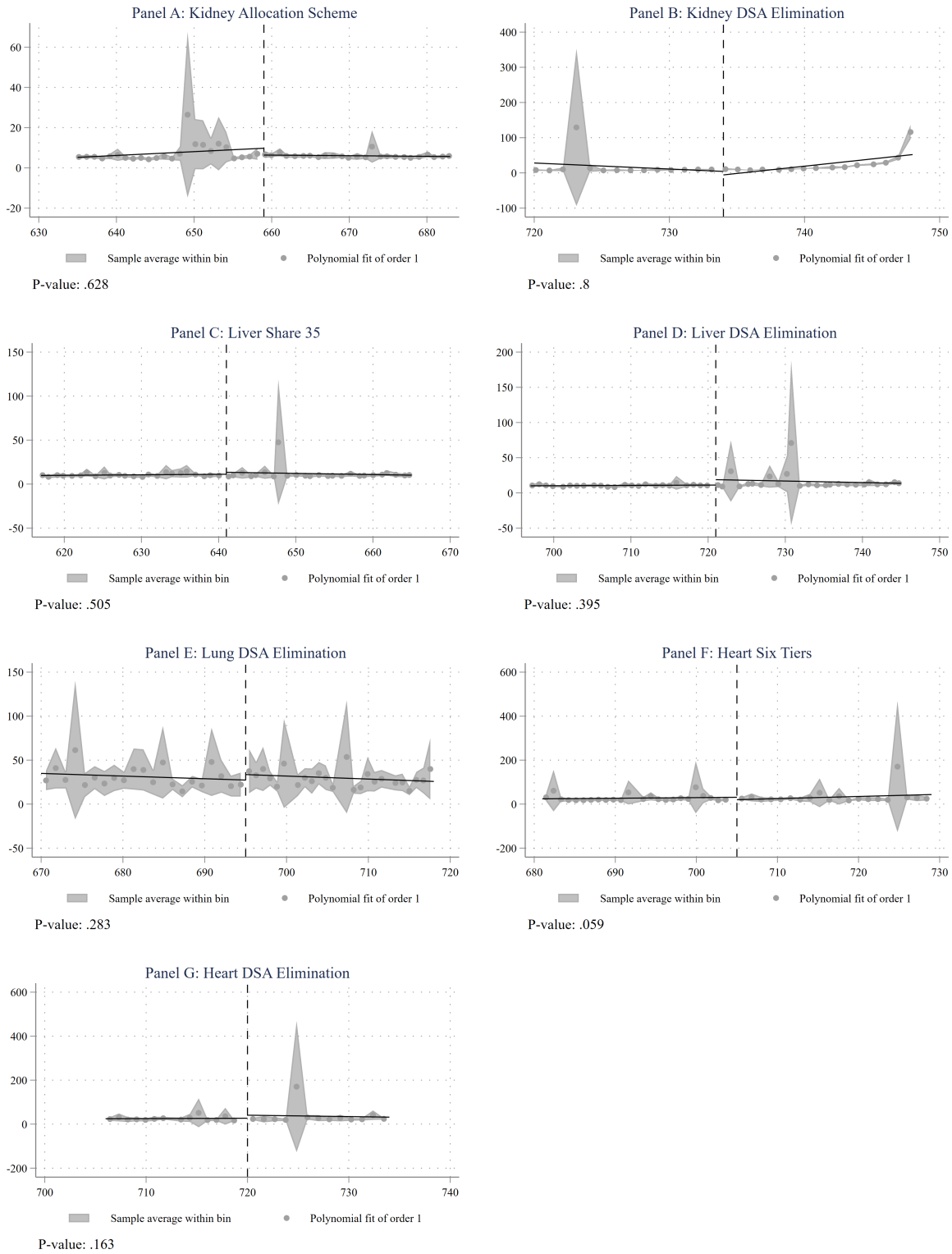
Notes: The outcome of interest in all models is an indicator variable for whether the organ used in a transplant was recovered within the same DSA as where the transplant occurred. The unit of observation is the individual transplant recipient. 95% confidence intervals are reported as shaded regions.

Figure 4: Waitlist Deaths Per 10,000 Waitlist Days



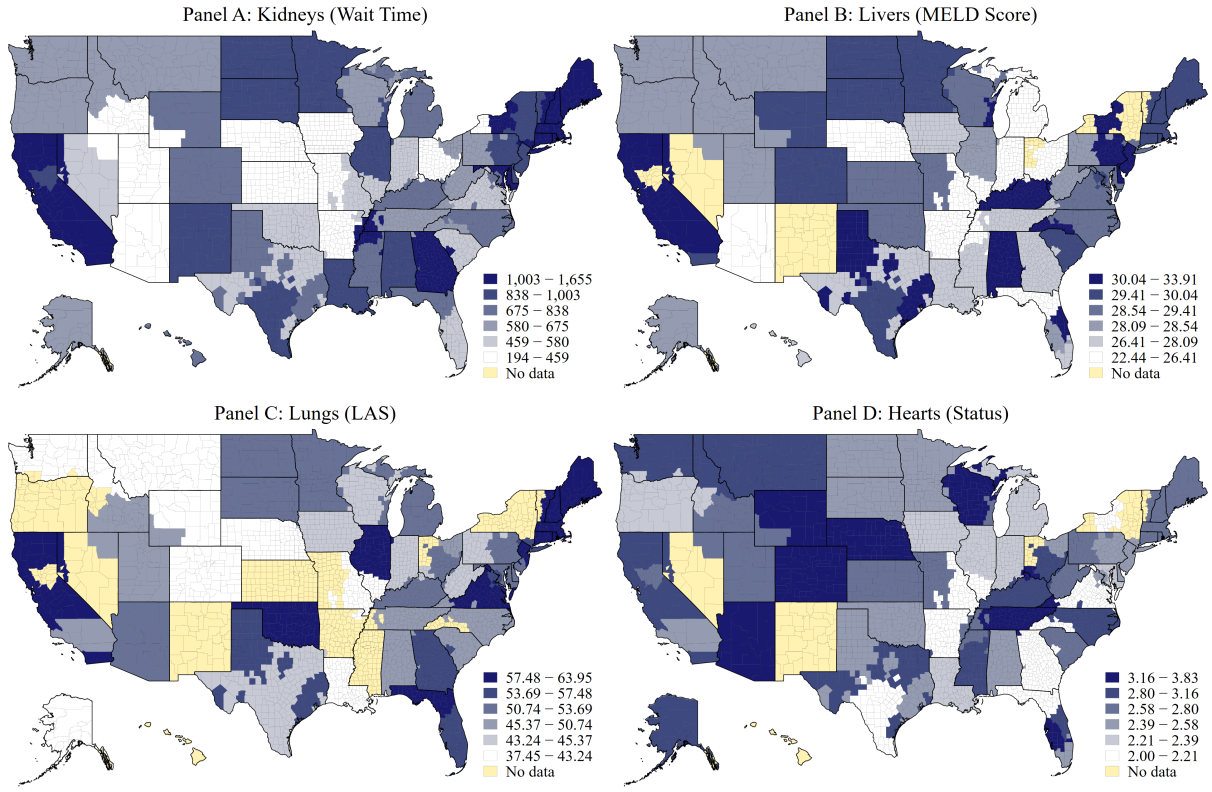
Notes: Waitlist deaths include all waitlist removals due to death or the candidate becoming too sick to receive a transplant. Waitlist death rates are reported for the entirety of 2021.

Figure 5: Regression Discontinuity in Waitlist Deaths Per 10,000 Waitlist Days



Notes: The outcome of interest in all models is the rate of deaths on waitlists per 10,000 patient waitlist days. The unit of observation is the transplant center at the month level. 95% confidence intervals are reported as shaded regions.

Figure 6: Organ-Specific Metrics



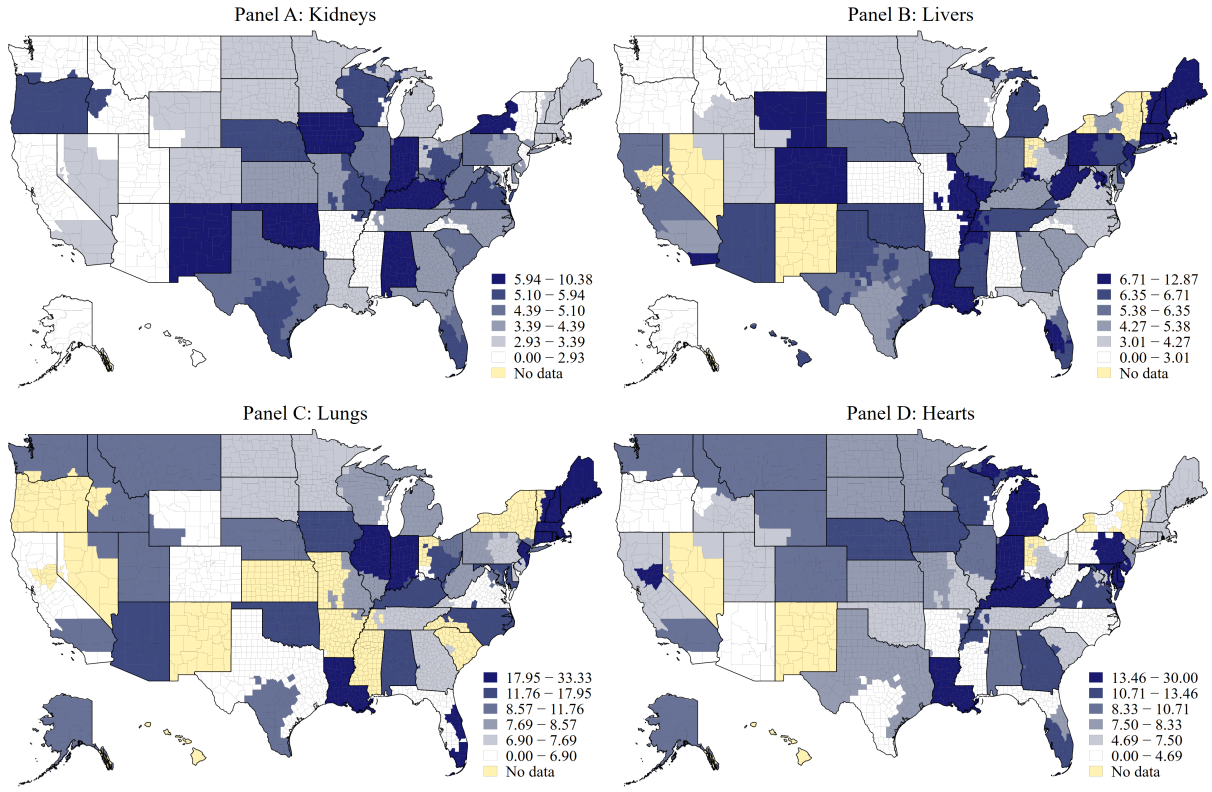
Notes: The metric reported for each organ is specified in the panel title. Metrics are reported for the entirety of 2021.

Figure 7: Regression Discontinuity in Organ-Specific Metrics



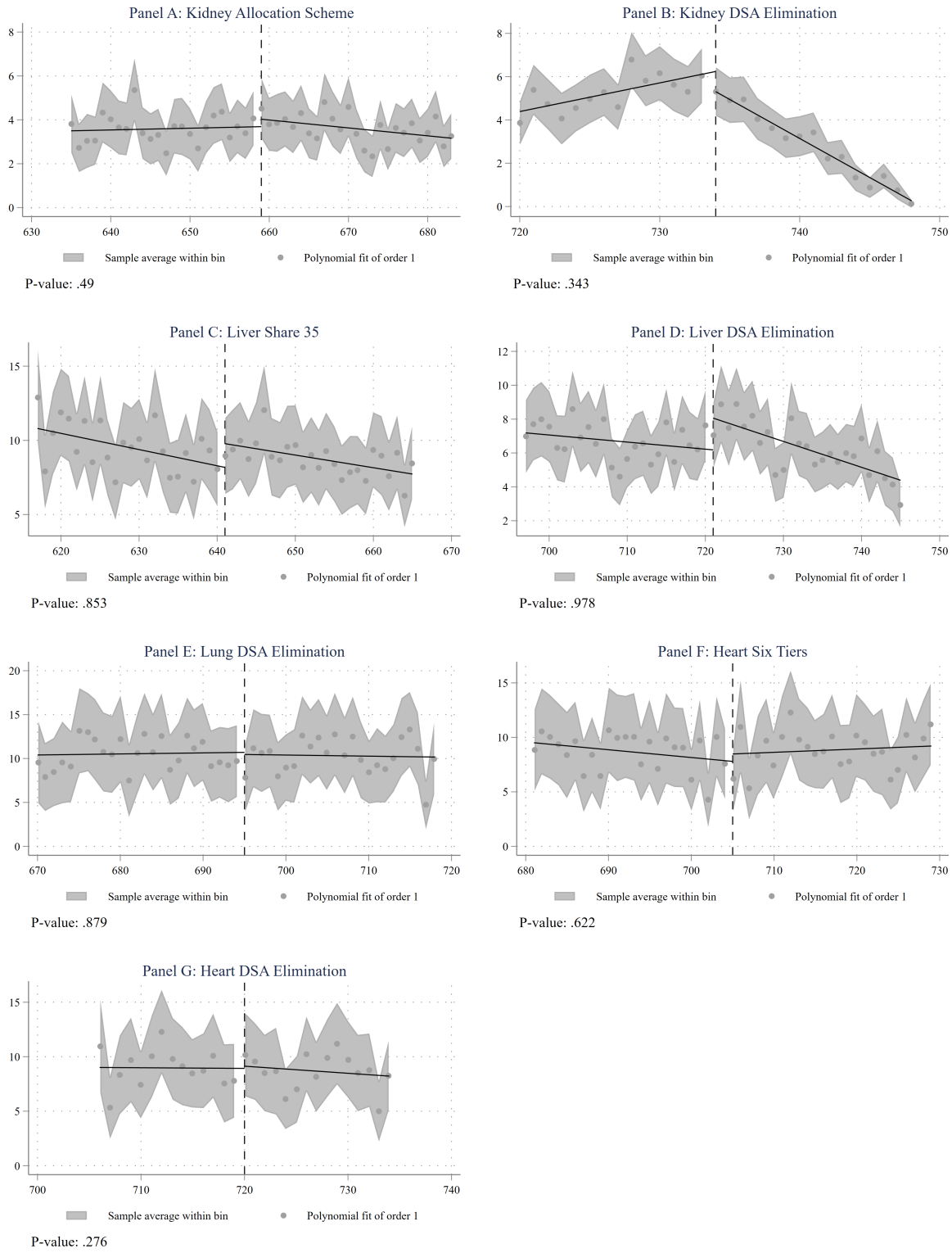
Notes: The outcome of interest in all models is the relevant organ-specific metric. The metrics for each organ are specified in the panel titles. The unit of observation is the individual transplant. 95% confidence intervals are reported as shaded regions.

Figure 8: One-Year Post-Transplant Death Rate



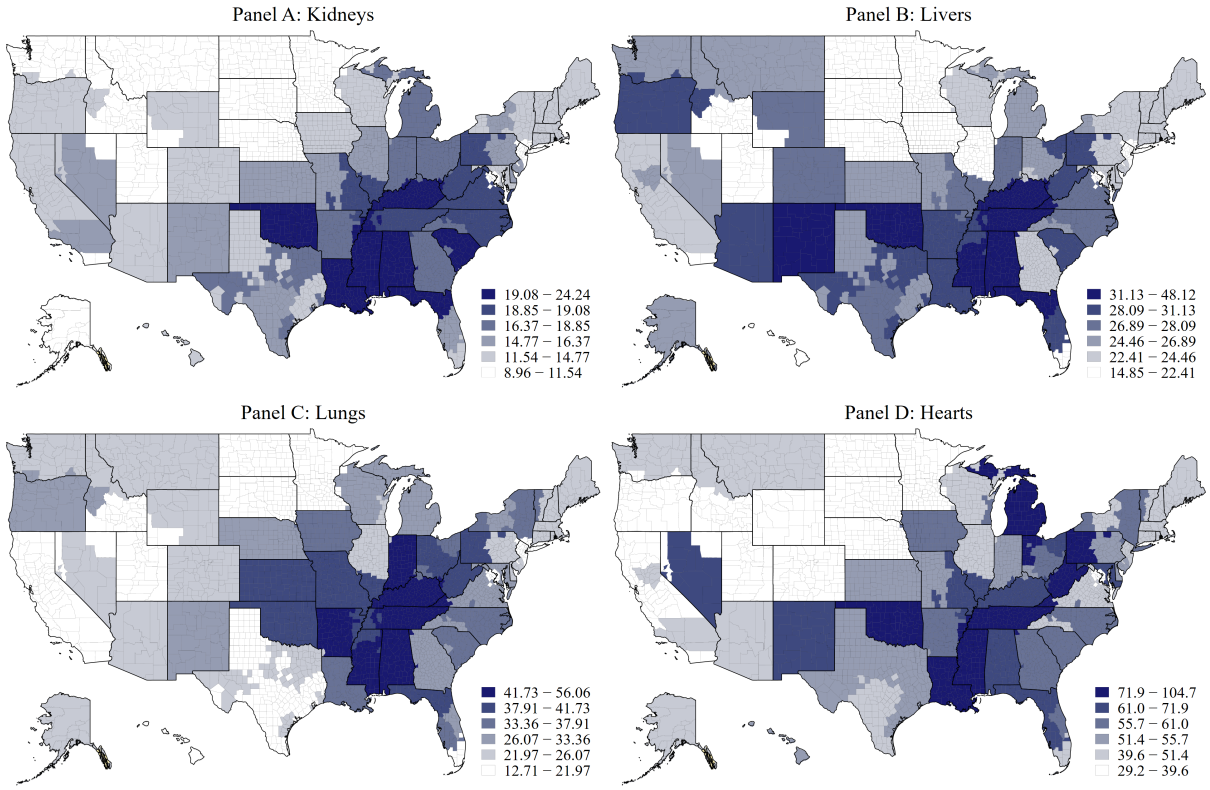
Notes: Deaths include all transplant recipients who died within one year of transplant. Deaths within one year of all transplants completed in 2021 are reported.

Figure 9: Regression Discontinuity in One-Year Post-Transplant Death Rate



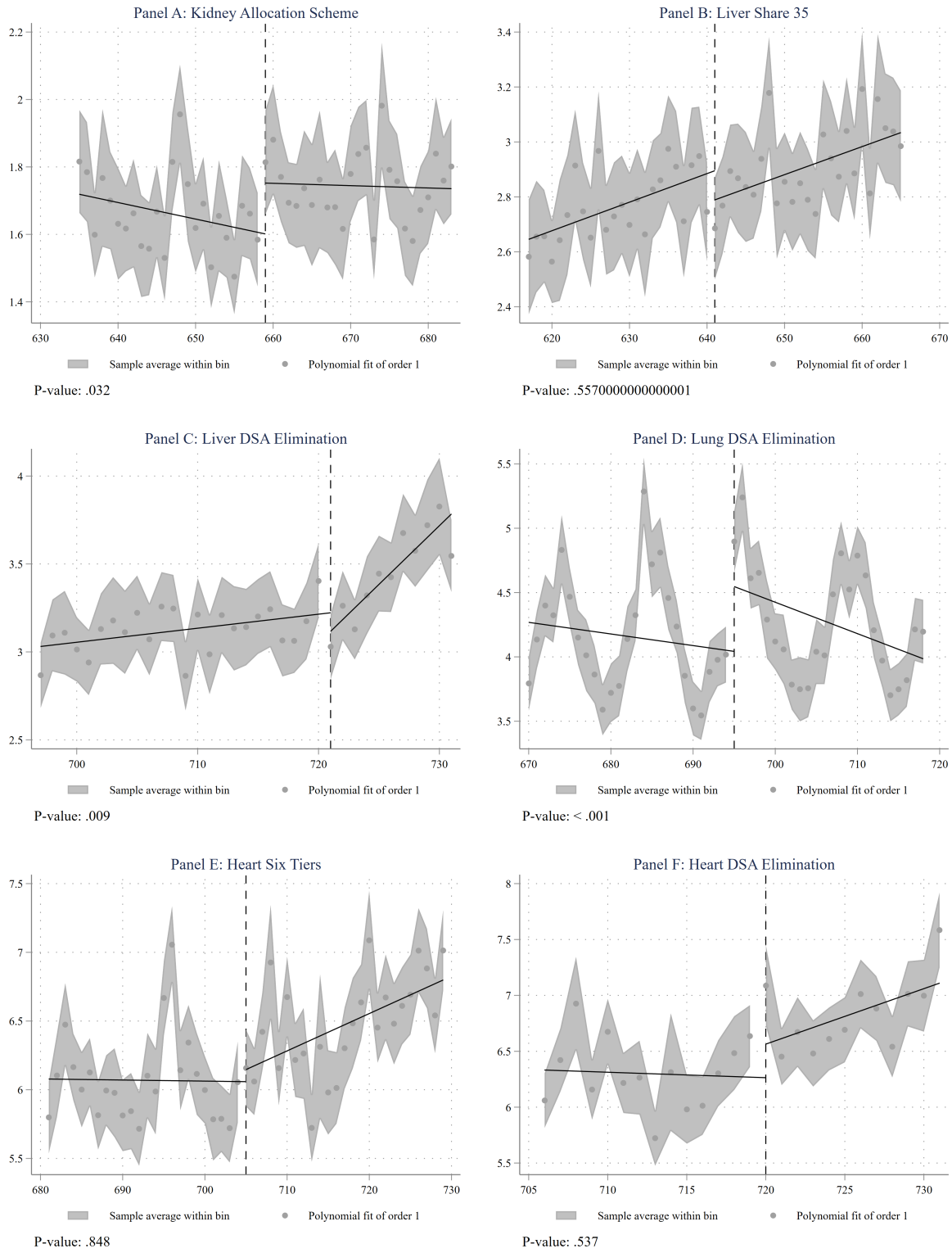
Notes: The outcome of interest in all models is the rate of deaths less than one year following transplant per 100 transplants. The unit of observation is the individual transplant recipient. For the purposes of assigning policy cut points, the date of transplantation is used. 95% confidence intervals are reported as shaded regions.

Figure 10: Transplant Amenable Deaths



Notes: Transplant amenable deaths for each organ type include all deaths that could have potentially been avoided with a timely transplant based on the ICD-10 reported as the underlying cause of death. Transplant amenable deaths per 100,000 individuals are reported for the entirety of 2019.

Figure 11: Regression Discontinuity in Transplant Amenable Deaths



Notes: The outcome of interest in all models is the rate of transplant amenable deaths per 100,000 individuals. The unit of observation is the county at the month level. 95% confidence intervals are reported as shaded regions.

Appendix
Sharing is Caring:
Does Organ Allocation Policy Work?

September 30, 2023

Table A1: Regression Discontinuity in Local Organ Usage (Quadratic)

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim.	(6) 6 Tiers	(7) H. DSA Elim.
RD Estimate	-12.315	-17.105	-15.280	-28.062	-24.890	-24.271	0.785
	(2.231)	(5.569)	(3.121)	(3.500)	(5.518)	(5.524)	(7.594)
	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.000]	[0.918]

Notes: The outcome of interest in all models is an indicator variable for whether the organ used in a transplant was recovered within the same DSA as where the transplant occurred. The unit of observation is the individual transplant recipient. Regression discontinuity estimates are reported for each of seven different allocation rule changes listed at the top of each column. Standard errors clustered at the transplant center level are reported in parentheses, and p values based on those standard errors are reported in brackets.

Table A2: Regression Discontinuity in Waitlist Deaths Per Day (Quadratic)

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim.	(6) 6 Tiers	(7) H. DSA Elim.
RD Estimate	-4.134	1.500	-1.866	3.518	30.567	14.126	63.432
	(3.375)	(2.360)	(1.593)	(3.290)	(16.939)	(11.762)	(56.396)
	[0.221]	[0.525]	[0.241]	[0.285]	[0.071]	[0.230]	[0.261]

Notes: The outcome of interest in all models is the rate of deaths on waitlists per 10,000 patient waitlist days. The unit of observation is the transplant center at the month level. Regression discontinuity estimates are reported for each of seven different allocation rule changes listed at the top of each column. Standard errors clustered at the transplant center level are reported in parentheses, and p values based on those standard errors are reported in brackets.

Table A3: Regression Discontinuity in Outcomes at Transplant (Quadratic)

Panel A: Individual Organ Metrics

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.)	(5) Lu. DSA Elim.	(6) 6 Tiers	(7) H. DSA Elim.
RD Estimate	-103.775	-73.464	0.415	1.119	-5.101	0.083	0.062
	(50.911)	(64.174)	(0.527)	(0.467)	(2.763)	(0.028)	(0.224)
	[0.042]	[0.252]	[0.431]	[0.017]	[0.065]	[0.003]	[0.782]

Panel B: Organ Cold Ischemia Time

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim. (L)	(6) Lu. DSA Elim. (R)	(7) 6 Tiers	(8) H. DSA Elim.
RD Estimate	0.932	0.482	0.415	1.119	46.974	16.102	16.052	-8.789
	(0.516)	(0.702)	(0.527)	(0.467)	(16.866)	(14.643)	(5.915)	(13.326)
	[0.071]	[0.492]	[0.431]	[0.017]	[0.005]	[0.271]	[0.007]	[0.510]

Panel C: Donor Warm Ischemia Time

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim.	(6) 6 Tiers	(7) H. DSA Elim.
RD Estimate	-0.316	0.131	1.572	0.898	0.171	0.008	-0.760
	(1.882)	(1.697)	(2.684)	(0.759)	(1.227)	(0.008)	(0.879)
	[0.867]	[0.938]	[0.558]	[0.237]	[0.889]	[0.311]	[0.387]

Notes: The outcome of interest in the models reported in Panel A is the relevant organ-specific metric. The metrics for each organ are as follows: kidneys – wait time, livers – allocation median end-stage liver disease score, lungs – lung allocation score, hearts (6 tiers) – reciept of either IABP or ECMO, and hearts (DSA elimination) – status. The outcome of interest in the models reported in Panel B is cold ischemia time. The outcome of interest in the models reported in Panel C is donor warm ischemia time. The unit of observation is the individual transplant. Regression discontinuity estimates are reported for each of seven different allocation rule changes listed at the top of each column. Standard errors clustered at the transplant center level are reported in parentheses, and p values based on those standard errors are reported in brackets.

Table A4: Regression Discontinuity in Deaths Less Than One Year Post-Transplant (Quadratic)

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim.	(6) 6 Tiers	(7) H. DSA Elim.
RD Estimate	0.525	-2.586	-0.105	-0.573	-0.021	-1.383	4.084
	(0.933)	(2.783)	(1.909)	(1.900)	(3.473)	(2.488)	(4.277)
	[0.574]	[0.353]	[0.956]	[0.763]	[0.995]	[0.578]	[0.340]

Notes: The outcome of interest in all models is the rate of deaths less than one year following transplant per 100 transplants. The unit of observation is the individual transplant recipient. For the purposes of assigning policy cut points, the date of transplantation is used. Regression discontinuity estimates are reported for each of seven different allocation rule changes listed at the top of each column. Standard errors clustered at the transplant center level are reported in parentheses, and p values based on those standard errors are reported in brackets.

Table A5: Regression Discontinuity in Transplant Ammenable Deaths (Quadratic)

	(1) K. All. Scheme	(2) Share 35	(3) Li. DSA Elim.	(4) Lu. DSA Elim.	(5) 6 Tiers	(6) H. DSA Elim.
RD Estimate	0.255	-0.038	-0.691	0.182	-0.370	0.287
	(0.134)	(0.161)	(0.346)	(0.503)	(0.357)	(0.427)
	[0.057]	[0.812]	[0.045]	[0.718]	[0.301]	[0.502]

Notes: The outcome of interest in all models is the rate of transplant amenable deaths per 100,000 individuals. The unit of observation is the county at the month level. Regression discontinuity estimates are reported for each of seven different allocation rule changes listed at the top of each column. Standard errors clustered at the transplant center level are reported in parentheses, and p values based on those standard errors are reported in brackets.

Table A6: Regression Discontinuity in Local Organ Usage (Controls)

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim.	(6) 6 Tiers	(7) H. DSA Elim.
RD Estimate	-11.846	-17.585	-14.415	-27.871	-25.363	-22.104	0.128
	(1.931)	(3.028)	(2.442)	(2.542)	(3.510)	(4.101)	(5.396)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.981]

Notes: The outcome of interest in all models is an indicator variable for whether the organ used in a transplant was recovered within the same DSA as where the transplant occurred. The unit of observation is the individual transplant recipient. Regression discontinuity estimates are reported for each of seven different allocation rule changes listed at the top of each column. Standard errors clustered at the transplant center level are reported in parentheses, and p values based on those standard errors are reported in brackets.

Table A7: Regression Discontinuity in Waitlist Deaths Per Day (Controls)

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim.	(6) 6 Tiers	(7) H. DSA Elim.
RD Estimate	-1.060	0.079	0.994	3.135	6.695	14.087	22.253
	(2.042)	(1.442)	(1.371)	(3.637)	(8.718)	(7.691)	(19.060)
	[0.604]	[0.956]	[0.469]	[0.389]	[0.443]	[0.067]	[0.243]

Notes: The outcome of interest in all models is the rate of deaths on waitlists per 10,000 patient waitlist days. The unit of observation is the transplant center at the month level. Regression discontinuity estimates are reported for each of seven different allocation rule changes listed at the top of each column. Standard errors clustered at the transplant center level are reported in parentheses, and p values based on those standard errors are reported in brackets.

Table A8: Regression Discontinuity in Outcomes at Transplant (Controls)

Panel A: Individual Organ Metrics

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim.	(6) 6 Tiers	(7) H. DSA Elim.
RD Estimate	-165.753	-27.357	0.389	1.228	-1.072	0.095	0.185
	(40.474)	(43.383)	(0.385)	(0.405)	(1.585)	(0.025)	(0.131)
	[0.000]	[0.528]	[0.312]	[0.002]	[0.499]	[0.000]	[0.160]

Panel B: Organ Cold Ischemia Time

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim. (L)	(6) Lu. DSA Elim. (R)	(7) 6 Tiers	(8) H. DSA Elim.
RD Estimate	0.682	0.652	0.389	1.228	29.955	10.965	15.943	-3.393
	(0.315)	(0.364)	(0.385)	(0.405)	(9.125)	(10.647)	(4.932)	(7.739)
	[0.030]	[0.073]	[0.312]	[0.002]	[0.001]	[0.303]	[0.001]	[0.661]

Panel C: Donor Warm Ischemia Time

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim.	(6) 6 Tiers	(7) H. DSA Elim.
RD Estimate	-0.726	1.141	1.900	0.060	1.200	0.008	-0.425
	(2.135)	(1.027)	(2.139)	(0.390)	(0.851)	(0.008)	(0.701)
	[0.734]	[0.267]	[0.374]	[0.877]	[0.159]	[0.319]	[0.545]

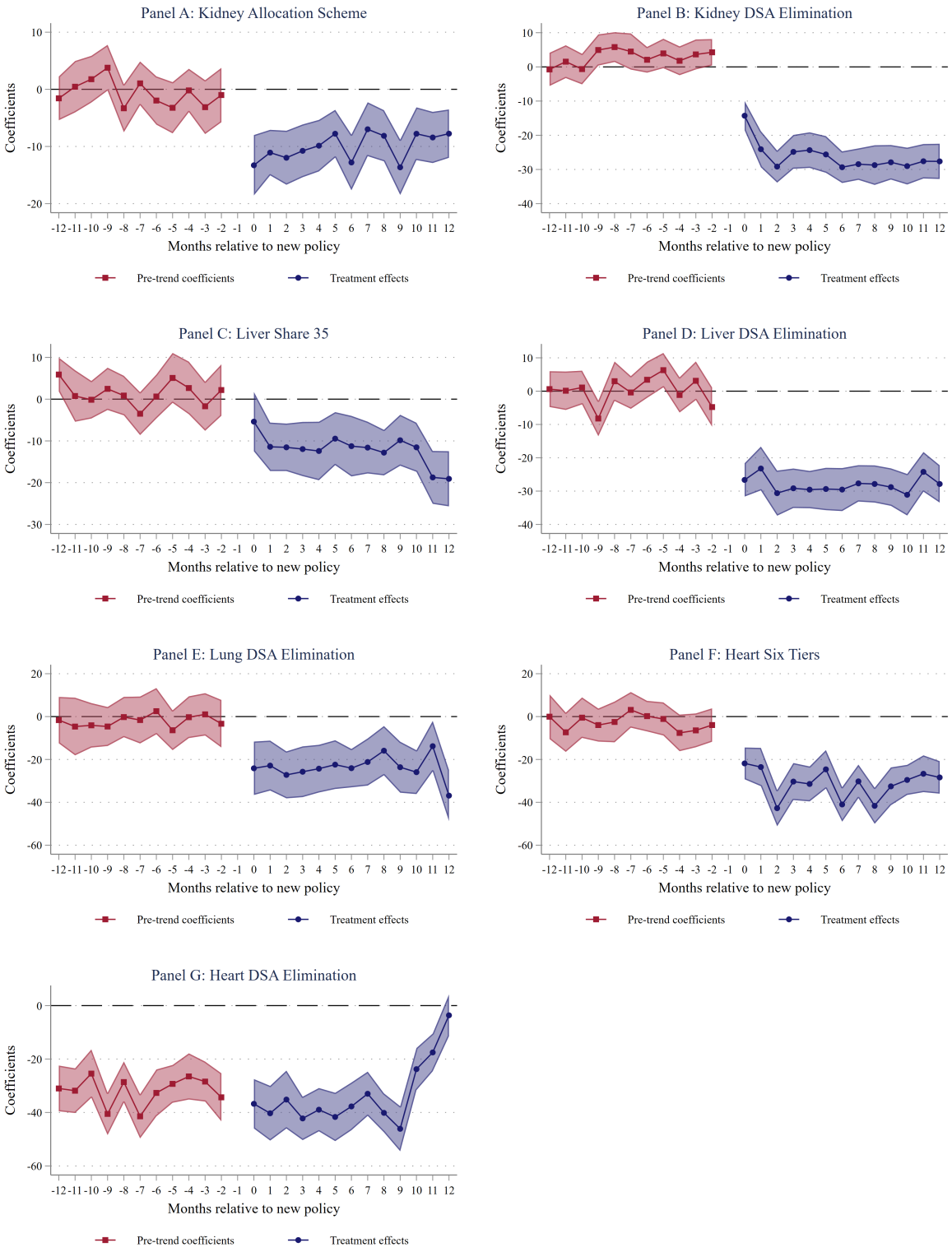
Notes: The outcome of interest in the models reported in Panel A is the relevant organ-specific metric. The metrics for each organ are as follows: kidneys – wait time, livers – allocation median end-stage liver disease score, lungs – lung allocation score, hearts (6 tiers) – reciept of either IABP or ECMO, and hearts (DSA elimination) – status. The outcome of interest in the models reported in Panel B is cold ischemia time. The outcome of interest in the models reported in Panel C is donor warm ischemia time. The unit of observation is the individual transplant. Regression discontinuity estimates are reported for each of seven different allocation rule changes listed at the top of each column. Standard errors clustered at the transplant center level are reported in parentheses, and p values based on those standard errors are reported in brackets.

Table A9: Regression Discontinuity in Deaths Less Than One Year Post-Transplant (Controls)

	(1) K. All. Scheme	(2) K. DSA Elim.	(3) Share 35	(4) Li. DSA Elim.	(5) Lu. DSA Elim.	(6) 6 Tiers	(7) H. DSA Elim.
RD Estimate	0.634	-1.109	0.234	0.063	0.273	-1.252	3.371
	(0.753)	(1.245)	(1.434)	(1.441)	(2.124)	(2.148)	(3.218)
	[0.400]	[0.373]	[0.870]	[0.965]	[0.898]	[0.560]	[0.295]

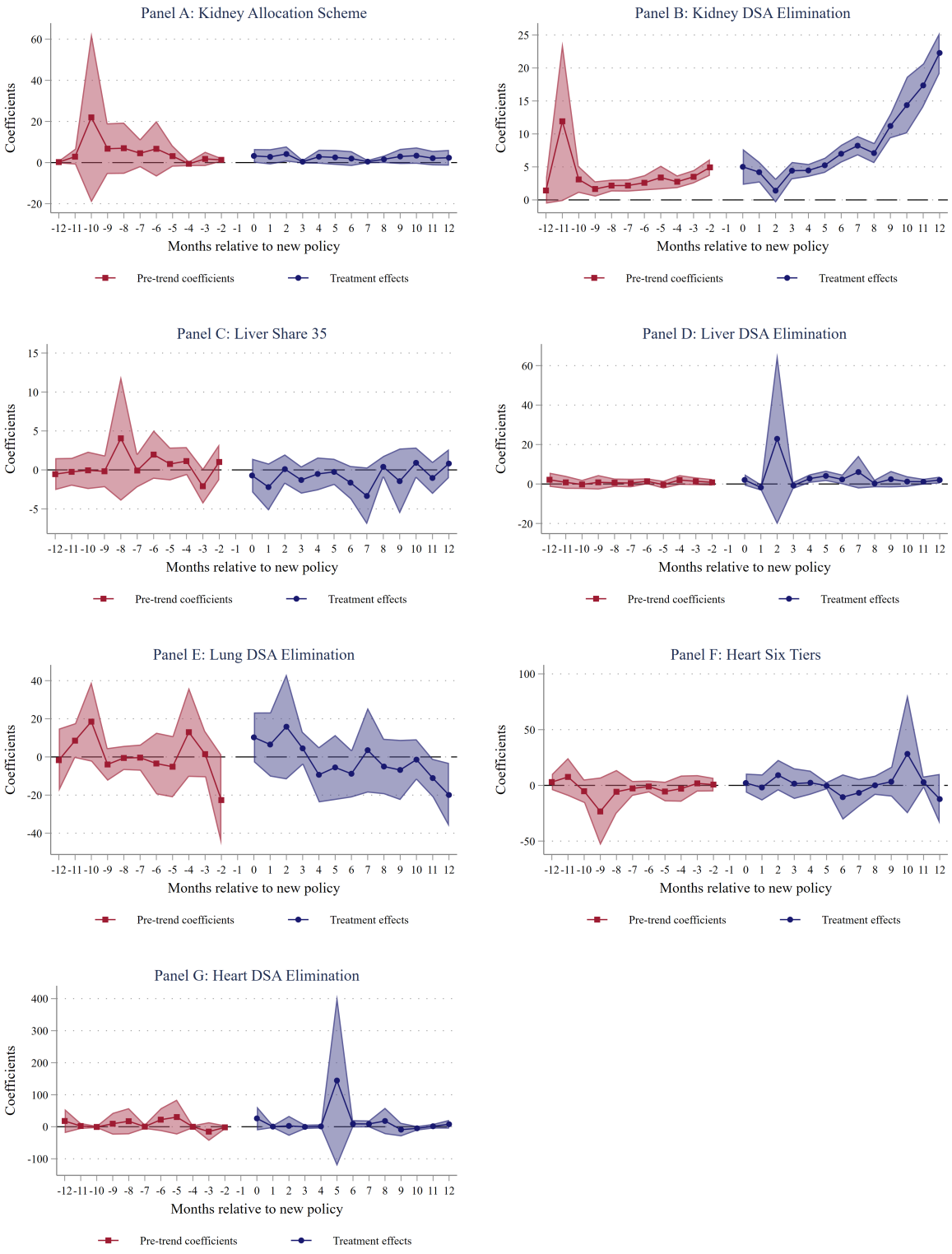
Notes: The outcome of interest in all models is the rate of deaths less than one year following transplant per 100 transplants. The unit of observation is the individual transplant recipient. For the purposes of assigning policy cut points, the date of transplantation is used. Regression discontinuity estimates are reported for each of seven different allocation rule changes listed at the top of each column. Standard errors clustered at the transplant center level are reported in parentheses, and p values based on those standard errors are reported in brackets.

Figure A1: Event Study for Local Organ Usage



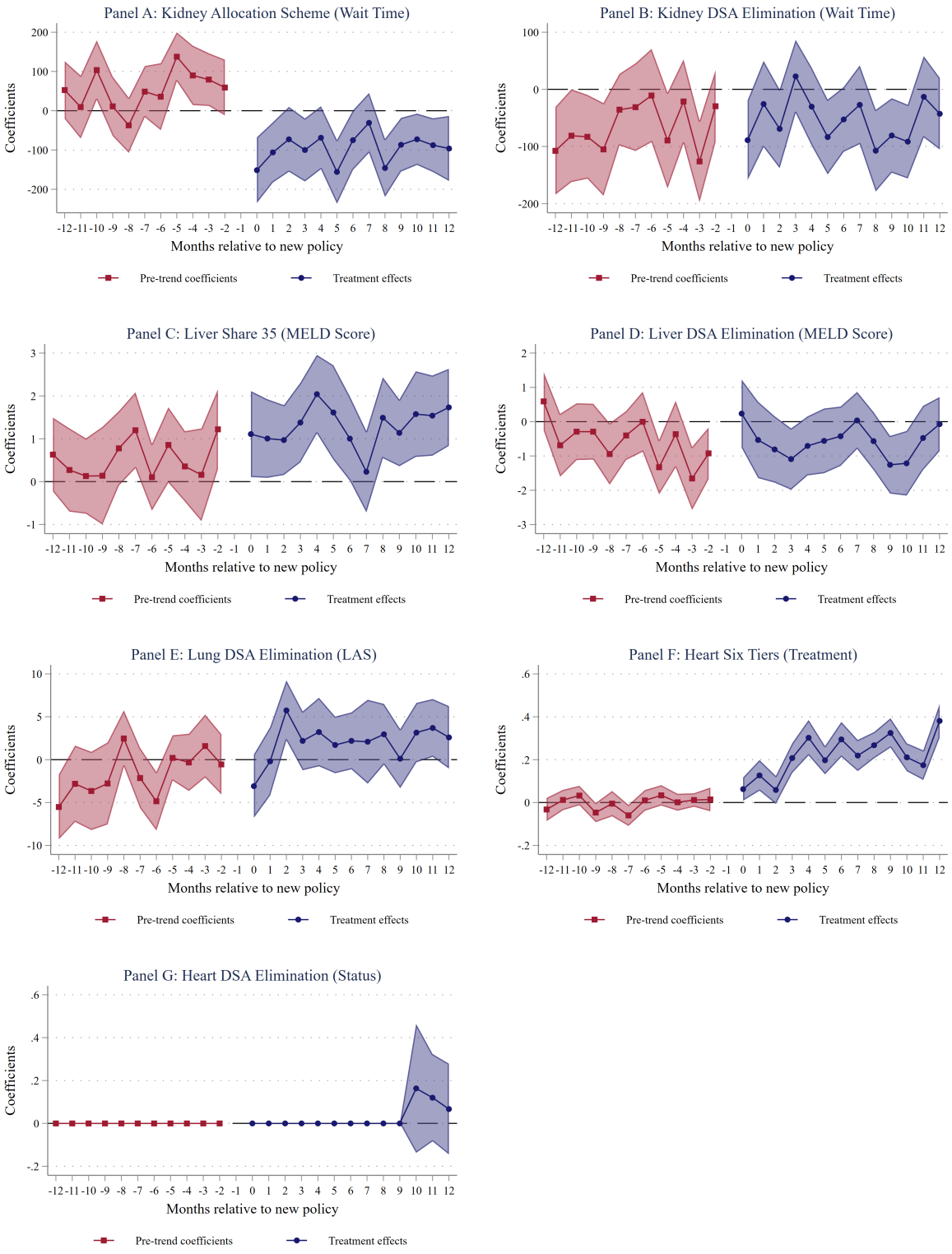
Notes: The dependent variable in all models is an indicator variable for whether the organ used in a transplant was recovered within the same DSA as where the transplant occurred. The unit of observation is the individual transplant recipient. 95% confidence intervals are reported as shaded regions.

Figure A2: Event Study for Waitlist Deaths Per 10,000 Waitlist Days



Notes: The dependent variable in all models is the rate of deaths on waitlists per 10,000 patient waitlist days. The unit of observation is the transplant center at the month level. 95% confidence intervals are reported as shaded regions.

Figure A3: Event Study for Organ-Specific Metrics



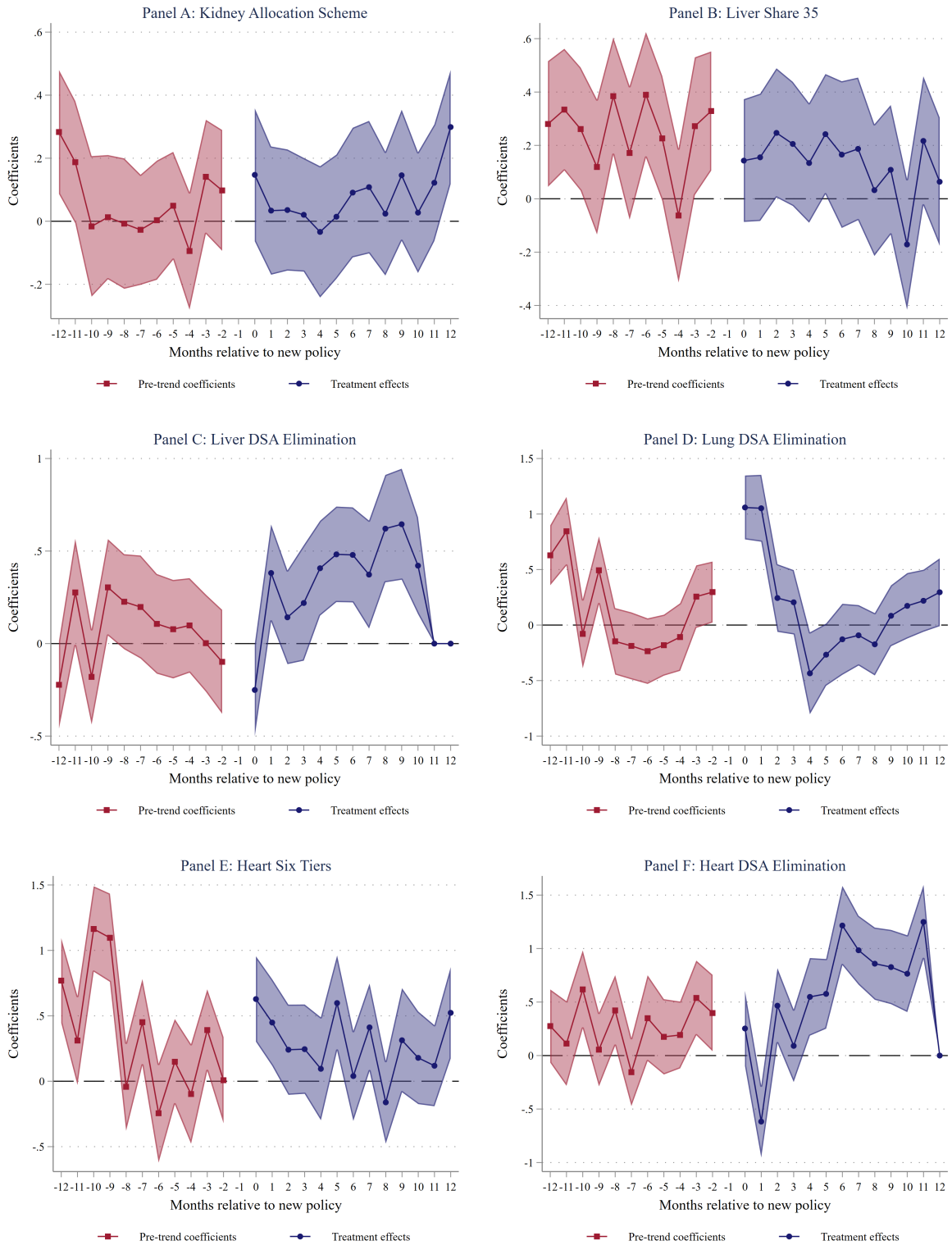
Notes: The dependent variable in all models is the relevant organ-specific metric. The metrics for each organ are specified in the panel titles. The unit of observation is the individual transplant. 95% confidence intervals are reported as shaded regions.

Figure A4: Event Study for One-Year Post-Transplant Death Rate



Notes: The dependent variable in all models is the rate of deaths less than one year following transplant per 100 transplants. The unit of observation is the individual transplant recipient. 95% confidence intervals are reported as shaded regions.

Figure A5: Event Study for Transplant Amenable Deaths



Notes: The dependent variable in all models is the rate of transplant amenable deaths per 100,000 individuals. The unit of observation is the county at the month level. 95% confidence intervals are reported as shaded regions.