Allocating Scarce Organs: How a Change in Supply Affects Transplant Waiting Lists

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Vast organ shortages have motivated recent efforts to increase the supply of transplantable organs, but little is known about the demand side of the market. We develop a model of organ demand and test its implications using the universe of U.S. transplant data from 1988 to 2013. Exploiting variation in supply induced by state-level motorcycle helmet laws, we demonstrate that each organ that becomes available from a deceased donor induces seven transplant candidates to join transplant waitlists, while living-donor transplants are entirely crowded out. Positive supply shocks also increase post-transplant survival rates due to improvements in expected donor-recipient match quality. (*JEL* I11, I18)

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I. Introduction

The National Organ Transplant Act of 1984 decreed that it is "unlawful for any person to knowingly acquire, receive, or otherwise transfer any human organ for valuable consideration for use in human transplantation." In the absence of a pricing mechanism for this scarce resource, the U.S. government oversees an allocation system for organs from deceased donors that attempts to balance equity and efficiency – as the national Organ Procurement and Transplantation Network (OPTN) defines it, a balance of "justice…and medical utility (trying to increase the number of transplants performed and the length of time patients and organs survive)" (OPTN, 2015).

The allocation system is complex and varies by organ, but it generally begins by generating a waitlist of medically compatible transplant candidates in a well-defined geographic area, with priority given to those who are most medically needy and have been waiting the longest. Geographic proximity plays a central role because organs have a limited window of viability between procurement and transplantation.[1] Significant organ shortages exist within this system, with roughly 122,000 persons currently awaiting a transplant in the U.S. Moreover, geographic disparities in candidate outcomes are striking; for example, in 2012 the probability of receiving a liver transplant within five years of joining a waitlist ranged from roughly 30 percent in New York to over 86 percent in Arkansas.[2]

In light of the shortages and disparities that characterize the current allocation system, researchers and policymakers have considered numerous strategies intended to improve both equity and efficiency. Efforts to increase the supply of organs include educational campaigns,

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[1] OPTN reports maximum preservation times of 4 to 6 hours for hearts and lungs, 8 to 12 hours for livers, 12 to 18 hours for pancreases, and 24 to 36 hours for kidneys (OPTN, 2015).
[2] From http://optn.transplant.hrsa.gov/, accessed 7/09/2017. Massie et al. (2011) provides a detailed account on disparities in waiting list outcomes across geographic regions.

donor registries and consent legislation, social media outreach, and coordination of paired kidney exchanges.[3] Proposed future reforms include moving to a system of presumed consent for donors, allowing financial exchanges for organs, and altering the organ allocation rules to induce more donations.[4] Efforts to address geographic disparities include expanding the size of the waitlist regions (Flavin, 2016).

Despite the multitude of efforts to improve the allocation system by focusing on supply, economists have largely ignored the demand side of the market. The studies of Fernandez et al. (2013) and Howard (2011) are notable exceptions that consider the effects of an increase in deceased kidney donors on the demand for kidneys from living donors. The limited focus on demand is perhaps surprising, as the effects of proposed changes to the allocation system will depend crucially on transplant candidates' behavioral responses.

In this paper, we ask how transplant candidates respond to shocks to the supply of organs within a geographic region and how such shocks affect the health of potential organ recipients. We model the behavior of transplant candidates in the context of local "markets" for organs, as defined by OPTN's geographic units. The benefit of signing up for a given market's waitlist depends on expected waiting time until transplant and expected organ quality, so that a positive shock to the supply of organs in one market will increase the benefit of joining that market. A supply shock also generates externalities in neighboring markets because of transplant candidates who are listed on multiple waitlists; when these candidates receive a transplant, they exit all waitlists on which they are listed. The overall effects of a supply shock on expected waiting times are ambiguous in all markets because of these demand-side responses. However, the

[3] Studies evaluating the success of these policies include Anderson (2015), Ausubel and Morrill (2014), Callison and Levin (2016), Cameron et al. (2013), Kessler and Roth (2014), Rodriguez et al. (2007), Roth et al. (2004, 2005), and Siminoff et al. (2009).
[4] See Abadie and Gay (2006), Bilgel (2012), Becker and Elias (2007), Kessler and Roth (2012), Lacetera et al. (2014), Li et al. (2012), and Wellington and Sayre (2011) for discussions of these and other proposed reforms.

effects will vary across individuals if, as our model suggests, those who respond to the shift in incentives are those who can most easily bear the costs of doing so.

With this basic model in mind, we use restricted-use data from the Scientific Registry of Transplant Recipients (SRTR) to measure how shifts in the supply of transplantable organs affect the behavior and outcomes of transplant candidates. The SRTR includes the universe of all transplant candidates in the U.S. since 1987 – nearly 1 million candidates in total – linked to detailed records of donors and transplant outcomes. We focus on variation in state-level motorcycle helmet laws as a source of plausibly exogenous variation in the local supply of transplantable organs. Using the synthetic control methods of Abadie et al. (2010), we estimate that repeals of helmet laws increase the supply of kidneys, livers, hearts, and lungs from donors killed in motor vehicle accidents by more than 20 percent.

We find that transplant candidates respond strongly to local supply shocks, along two dimensions. First, for each new organ that becomes available in a market, roughly seven new candidates join the local waitlist. Using zip code information on transplant candidates' residences and the transplant center(s) at which they are registered, we demonstrate that candidates who live outside of the local market – who have relatively high marginal costs of listing – disproportionately drive the demand responses. Moreover, our model of candidate behavior implies that these estimates represent lower bounds on waitlist growth because of candidates' ability to list on multiple waitlists.

A second behavioral response to the supply shocks, which may account for some of the increase in flows onto deceased-donor waitlists, involves a substitution away from transplants from living donors. The crowd-out of living-donor transplants is most pronounced for potential transplants from donors who are neither blood relatives nor spouses of the candidate, suggesting that these are the marginal cases in which the relative costs of living- and deceased-donor transplants are most influential.

Taken together, these findings show that increases in the supply of transplantable organs generate behavior that at least partially offsets a shock's direct effects. Presumably as a result of this offset, the average waiting time for an organ does not decrease in response to a positive supply shock. However, we find evidence that an increase in the supply of deceased organs increases the probability that a transplant is successful, defined as graft survival for one and three years post-transplant.

The following section explains the institutional setting of the market for transplants and describes our data sources. Section III presents estimates of the relationship between helmet laws and the supply of transplantable organs. In Section IV we present a simple two-market model of the organ allocation process, in which organs are rationed by waiting lists. In Section V we estimate candidates' responses to supply shocks, and Section VI considers how the supply and demand for organs combine to affect candidates' outcomes. Section VII concludes.

II. Data and Institutional Details

Data on Organ Donations and Transplants

This study uses data from the Scientific Registry of Transplant Recipients (SRTR). The SRTR data system includes data on all donors, waitlisted candidates, and transplant recipients in the US, submitted by the member institutions of the OPTN. The Health Resources and Services Administration (HRSA), U.S. Department of Health and Human Services, provides oversight to the activities of the OPTN and SRTR contractors. The SRTR data, which comes from hospitals and immunology laboratories, include detailed candidate-level information such as time spent on the waitlist, transplant centers at which each candidate is registered, health markers, demographics such as zip code of residence, and reason for leaving the waitlist.

Each observation in the SRTR represents a registration, so we can also observe individuals who are listed at multiple transplant centers. These data can be matched to detailed donation data to view the circumstances of the donor's death in each transplant recipient's case. Patients who receive transplants from living persons were not required to register on waiting lists, but the data identify living-donor transplant recipients and their transplant outcomes. For example, between 1988 and 2013, roughly one-third of all kidney transplants were from living donors to patients who never registered on a waitlist.

Transplant waiting lists

Patients needing a transplant from a deceased donor must register on one or more of OPTN's organ waiting lists. To do so, they must obtain authorization from a physician who is associated with one of roughly 300 transplant centers in the United States.[5] A transplant coordinator at the transplant center oversees the process of medical testing to determine medical eligibility and lists the candidate on the waiting list for an organ from a deceased donor. Each transplant center is located in one of 58 donation service areas (DSAs), which are crucial organizational units in the organ allocation process. An Organ Procurement Organization (OPO) is the local monopoly within its DSA, exclusively responsible for coordinating and facilitating donation services between donors and transplant centers.[6] This includes evaluating potential donors, arranging for surgical removal of organs, and arranging for their distribution to candidates on waiting lists. As Figure 1 shows, the borders of the DSAs broadly follow state

[5] OPTN maintains a directory of transplant centers at http://optn.transplant.hrsa.gov/converge/members/search.asp. Note that not all transplant centers perform all types of organ transplants.
[6] For consistency, we will use DSA throughout the rest of the paper to refer to the geographic areas.

boundaries, although some large states have multiple DSAs while some DSAs include multiple states or portions of states.

Transplant candidates may also register on multiple waiting lists in different DSAs, a process known as “multilisting”. Beyond the costs of requiring transplant candidates to be able to physically arrive in time to receive an organ donation while the organ is viable, there may also be transplant center-specific rules about the process required for a multilisting – a candidate may have to go through a separate evaluation for each list, which may not be covered under insurance, and some transplant centers may refuse persons who are waitlisted at other transplant centers (United Network for Organ Sharing, 2014). Further, a patient’s accrued wait time may or may not transfer to the new listing.[7]

The SRTR data show that multilisting is not common, with only 6 percent of all candidates choosing to do so (see Online Appendix A for details about how we identified multilisted candidates and spells in the data: https://msu.edu/~telder/Allocating_Appendix.pdf). However, those who multilist are systematically different from those who do not, with higher probabilities of having attended some college (46 percent versus 36 percent), higher rates of employment (44 percent versus 33 percent), and lower rates of insurance coverage via Medicaid (5 percent versus 11.5 percent). Not surprisingly, they are also more likely to register outside their own or a bordering DSA (12 percent versus 4 percent).

Table 1 shows aggregate flows onto waitlists by organ and year, including multilistings. In recent years more than 50,000 new candidates joined transplant waitlists annually, with kidneys accounting for an increasingly large share of the inflows (roughly 65 percent in 2012 and 2013). Between 10,000 and 12,000 candidates joined the waitlist for livers each year in the

[7] See http://optn.transplant.hrsa.gov/learn/about-transplantation/transplant-process/ for more details on the waiting list process.

last decade, with little change over this period in comparison to the dramatic growth for kidneys. Waitlist additions for hearts and lungs have also been relatively steady over time, while additions to pancreas waitlists have fallen since their peak in the year 2000. Fewer than 300 persons enter waitlists for intestines in most years.

Table 2 shows counts of outflows from transplant waitlists by year. Comparing the last column in Table 2 to the last column of Table 1 shows that annual outflows are consistently smaller than inflows, implying that waiting lists are growing over time. Receiving a transplant from a deceased donor is the most common route off the lists, accounting for 22,935 of the 52,480 exits in 2013. When a deceased-donor organ becomes available within a given DSA, a computer system generates a pool of eligible recipients from the waitlist based on blood type, other compatibility measures, and candidates' willingness to accept the quality of the organ offered (OPTN, 2015).[8] Within the pool of potential matches, the computer generates a ranking of candidates based on the geographic distance from the donor organ, time on the list, and urgency status. The weight given to and measurement of each of these characteristics depends on the organ, and characteristics such as the ages of the donor and recipient also play a role.

Typically, the OPO offers the deceased donor's organ to the candidate with the best match in the DSA's pool of matches, making geography a key component of the allocation process.[9] If the candidate's physicians accept the organ, the transplant occurs; otherwise, the organ is offered to the next person on the list. The next offer may be made within the DSA or to a good match outside the DSA (to the region first and then nationally, in the case of kidneys).[10]

[8] Since 1999, UNet is the computer system that generates potential matches. An additional system entitled DonorNet was added in 2003, and its use was mandated in 2007.
[9] There are exceptions to this geographic allocation process. Sharing arrangements exist between OPOs inter- or intra-regionally, although OPTN's Board of Directors must approve such arrangements.
[10] In the SRTR data, we estimate that about 2/3 of all organs are transplanted in the same DSA in which they are procured. This number has grown over time, with the highest share for kidneys and kidney/pancreas transplants.

A candidate may also leave the transplant waitlist for other reasons. Table 2 shows that, in combination, death and deteriorating health (labeled "too sick" in the table) is the second most common reason for exiting a waitlist.[11] In the case of kidneys and, rarely, other organs, a person might leave the waitlist because they received an organ from a living donor – approximately 10 percent of candidates leave waitlists via this route. Some candidates exit a waitlist because they transfer to other centers. In addition, if a candidate is awaiting a multi-organ transplant, such as a kidney and pancreas, and receives one of the organs, they exit from the multi-organ waitlist. Finally, the "other" category is largely composed of cases in which the candidate's health improves enough that they are no longer unhealthy enough to qualify for an organ.

Table 3 shows variation over time in the number of waitlist registrations, both overall and by organ. These are counts at a point in time during the year, and the number of registrations exceeds the number of transplant candidates because of multilisting across transplant centers and for multiple organs. Similarly to Table 1, the most striking pattern here is the dramatic growth in the number of kidney registrations, although there have been more than 14,000 liver registrations in recent years as well.

Although Tables 1-3 show how inflows to and outflows from waiting lists evolved over time, the aggregate statistics mask an especially salient feature of the organ allocation system: expected waiting time until transplant and the health of the average transplant recipient vary dramatically by organ and DSA. For example, as the 2012 OPTN Annual Report describes, the percentage of liver candidates who receive a transplant within 5 years of listing ranged from 30.5% in New York to 86.1% in Arkansas (OPTN, 2012, p. 70). Similarly, "a striking (but not

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Some DSAs do not have any transplant centers for a particular organ in its boundaries; for example, intestinal transplants are sufficiently rare that fewer than 25 DSAs perform a single intestinal transplant in most years.

[11] Before 1995, the "too sick" category was labeled as "medically unsuitable", which also included candidates whose condition had improved to an extent that a transplant was not needed.

new) observation is the tremendous difference … in the percentage of wait-listed patients who undergo deceased donor kidney transplant within 5 years," varying from roughly 25% in California DSAs to 67% in states like Wisconsin (OPTN, 2012, p. 13). Massie et al. (2011) report that liver transplant candidates with equivalent MELD scores, which are used to quantify a transplant candidate's medical urgency, have vastly different probabilities of receiving a transplant, depending on the DSA in which they are registered. Our paper seeks to shed light on the role that transplant demand plays in these geographic disparities.

Helmet laws and waiting lists

We use changes in motorcycle helmet laws to uncover plausibly exogenous shifts in the supply of organ donors. Specifically, we hypothesize that the repeal of a universal helmet law, which requires all motorcyclists to wear helmets, increases the number of helmetless motorcycle riders. This in turn increases the probability of brain death – the principal criteria for becoming a deceased organ donor in most cases. Table 4 lists the timing of helmet law changes between 1988 and 2013, consisting of 7 introductions and 7 repeals of universal laws. Note that all of the repeals replace universal laws with "partial" helmet laws that apply only to those under the age of 18.

Using state-level OPTN data from 1994 to 2007, Dickert-Conlin, Elder and Moore (2011; "DCEM" hereafter) use 6 state-level repeals and 1 enactment of a universal helmet law to estimate that repealing universal helmet laws increases the supply of organ donors who die in motor vehicle accidents by roughly 10 percent.[12] We expect that an increase in donors will affect transplants and candidate outcomes, which DCEM did not consider, with the effects

[12] DCEM's results are largely driven by a 31 percent increase in male donors aged 18 to 34, who are disproportionately likely to die in motorcycle accidents. Their estimates imply that every motorcyclist death due to the lack of a universal helmet law produces 0.124 additional organ donors.

varying by organ for a number of reasons. First, a donor can contribute multiple organs to the deceased-donor waitlist, including two each of kidneys and lungs. Second, the probability of a specific organ being transplanted varies dramatically across organs. Our calculations based on the SRTR data show that an organ donor who died in a motor vehicle accident (MVA) contributed an average of 3.85 transplanted organs in 2013, including 1.81 kidneys and 0.81 livers. Only half of the MVA donors contributed hearts and even fewer contributed a pancreas or lung.[13] These numbers are larger than the analogous ones for donors killed in all other circumstances (we refer to these donors as "non-MVA donors" henceforth); for example, in 2013 each non-MVA donor contributed an average of 2.93 organs. This discrepancy is consistent with helmet law repeals disproportionately affecting relatively young, healthy individuals, who account for most helmetless motorcyclist fatalities.

III. The Effects of Motorcycle Helmet Laws on the Supply of Organs

To measure shocks to the supply of organs, we use the DSA as the unit of observation because it is the primary geographic unit involved in allocating organs. The Center for Medicare and Medicaid Services assigns counties to DSAs, and the OPO in the DSA coordinates all donations and transplants. We use the most recent county-DSA concordance provided by SRTR, which is imperfect but appears robust to the alternative choices described in Online Appendix B. We exclude Puerto Rico, leaving 57 DSAs in our analysis.

We want to measure the effect of the share of the DSA's population living in a state *without* a universal helmet law in that year on organ donations and transplants. To illustrate, consider a standard difference-in-difference specification:

$$(1) \qquad D_{dt} = \alpha_d + \delta_t + \gamma\left(nolawshare\right)_{dt} + \varepsilon_{dt} \ .$$

[13] Within the MVA category, the SRTR data do not distinguish between motorcyclists and non-motorcyclists.

In equation (1), d indexes the DSA, t indexes the year, ranging from 1988 to 2013, and $nolawshare_{dt}$ is the share of the DSA's population not covered by a universal helmet law for at least six months in year t. We are interested in D_{dt} both as a measure of the number of deceased organ donors and as a measure of the number of specific organs (kidney, liver, heart, lung, pancreas and intestine) that are transplanted from MVA donors.[14] In all cases, we measure D_{dt} per million DSA residents using National Cancer Institute (2015) county population estimates.

As an example of our key independent variable, $nolawshare_{dt}$, consider the DSA that incorporates counties in western Pennsylvania, West Virginia and one county in New York (see Figure 1). All of those counties are in states that had universal helmet laws until August of 2003, when Pennsylvania repealed their law. Therefore, in 2004, $nolawshare_{dt}$ increases from 0 to about 0.75, which represents the share of the DSA's population living in Pennsylvania.

In specification (1), the DSA and year indicators, α_d and δ_t, respectively, account for unobserved parameters that are constant within a DSA across time and within a year across DSAs. However, this specification imposes the assumption that the treatment and control groups have parallel pre-treatment trends in the dependent variables. We pursue a generalization of the difference-in-difference approach that allows for the role of unobserved DSA-specific factors to vary over time:

(2) $$D_{dt} = \mu_d \lambda_t + \gamma(nolawshare)_{dt} + \varepsilon_{dt},$$

where $\mu_d \lambda_t$ represent DSA-specific fixed effects with time-varying coefficients. Specifically, we use a data-driven approach to control for $\mu_d \lambda_t$ by constructing counterfactuals using the synthetic control method described in Abadie and Gardeazabal (2003) and Abadie et al. (2010).

[14] We treat each organ as a separate transplant, although in some cases, two organs might go to the same individual. For example, heart-lung and kidney-pancreas are two common pairings of dual transplants.

Intuitively, the synthetic control approach involves constructing a weighted average of all DSAs that were *not* in states with helmet law repeals, with the weights chosen so that the trajectories of the outcome variables in the pre-repeal period closely track those of the DSAs in states with helmet law repeals. Because the synthetic control is constructed from DSAs with no changes in helmet laws, the outcome trajectories of the synthetic control can be used as the counterfactuals in the post-treatment period.[15]

We extend the original synthetic control approach to a setting with multiple treatment groups. Specifically, we aggregate the 13 DSAs in states with helmet law repeals into a single treatment unit, and we weight the 44 DSAs in states with no repeals to match the pre-repeal outcomes of the aggregated treatment DSAs. We calculate the set of weights **W** for these 44 control DSAs by minimizing the distance between the pre-repeal outcome trajectories of the aggregated treatment group and the synthetic control:

$$(3) \qquad \mathbf{W} = \underset{w_k \in [0,1]}{\arg\min} \| \mathbf{Y} - \sum_{k=1}^{44} w_k \mathbf{Y}_k \|,$$

where the weights w_k sum to 1, the vector **Y** denotes the outcomes in the aggregated treatment group in each of the 6 years prior to a repeal, and $\mathbf{Y}_k$ denotes the outcomes in control DSA k in over the same time period. Because the 13 treatment DSAs experienced repeals at different

[15] In practice, the synthetic control approach necessitates ignoring helmet law introductions altogether and focusing solely on repeals. Because our primary empirical concern stems from the possibility of differential trends between states that change their helmet laws and states that do not, we require reliable estimates of the pre-existing trends in outcomes in those states. For the majority of our analyses below, reliable SRTR data became available starting in 1992, and only 1 of the 7 law introductions shown in Table 4 occurred after 1992. For some outcomes, we have data available starting from 1988, but this still results in too few pre-enactment years to reliably estimate pre-existing trends. In contrast, we can use variation induced by helmet law enactments in simple difference-in-difference models corresponding to equation (1). In all cases, the estimates vary only modestly depending on whether we include pre-introduction data or not; for example, our estimates change very little depending on whether we include information from California and Maryland prior to 1992 or ignore those years altogether.

times, we rescale time into "years relative to a repeal year", and we randomly assign a synthetic repeal year to each of the DSAs in the control group.[16]

To illustrate the synthetic control approach in our setting, Figure 2 shows the estimated effect of helmet law repeals on all transplants from donors killed in MVAs. In the top panel, the line labeled "Treated DSAs" shows the average number of transplants per million DSA residents in all of the treatment DSAs, by year relative to the helmet law repeal (where the repeal year is defined as the first year that a helmet law was in place for fewer than 6 months). The average number of transplants hovers around 21 for the five years prior to the repeal year, then increases to roughly 24 in the following year.

The figure implies that the synthetic control group matched the treatment group's pre-repeal trends well – the two series track each other closely in the 6 years up to and including the repeal year. They diverge immediately in the following year, though, with a treatment-control difference of approximately 5 transplants in the first year following the repeal. The synthetic control group's transplants gradually decline in the years following the (synthetic) repeal year, reflecting the downward trend in deceased MVA donors over time.

The bottom panel of Figure 2 presents intuition about the statistical significance of the estimates, based on the logic of permutation tests (see Abadie et al., 2010, Conley and Taber, 2011, and Edgington and Onghena, 2007, for more discussion of inference based on permutation tests in panel data contexts). Specifically, to assess the likelihood that the patterns in the top panel are driven by sampling variation, we iteratively and randomly reassign treatment status within the 44 control DSAs, assigning 13 of them to a placebo-treatment group while leaving the remaining 31 as control units. We then estimate placebo treatment effects by applying the

[16] Dube and Zipperer (2015) and Kreif et al. (2016) also extend the synthetic control approach to settings with multiple treatment units receiving treatment at different time periods.

synthetic control method, using a weighted average of the 31 remaining control units to match the pre-treatment trends for the placebo-treatment group.

The figure presents 200 such placebo-treatment effects, each represented by a thin line, with the effect varying by year relative to the placebo repeal year. The thick line represents the actual estimated treatment effect, which is simply the vertical distance between the treated and synthetic control lines in the top panel. The number of placebo treatment effects that are more extreme than the actual estimated treatment effect implies *p*-values for the null hypothesis of no real treatment effect. For example, one year post-repeal, five of the placebo treatment effects are larger in absolute value than the actual estimated treatment effect (four are positive and one is negative), implying a *p*-value of 5/200 = 0.025. Analogous *p*-values at 4 and 7 years post-repeal are zero. We emphasize that this is a suggestive exercise, rather than a precise test of statistical significance; because there are 44 control DSAs, there are $\left(\frac{44!}{31!13!}\right)$, or nearly 52 billion, possible placebo-treatment effects involving 13 treatment units.[17] Nonetheless, the figure shows that for most years following a repeal, the estimated treatment effect lies in the upper tail of the distribution of the placebo-treatment effects.

Because we consider a large number of outcomes, hereafter we focus on estimates of the effect of helmet laws on outcomes averaged over all post-repeal years, rather than presenting graphical evidence in each case like that shown in Figure 2. Specifically, the synthetic control method produces weights for each control DSA, and we use these weights to estimate a synthetic control group. We then estimate weighted difference-in-difference specifications, with each

[17] The formal use of permutation tests for exact finite-sample inference requires considering all possible permutations. In the case of a single treatment unit, such as those considered by Abadie and Gardeazabal (2003) and Abadie et al. (2010), the number of placebo treatment effects is simply equal to the number of control units. For example, Abadie et al. (2010) consider the effect of a tobacco control program in California, relative to 19 control states. There are 19 possible placebo treatments available, implying that the set of possible *p*-values is given by k / 19, where $k \in \{0,1,\ldots,19\}$ is the number of estimated placebo-treatment effects that are greater or equal (in absolute value) to the actual estimated treatment effect.

control DSA's weights generated from the synthetic control procedure. This procedure produces consistent estimates even under the data generating process given by equation (2) because the synthetic control procedure produces a synthetic DSA-specific secular trend that is equal to the average of the secular trends for the treatment DSAs. In other words, under the assumptions of Abadie et al. (2010), the synthetic control procedure produces a weighted control group that matches the treatment group's average value of $\mu_d \lambda_t$ in all time periods.

Table 5 presents the estimates based on these specifications. The top row of column (1) shows results for all MVA organ transplants, as in Figure 2. The estimate implies that repealing a universal helmet law results in an average of 3.872 more organs transplanted per million DSA residents, with a bootstrapped standard error of 0.965.[18] This is a 21 percent increase relative to the mean of 18.516 transplants per million persons, as shown in brackets. For comparability with Figure 2, the point estimate is analogous to the average, across all post-repeal years, of the treatment series relative to the synthetic control series.

Using the same set of weights throughout the table, the remaining estimates in column (1) show organ-specific treatment effects. For example, the estimate for kidneys implies that helmet law repeals increase the number of kidneys transplanted by 1.760 per million DSA residents, or roughly 19.2 percent of the mean number of kidneys transplanted [9.144]. Liver transplants increase by 0.865 per million persons (21.9 percent relative to the sample mean of 3.947), heart transplants increase by 0.554 (21.5 percent), and lung transplants increase by 0.454 (34.2 percent). The estimates are positive for pancreatic and intestinal transplants but are not

[18] We calculate all standard errors using a bootstrapping procedure in order to account for sampling error in constructing the synthetic control weights. Specifically, we construct 200 replicate samples by sampling the 13 treatment DSAs and 44 control DSAs with replacement (this clustered bootstrap produces an empirical distribution of the estimates that is robust to within-DSA clustering over time). For each replicate sample, we apply the synthetic control procedure to generate weights and then estimate weighted difference-in-difference specifications. We then compute standard errors from the empirical distribution of the estimates across the replicate samples.

statistically significant at standard levels. In Online Appendix C, we also include estimates from simpler difference-in-difference specifications corresponding to equation (1). The resulting estimates are similar to those from the synthetic control approach in all cases; for example, the estimate in the top row of column (1) in Table OA5 is 3.429, as compared to 3.872 in Table 5.

Column (2) of Table 5 shows the estimated effect of helmet law repeals on organ donors, as in DCEM. The point estimate is 0.830 (with a standard error of 0.290), which represents a 16 percent increase relative to the baseline mean. Columns (3) and (4) show analogous results for non-MVA transplants and donors as a falsification test; all estimates in these columns are statistically insignificant and small relative to their sample means.

In sum, the estimates in Table 5 show that helmet law repeals increase the supply of transplantable organs and the number of donors killed in MVAs, while having no effect on the number of donors killed in non-MVAs. We next turn our attention to analyzing how potential transplant candidates respond to these supply shocks.

IV. An Equilibrium Framework of Transplant Candidate Behavior

In this section we present a simple model of transplant candidates' listing decisions that generates predictions for how candidates respond to supply shocks in a local organ market. We begin by assuming that candidates' homes are uniformly spatially distributed on the unit interval [0,1], with the total mass of candidates equal to one. There are two DSAs, denoted X and Y, respectively, each with one transplant center. These transplant centers are located at the endpoints of the [0,1] interval, with X's transplant center located at 0 and Y's center located at 1.

Assume that the only costs facing potential candidates are transportation costs associated with traveling from one's home to the transplant center, that is, there is no monetary cost to sign up on a waitlist or to receive a transplant.[19] Travel costs are quadratic in distance, so if a candidate lives at location m, the cost of travelling to 0 is cm^2 and the cost of travelling to 1 is $c(1-m)^2$, with $c > 0$.

A transplant candidate will sign up for a waitlist if the expected benefit from doing so, B_j, where $j \in \{X, Y\}$, exceeds the travel cost. Let m_j denote the location of the marginal candidate who is indifferent between signing up on waitlist j and not.[20] Figure 3 illustrates a hypothetical pair of marginal candidates, m_x and m_y, along with the set of inframarginal candidates that sign up for each waitlist. As shown in the figure, it is possible to have overlap, so that candidates located between m_y and m_x sign up for both waitlists. These multilisting candidates leave both waitlists when they receive a transplant.

The benefit from signing up on a given list depends on the list's expected waiting time as well as expected organ quality.[21] We assume that, all else equal, the expected waiting time increases with the number of candidates on the list, and it decreases with the size of the overlap. A larger overlap decreases waiting time because, for a given number of candidates on a list, the "queue" moves more quickly when there are more candidates that are also signed up on another list – some of those candidates ultimately receive an organ via the other list, thereby exiting both. We impose that the "overlap effect" is smaller than the direct effect of a change in m_j on wait

[19] Costs might also include insurance costs that differ depending on where transplant centers are located, information costs, health conditions that determine where a person is on a waiting list in a DSA, and the availability of outside options such as living donors. Our comparative statics remain unchanged if we include fixed listing costs in the model in order capture these differences.

[20] There are many dimensions of marginal candidates because once a candidate joins, her place on the list is not well-defined. There is not an actual waiting list, but rather a pool of candidates generated each time a deceased organ becomes available. Depending on health status, transplant compatibility measures, and, in some cases, waiting time a candidate accrued and transferred from another list, a person who is a recent addition on the waitlist may be higher on the list generated for a particular organ than those who registered earlier.

[21] Lindsay and Feigenbaum (1984) propose a market-clearing model for waiting lists for medical procedures that also focuses on the role of expected waiting time in the decision to join a list. Their model describes a context involving a single market (the British National Health Service), rather than the multiple markets that characterize the organ allocation system in the U.S.

time; for example, if m_x rises so that there are more candidates on list *X* but also more candidates on both lists, expected waiting time in *X* will increase. We view this condition as quite likely to hold in practice.

Expected waiting time is also decreasing in market "thickness" t, the supply of organs in a given DSA. For simplicity, and because our primary interest lies in characterizing comparative statics when t changes exogenously, we only allow thickness to vary in DSA *X*. Thus, expected waiting time in *X* is $w_x(m_x, m_y, t)$, with first derivatives given by $\frac{\partial w_x}{\partial m_x} > 0$, $\frac{\partial w_x}{\partial m_y} > 0$, and $\frac{\partial w_x}{\partial t} < 0$, respectively. Note that $\frac{\partial w_x}{\partial m_y} > 0$ because of the "overlap effect" – when m_y increases, so that the number of candidates registered in *Y* declines, expected waiting times in *X* increase because of reduced overlap. Similarly, expected waiting time in *Y* is given by $w_y(m_y, m_x)$, with $\frac{\partial w_y}{\partial m_y} < 0$ and $\frac{\partial w_y}{\partial m_y} < 0$.

We further assume that organ quality in DSA *X*, $q_x(t)$, also depends positively on the thickness of the market, so that $\frac{\partial q_x}{\partial t} > 0$. Because of the matching process for allocating deceased-donor organs, a larger pool of organs may increase the efficiency of the allocation process and improve match quality, even holding the quality of the overall pool of organs constant (see Roth et al., 2004, for a discussion of the effects of expanding organ pools in living kidney exchanges). In our setting, the source of the supply shift may generate a quality change directly, as DCEM's (2011) results show that the increase in the supply of organs from helmet law repeals is concentrated in men aged 18 to 35, who are likely in better pre-donation health than donors from other circumstances of death.

The following two equations define the marginal candidates m_x and m_y:

(4) $$H_x(m_x, m_y, t) \equiv B_x\left(w_x(m_x, m_y, t), q_x(t)\right) - cm_x^2 = 0$$

(5) $$H_y(m_x, m_y) \equiv B_y(w_y(m_y, m_x), q_y) - c(1 - m_y)^2 = 0,$$

where $B_j(\cdot)$ is the expected benefit of signing up for list $j \in \{X, Y\}$. For a given value of *t*, these two equations in two unknowns (m_x and m_y) define the equilibrium. Under the assumption that the direct effect of a change in the number of candidates on expected waiting time is larger than the "overlap effect", so that $\frac{\partial w_x}{\partial m_x} \geq \frac{\partial w_x}{\partial m_y}$ and $\left|\frac{\partial w_y}{\partial m_y}\right| \geq \left|\frac{\partial w_y}{\partial m_x}\right|$, this equilibrium is unique:

Proposition 1. If $\frac{\partial w_x}{\partial m_x} \geq \frac{\partial w_x}{\partial m_y}$ and $\left|\frac{\partial w_y}{\partial m_y}\right| \geq \left|\frac{\partial w_y}{\partial m_x}\right|$, then the equilibrium defined by the values of m_x and m_y that solve (4) and (5) is unique.

(Proof in Online Appendix D, Section OD.1)

Given uniqueness, we can characterize how shocks to the supply of organs in market *X* affect candidate behavior in both markets. Figure 4 shows the functions defined by (4) and (5) in $\{m_x, m_y\}$ space. Note that both functions are strictly downward-sloping (this is demonstrated in the proof of Proposition 1). Suppose *t* increases from, say, t_0 to t_1. This positive supply shock increases B_x for two reasons: it decreases expected waiting time and it increases expected organ quality. As B_x increases, more candidates sign up on waitlist *X*; for a given m_y, m_x must increase to restore equality in (4). These marginal candidates live farther from point 0 and therefore have higher transportation costs than those who listed in *X* before the shock. Thus, the H_x curve shifts to the right, as indicated by the dashed red line in the figure. As a result, m_x increases and m_y falls, implying that *both* waitlists get longer and the overlap increases (recall that a reduction in m_y corresponds to more candidates registered in *Y*). To see why m_y falls, note that the increase in m_x – due to the direct effect of the shock – decreases expected waiting time in *Y* by increasing overlap. In response, more candidates register in *Y*. Section OD.2 of Online Appendix D presents these results formally.

This simple model predicts unambiguously that, following a positive supply shock in DSA *X*, more candidates join the waitlist in *X* (and in *Y*). In addition, the marginal joiners have higher travel costs than those who would join in the absence of the shock – they are disproportionately likely to be those who do not live within the DSA's coverage area. Expected organ quality also increases in the DSA that received the shock. Finally, the effect on expected waiting time is ambiguous because more candidates register for waitlists (in all markets). We turn next to testing these predictions with SRTR data on candidates linked to transplants and donors.

V. Waitlist Responses to the Change in the Supply of Organs

Waitlist additions

We turn next to assessing the effect of an increase in the supply of organs within the local DSA on the quantity of candidates joining the waitlist. Like transplants, we use a synthetic control approach. Figure 5 presents the number of persons added to the waitlist in DSA *d* and year *t*, per million DSA residents, for the treated DSAs and synthetic control DSAs. Data on waitlists began in 1987, but the statistics on waitlist sizes are unreliable in the early years as transplant programs established themselves, so we use data from 1992 to 2013. The top panel shows that in the treated and synthetic DSA groups, the number of additions trends upward prior to the repeals. This upward trend continues for the treated DSAs, with increases to around 180 per million population from 160 at the time of the repeal, but flattens out for the synthetic control group.

The bottom panel of Figure 5 presents placebo tests analogous to the bottom panel in Figure 2. The thick line again represents the actual estimated treatment effects, that is, the vertical distance between the two lines in the top panel, while the thinner lines represent the placebo-treatment effects. The estimated effect is small in the two years following a repeal but grows to 20 to 35 additions per million DSA residents in the third year after a repeal and beyond. The implied *p*-values are zero in years 3 and 4 post-repeal and 0.05 in year 8 post-repeal, but larger in other years. Again, we are presenting results for 200 randomly-chosen placebo tests (out of nearly 52 billion possible combinations).

Before proceeding, we emphasize that the estimates in Figure 5 capture how waitlist additions evolve in DSAs following helmet law repeals, in comparison to additions in DSAs that are not in states with repeals. However, as the behavioral model in Section IV shows, an organ supply shock potentially increases additions onto waitlists in multiple DSAs. Because positive supply shocks increase waitlist exit rates among candidates who are registered on multiple waitlists, expected waiting times decline in neighboring markets, which will possibly induce more candidates to join neighboring waitlists. As a result, the estimates in Figure 5 may understate the effects of supply shocks on candidate behavior because the "control groups" are also affected by the shocks.

Because a change in a single DSA potentially affects all DSAs, there is not an obvious "uncontaminated" control group to analyze. Nonetheless, we assess the potential importance of spillover effects in two ways. First, we re-estimate the models underlying Figure 5 excluding all DSAs that share a border with DSAs that experienced helmet law repeals, under the assumption that these bordering DSAs are the ones that are most likely to have spillover effects. Our results change only modestly when we limit the sample in this way.[22] The insensitivity of the estimates to these sample exclusions suggests that the "overlap effect" of an increase in supply is small in practice. Second, we have also estimated models in which the unit of observation is not a DSA, but a pair of DSAs – we assess how the number of candidates who live in DSA *j* and register on the waitlist in DSA *k* is affected by helmet law repeals. Again, we find qualitatively similar results from this procedure in comparison to those shown in Figure 5. In sum, our model of candidate behavior implies that the behavioral responses to helmet law repeals are even larger than those shown in Figure 5, although the results from the alternative specifications suggest that the understatement is likely to be small.

In Table 6 we present estimates of DSA- and year-specific waitlist inflows as a function of the share of the DSA's population living in a state without a universal helmet law in place in that year, using the weights generated in the synthetic control procedure. We consider waitlist additions in the aggregate and separately by organ for kidneys, livers, hearts, lungs, intestines, and pancreases.

Column (1) of Table 6 shows that repealing helmet laws increases the number of candidates joining waitlists by 29.864 per million persons, with a standard error of 9.553. This is a 19 percent increase in waitlist inflows relative to the sample mean of 154.807. The organ-specific estimates suggest that repeals increase inflows onto waitlists for kidneys (by 19 percent relative to the sample mean), livers (16 percent), and lungs (40 percent), with smaller effects on hearts, pancreases and intestines.[23] We caution that, with the exception of kidneys, the organ-specific estimates are, at most, borderline significant at conventional levels.

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[22] For example, the estimate in column (1) of the top row of Table 6 changes from 29.864 to 30.583, while the estimates in columns (2) and (3) change from 17.174 to 18.223 and from 11.168 to 12.360, respectively.

[23] We do not include multi-organ additions (heart-lung or kidney-pancreas) in the regressions, in an effort not to double count these additions on multiple lists.

Columns (2) and (3) reveal additional information about which candidates respond to supply shocks.[24] Using zip code data for candidates and the transplant centers at which they have registered, we generate separate counts of the number of waitlist candidates who live inside and outside the DSA's boundaries. From the sample means, we estimate that roughly 28 percent of all waitlist inflows consist of candidates who live outside the DSA's boundaries. However, waitlist inflows induced by repeals of helmet laws are disproportionately concentrated among out-of-DSA candidates, with approximately 35 percent (10.569/29.864) of the marginal inflows coming from outside the DSA. The disparity is especially pronounced for kidneys – 39 percent of the marginal candidates come from outside the DSA, compared to a baseline of roughly 20 percent. As the model in Section IV predicts, marginal candidates induced to enter a waitlist live relatively far away from the DSA compared to existing candidates.

The waitlist inflows shown in Table 6 and Figure 5 represent new registrations but not necessarily new transplant candidates to the extent that candidates are multilisting, which corresponds to the "overlap" described in the model. Table 7 differentiates the effects of helmet law repeals on waitlist inflows separately for candidates who multilist and those who do not. The first three columns, under the "No Multilistings" heading, show estimates for those candidates who only list in one transplant center during their waitlist spell. These candidates respond to supply shifts; for example, the estimate in the top row of the "All Additions" columns is 15.939, which is roughly 13 percent of the sample mean of inflows among this group.

[24] The weights in each regression are generated by the synthetic control estimates for all additions shown in Figure 5; we do not estimate separate weights for each organ or separately for in-DSA and out of-DSA additions. We do this for ease of interpretation – for example, our in-DSA and out-of-DSA additions sum to the total additions when we use the same weights in all columns. This, of course, assumes that the pre-trends are similar across the samples, which may not be accurate, but the magnitudes and standard errors change little when we estimate each specification with its own set of synthetic control weights.

However, multilisting candidates respond even more strongly – the estimate of 13.935 in column (4) is nearly 40 percent of the sample mean of inflows among this group.

Table 7 also shows that the estimates vary noticeably across organs. For kidneys, where multilisting is most common, annual inflows of multilisters increase by 9.874, or 46 percent, following helmet law repeals. In contrast, helmet laws have no statistically significant effect on waitlist inflows among kidney transplant candidates who only register at a single transplant center, as shown in columns (1)-(3). The annual inflow of lung transplant candidates to waitlists also increase at statistically significant levels among non-multilisted and multilisted candidates. The increases are 3.753, or 39 percent, and 0.857, or 45 percent, respectively.

The overall picture of Tables 6 and 7 suggests that candidates do respond to supply shocks on the extensive margin (the decision of whether to list at all), but that responses on the intensive margin (where to list, conditional on listing) are substantially larger, relative to listing behavior that existed prior to the shocks. This seems plausible, as it seems unlikely for candidates in need of a life-saving organ to respond most strongly along the "list or not" margin. However, there is one salient mechanism which could drive extensive-margin responses – substitution into and out of the market for living-donor transplants.

Substitution away from living donor transplants

The preceding results showed that waitlists grow in response to a local shock to the supply of organs, with much of this growth due to candidates living in areas served by a neighboring DSA. For most organs, the deceased-donor waiting list is a transplant candidate's only option. However, kidneys are an obvious exception, as 34 percent of all kidney transplants involve live donors. Most living donors are blood relatives (69 percent), spouses (11 percent), or friends (16 percent).

The principal costs of joining a deceased-donor waitlist, as opposed to asking a relative or close friend for a donation, are those associated with having to wait for a compatible organ. These costs are potentially substantial – as Table 2 showed, over 10 percent of those exiting waitlists each year do so via their death. However, living donations impose obvious costs to the donor, and to the extent that candidates internalize these costs, some will be induced to join a waitlist if the associated benefits increase. As a result, crowd-out of living donation may occur if the supply of deceased-donor organs increases.

In order to assess the effects of helmet law repeals on living-donor transplants, we again pursue a synthetic control approach. Figure 6 presents the average number of living donors, expressed per 1 million DSA residents, for the treated DSAs and synthetic control DSAs. The top panel shows that the number of living donors is nearly identical for the treated and synthetic control groups prior to the repeal year, but that the two series diverge immediately afterward. In all subsequent years, the number of living donors is substantially lower in treated DSAs than in the synthetic control DSAs. The bottom panel presents placebo tests, again showing 200 randomly-chosen placebo treatments along with the actual treatment effect in bold. The implied *p*-value is 0.03 in the year immediately following the repeal, but is larger in subsequent years because the estimated treatment effect shrinks between the first and second year following the repeal.

Table 8 shows the weighted difference-in-difference estimates from specification (2), with transplants from living donors as the dependent variable over the 1988 to 2013 period. The first row aggregates all living donor transplants, while the remaining rows disaggregate by the donor's relationship to the intended recipient.[25] Again we use the same set of weights

[25] We do not disaggregate by organ here, as almost all of the living donor transplants involve kidneys.

throughout the table; specifically, we use the weights based on the aggregated living donor measure.

Overall, the repeal of a helmet law reduces living-donor transplants by 4.421 per million DSA residents, with a standard error of 1.305. Across all donor relationship types, deceased donations result in economically and statistically significant decreases in living donations. Siblings, who donate more organs than any other relationship type, reduce donations by 1.205 per million persons, a 25 percent decline relative to the baseline donation rate. Similarly, donations from parents, children, other relatives, and spouses decline by 36, 21, 33, and 31 percent relative to baseline, respectively. The largest estimate in the table is for "all other directed donations", which are donations in which the donor and recipient are acquainted but are not family members. Helmet law repeals decrease the prevalence of these donations by more than 50 percent of the baseline average.[26]

Our estimates from Tables 6, 7, and 8 provide evidence that positive organ supply shocks increase local demand for deceased-donor organs while simultaneously decreasing living-donor transplants, suggesting that the relative costs of living- versus deceased-donor transplants plays a key role in the decision to sign up for *any* deceased-donor waitlist. Keep in mind that the decline in living donations in Table 8 (-4.421) is driven mostly by kidney transplants and is much smaller than the overall increase in waitlist additions shown in Table 6 (29.864), which reflects growth in all transplant lists.

[26] Fernandez et al. (2013) disaggregate the crowd-out of living kidney donors using helmet laws as one instrument for a change in the supply of cadaveric kidney donors. Their overall measures of crowd-out range between 0.2 and 0.6. At the state-year level, they find no statistically significant effect of an increase in cadaveric kidney donors on blood-related donors or anonymous donors. They consistently find statistical significance in their crowd-out estimates only for spouses and friends. Howard (2011) estimates kidney donation crowd-out measures of 0.2, using a structural model of differential waiting time across regions.

Finally, we note that the effects on the demand for deceased organs suggested by Tables 6 through 8 are also much larger than the magnitude of the supply shocks themselves. For example, the central estimates imply that helmet law repeals increase organ transplants by 3.872 per million DSA residents, inducing 29.864 additional candidates to join the local waitlist and 4.421 fewer candidates to receive transplants from living donors. Because the effect on demand is more than seven times as large as the supply shock itself and results in full crowd-out of living donors, it is not at all obvious that positive shocks are effective at improving outcomes for candidates on local waitlists. We turn to this question next.

VI. Health Outcomes for Transplant Candidates

In the context of the market for transplantable organs, an obvious – and crucially important – question is whether positive supply shocks improve health outcomes for those on local waitlists. The answer to this question is not straightforward. A central implication of the behavioral model presented above is that rational agents can "offset" much of the local effects of supply shocks through shifts in organ demand. For example, a shock's effect on expected waiting time until transplant is ambiguous because of an ensuing surge in the number of candidates listing in the DSA. On the other hand, research by Roth et al. (2004) and DCEM (2011) suggests that expected organ quality – or expected match quality between donors and recipients – improves in response to increases in market thickness and a relatively healthy donor population.

Countering these predictions, for kidneys at least, is the evidence that increases in deceased donors crowd out living-donor transplants, which have been shown to have better post-transplant outcomes than deceased-donor transplants (Cecka, 1997; Matas et al., 2001). Further, our simple model assumes that candidates are homogenous apart from travel costs, so that marginal candidates induced to enter a waitlist simply live relatively far away from the DSA compared to existing candidates. In reality, it is possible that marginal joiners have systematically different initial health status than inframarginal candidates, resulting in differential post-transplant outcomes.[27] In sum, predictions about average health outcomes for kidney transplant candidates are ambiguous. For other organs that do not have a living donor option, our model (and that of Roth et al., 2004) implies that post-transplant outcomes should improve due to increased market thickness.

We use two principal measures of transplant candidate outcomes: expected waiting time until transplant and post-transplant graft survival. To measure expected waiting time, we generate a DSA-year count of the number of candidates who received a deceased-donor organ transplant within 9 months and 18 months, respectively, of originally signing up on a waitlist.[28] Our sample includes only candidates on a waiting list for a deceased organ transplant. As in our earlier specifications, we norm these counts by the DSA population in millions. The most salient post-transplant outcome is graft survival, which refers to whether the transplanted organ is still functioning. Transplants may fail for a number of reasons, including infections, post-surgical complications, and, most commonly, rejection by the body's immune system.[29] We create

[27] In a set of regressions similar to equation (2), we find that waitlist additions for kidneys are more likely to be on dialysis and have higher PRA scores after helmet law repeal, which suggests that less healthy and harder-to-match patients are entering the waitlists. There is also some evidence that the marginal waitlist additions are more likely to have Medicare as their primary insurance. We find no evidence that other demographic characteristics of the marginal joiners, such as mean education and race, change in response to supply shocks.

[28] We have experimented with other measures of waiting time, such as median time until transplant, and also with indicators that vary by organ (as the distribution of waiting times vary significantly by organ). For median time, we include all spells that started at least three years before the end of the sample period and assign a duration of three years to all censored spells; this censoring correction is valid under the assumption that the true conditional (on observable candidate characteristics) median duration until transplant is less than three years, which seems probable based on OPTN's published statistics. Regardless of how waiting time is coded, we find little evidence of an effect of helmet law repeals.

[29] Chronic rejection, which refers to long-term loss of function in transplanted organs due to excessive scar tissue formation, is inexorable even with the administration of anti-rejection drugs (see Jaramillo et al., 2005, among others). However, this process typically evolves slowly. The greatest risk factor for accelerating the rejection process is patient non-compliance with prescribed immunosuppressant drug regimens.

indicators for graft survival measured 1 and 3 years post-transplant, with each indicator equaling one if the transplanted organ is still functioning, and zero if the transplant failed and/or the patient died. Our dependent variables, measured at the DSA-year level, are the share of all transplants that last at least one year or three years, respectively. Our sample includes all transplant recipients, after eliminating censored observations; for example, when analyzing one-year graft survival rates, our analysis sample includes all transplants occurring on or one year before the end of 1992 to 2013 sample period.

Table 9 shows estimates from models relating transplant candidate outcomes to *nolawshare,* including full sets of DSA and year indicators and weighting by synthetic control weights. In columns (1) and (2), we use weights based on transplant receipt within 9 months for all organs aggregated. In columns (3) and (4), we use weights based 1-year graft survival for all organs aggregated. The estimates in columns (1) and (2) show that, overall and separately by organ, there is mixed evidence that the positive supply shocks generated by helmet law repeals reduce expected waiting times for organs. The estimates for lungs are positive and significant: the number of waiting list candidates who received a lung transplant within 9 months increases by 2.008 persons per million DSA residents. The estimates for livers, pancreases, and intestines are also positive, but not remotely close to statistically significant. In contrast, our estimates show that fewer candidates receive kidneys, and hearts within 9 months, and the estimate is marginally statistically significant for kidneys. As noted above, the demand shifts are much larger than the supply shocks that cause them, so it is perhaps not surprising that waiting times do not universally decrease in response to supply shocks.

Columns (3) and (4) show estimates of the effects of *nolawshare* on graft survival at 1 year and 3 years, respectively. For livers, hearts, lungs, and pancreases, repeals of helmet laws significantly increase graft survival rates at 1 year, both statistically and practically. For example, for livers the estimate is 0.022 (with a standard error of 0.012), implying that a helmet law repeal increases the number of transplant recipients whose transplanted liver is still functional by 2.2 percentage points, relative to a baseline graft survival rate of 83.0 percentage points. Effect sizes on hearts, lungs, pancreases, and intestines are even larger, although statistically insignificant in the case of intestines. Column (4) in the table shows estimates for 3-year graft survival rates, which are generally similar to the 1-year estimates, although the coefficients are less likely to be statistically significant at standard levels.

Notably, we find no beneficial effects on graft survival for kidney transplants. We suspect that this may be due to living donor crowd-out, but with no formal way to estimate a counterfactual in which crowd-out does not occur, we attempt to make some headway using simple calculations. Roughly 33 percent of all kidney transplants involve a living donor, and in the full SRTR sample one-year graft survival rates are approximately 6 percentage points higher for living-donor transplants (96 percent) than for deceased-donor transplants (90 percent). Estimates from Table 8 show that, following a helmet law repeal, living-donor kidney transplants decrease by 30 percent, or roughly 9 percentage points – from 33 percent to 24 percent of all kidney transplants. Overall graft survival is a weighted average of living- and deceased-donor graft survival rates, so all else equal, a 9 percentage-point reduction in the fraction of kidney transplants would reduce graft survival rates from 0.92 ($= 0.96\times0.33 + 0.90\times0.67$) to 0.914 ($=0.96\times0.24 +0.90\times0.76$). In other words, the crowd-out effect may decrease survival rates by only 0.6 percentage points, which makes it unlikely that crowd-out plays a major role in explaining why graft survival rates do not increase for kidney candidates.

In summary, shocks to the local supply of organs do not appear to decrease waiting times for transplants, relative to areas that did not experience a shock, but do appear to improve post-transplant outcomes for all organs except kidneys. We do not identify the mechanism driving these improved outcomes; more efficient matches in a larger pool of donors, healthier donors, and healthier recipients are all candidates. We leave this question to future work. Regardless of mechanism, improved outcomes could be one reason why transplant candidates respond so dramatically following increases in the supply of organs.

VII. Conclusions

By law, the allocation system in the U.S. deceased-donor organ market operates without formal prices. Instead, waiting lists arise within defined geographic allocation regions designed to balance equity and efficiency. We propose a model where transplant candidates join waiting lists based on their travel distance to the transplant center, expected waiting time, and expected organ quality. Increasing the local supply of organs raises the benefit of entering a waitlist by lowering expected waiting time and increasing donor-recipient match quality.

We test the implications of the behavioral model using the universe of organ transplants between 1988 and 2013. We find that large increases in the supply of deceased organ transplants, arising from state repeals of motorcycle helmet laws, trigger even larger behavioral responses from the demand side of the market. For each new organ that becomes available in a market due to the death of a donor killed in a motor vehicle accident, roughly seven new candidates join the local waitlist.

The ability of transplant candidates to offset supply shocks raises questions about whether the allocation system's geographic boundaries give rise to inefficiencies and inequities. Specifically, our results demonstrate that the location where a candidate registers and the decision to seek a deceased donor rather than a living donor are endogenous to the supply of organs in a geographic area. Therefore, a positive supply shock in one geographic area generates positive externalities in nearby areas, which may have differential effects on transplant candidates based on their ability to take advantage of those externalities. Empirically, the dramatic behavioral response in waitlist additions is driven by "multilisted" candidates – those who have already joined waitlists in other geographic regions – and by candidates who, in the absence of the supply shock, might have instead received transplants from living donors. The crowd-out of living-donor transplants is most relevant to the case of kidneys, for which more than thirty percent of all transplants involve living donors.

Transplant candidates who have informational or financial advantages might be most able to capitalize on the between-market variation in expected waiting time or quality. For example, several articles in the popular press alluded to the lack of "fairness" in the organ allocation system in 2009 when Apple co-founder Steve Jobs, who lived in California at the time, obtained a liver transplant in Memphis, which had a median waiting time roughly one-third of the national average.[30] While Mr. Jobs was clearly an outlier with respect to financial and informational resources, the SRTR data show that multilisted candidates as a whole have relatively high levels of resources, as measured by educational attainment, employment rates, and private insurance coverage. These characteristics may be correlated with better access to information, such as the multilisting web site, http://www.txmultilisting.com/home.htm, which is dedicated to finding the DSAs with the shortest waitlists. Multilisted candidates are also healthier, *ex ante*, as measured by health conditions that are used to define medical need for transplants. Given these findings,

[30] A substantial part of the criticism was based on the argument that Mr. Jobs used his financial means to acquire a liver that might have been more "beneficial" if it had instead been transplanted to a candidate without metastatic pancreatic cancer, which eventually led to Mr. Jobs' death in 2011. See http://www.cnn.com/2009/HEALTH/06/24/liver.transplant.priority.lists/index.html?iref=24hours for an example of this criticism.

the externalities between DSAs raise questions about whether persons with the highest ability to cover travel costs, rather than the highest medical needs, are benefiting from the allocation system. In the current DSA-based allocation system, informational campaigns and travel cost subsidies may help to ameliorate these concerns.

Similarly, a move toward a more national allocation system, such as that used in Spain, may also improve transplant outcomes, especially for the most disadvantaged candidates (Deffains and Ythier, 2010). Broader geographic boundaries would arguably mitigate the geographic disparities in waiting times and health outcomes that plague the current system. Based on this logic, the OPTN is currently considering a revision to the allocation system for livers that involves the creation of eight “mathematically-optimized” districts as an alternative to the current system of 58 DSAs (Flavin, 2016). As methods of organ preservation and transport continue to improve, eliminating geographic considerations in organ allocation altogether may ultimately become feasible, potentially inducing gains in both equity and efficiency.

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Table 1: Waiting List Additions (Registrations), by Organ and Year

Listing Year	Kidney	Liver	Heart	Lung	Pancreas	Intestine	Kidney/ Pancreas	Heart/ Lung	Total
1988	12,189	2,182	2,835	121	260			219	17,811
1989	12,764	2,950	2,933	209	540			226	19,632
1990	13,370	3,683	3,608	518	704		48	176	22,107
1991	13,694	4,176	3,855	977	694		177	128	23,702
1992	15,204	4,807	3,967	1,198	379		719	159	26,433
1993	16,075	5,522	3,834	1,357	208	59	1,060	163	28,278
1994	16,530	6,229	3,725	1,569	200	85	1,217	159	29,714
1995	17,884	7,329	4,244	1,752	229	91	1,387	138	33,054
1996	18,327	8,054	3,877	1,837	282	88	1,378	153	33,996
1997	19,049	8,620	3,757	1,939	328	134	1,411	140	35,378
1998	20,171	9,537	3,938	2,084	396	152	1,534	137	37,949
1999	21,000	10,520	3,541	1,990	527	149	1,803	109	39,639
2000	22,285	10,880	3,449	1,974	789	170	2,005	116	41,668
2001	22,334	11,126	3,400	2,032	949	219	1,788	106	41,954
2002	23,483	9,645	3,230	1,887	898	203	1,743	88	41,177
2003	24,409	10,324	2,939	1,953	917	205	1,644	69	42,460
2004	27,123	10,856	2,882	2,000	984	250	1,729	78	45,902
2005	29,139	10,987	2,836	1,564	889	284	1,786	59	47,544
2006	31,500	11,037	3,037	1,775	880	317	1,671	77	50,294
2007	32,860	11,083	3,112	1,959	779	281	1,619	50	51,743
2008	33,051	11,175	3,384	2,005	747	267	1,603	53	52,285
2009	34,089	11,262	3,515	2,280	662	260	1,569	64	53,701
2010	34,895	12,010	3,527	2,469	595	241	1,549	57	55,343
2011	34,245	11,925	3,448	2,464	526	184	1,350	56	54,198
2012	35,605	11,611	3,660	2,346	482	159	1,453	46	55,362
2013	37,353	12,020	3,985	2,530	478	180	1,272	46	57,864
Total	648,278	235,421	93,460	45,924	15,573	4,069	34,107	3,056	1,079,888

Notes:
These numbers are calculated at a single point in time in each year. Source: authors' calculations from SRTR data. Blank cells indicate that the count is below 25.

Table 2: Waiting List Exits by Year and Reason for Leaving

Year	Deceased Donor Tx	Living Donor Tx	Transferred to another center	Too Sick	Died	Other	Total Waitlist Exits
1988	9,946	314	712		1,580	2,182	15,217
1989	10,626	410	921		1,784	2,390	16,692
1990	12,473	528	1,122		2,056	2,578	19,445
1991	13,033	634	1,165		2,532	2,602	20,775
1992	13,328	798	1,267		2,769	2,437	21,622
1993	14,587	937	1,650		3,140	2,661	24,184
1994	15,098	1,218	1,444		3,343	2,953	25,435
1995	15,834	1,497	1,961	703	3,708	2,960	27,055
1996	15,868	1,723	1,962	1,061	4,288	3,079	27,981
1997	16,170	1,978	2,207	1,149	4,832	2,839	29,176
1998	16,904	2,259	2,319	1,228	5,537	2,930	31,178
1999	16,919	2,692	2,662	1,369	6,835	3,248	33,728
2000	17,240	3,455	3,285	1,473	6,455	3,124	35,039
2001	17,554	4,002	3,385	1,584	7,065	2,972	36,574
2002	18,188	4,159	3,303	1,862	7,202	4,764	39,498
2003	18,561	4,350	3,292	1,646	7,138	4,014	39,019
2004	19,949	4,765	3,702	1,632	7,373	4,046	41,491
2005	21,117	4,952	4,767	1,905	7,373	4,262	44,378
2006	22,135	5,063	4,388	2,119	7,370	4,898	45,974
2007	21,999	4,911	4,462	2,463	7,135	6,155	47,129
2008	21,703	5,121	4,357	2,947	7,170	7,006	48,305
2009	21,815	5,633	4,290	3,427	7,158	6,078	48,403
2010	22,058	5,766	4,494	3,880	7,049	6,316	49,564
2011	22,457	5,425	4,716	4,441	7,301	6,615	50,955
2012	22,141	5,361	5,046	4,739	6,986	6,790	51,063
2013	22,935	5,534	5,173	5,242	6,733	6,863	52,480

Notes:
The “Other” category includes “removed in error”, “changed to kidney/pancreas”, “deceased donor emergency transplant”, “deceased donor multi-organ transplant”, “inactive program”, “died during transplant”, “unable to contract transplant and refused transplant”, “medically unsuitable”, and “health improved; transplant not needed”. The “medically unsuitable” category was split into “health improved; transplant not needed” and “too sick” in 1995. Blank cells indicate that the count is below 25.

Table 3: Registrations on Waitlists, by Organ and Year

Year	Kidney	Liver	Heart	Lung	Pancreas	Intestine	Kidney/ Pancreas	Heart/ Lung
1988	12,446	553	969	87	142			180
1989	14,975	699	1,266	121	282			204
1990	16,705	1,020	1,679	341	394		61	186
1991	18,449	1,443	2,138	655	351		233	145
1992	21,519	2,112	2,625	929	138		737	178
1993	24,226	2,805	2,777	1,201	205	43	862	196
1994	26,761	3,791	2,832	1,570	251	71	1,003	202
1995	30,083	5,288	3,336	1,848	315	78	1,152	200
1996	33,371	6,930	3,519	2,201	358	78	1,366	231
1997	36,665	8,831	3,664	2,533	379	87	1,514	223
1998	39,989	10,936	3,882	2,977	454	93	1,729	244
1999	42,703	13,113	3,728	3,227	517	100	2,111	216
2000	46,095	15,074	3,713	3,380	746	135	2,419	191
2001	48,953	16,615	3,640	3,516	1,043	160	2,448	190
2002	51,469	15,505	3,468	3,519	1,143	173	2,476	176
2003	54,348	15,576	3,208	3,586	1,315	162	2,392	168
2004	58,111	15,405	2,933	3,571	1,387	179	2,367	151
2005	60,994	15,207	2,689	2,900	1,372	176	2,429	118
2006	64,306	14,637	2,516	2,599	1,441	198	2,290	109
2007	67,301	14,106	2,360	2,077	1,322	176	2,184	82
2008	72,087	13,777	2,490	1,888	1,259	168	2,178	69
2009	77,296	13,823	2,763	1,760	1,176	181	2,125	56
2010	82,413	14,262	2,980	1,734	1,094	220	2,142	43
2011	85,819	14,391	2,958	1,631	1,003	231	2,039	42
2012	90,828	14,208	3,203	1,560	919	218	2,052	29
2013	96,520	14,301	3,512	1,562	906	224	1,978	28
Total	1,289,423	264,947	75,500	53,007	19,948	3,153	42,312	4,015

Notes:
These numbers include both active and inactive patients on waitlists and are calculated at a single point in time in each year. Source: authors' calculations from SRTR data. Blank cells indicate that the count is below 25.

Table 4:
Changes in State Motorcycle Helmet Laws, 1988-2012

Year	Universal to Partial	Partial to Universal
1988		OR(6)
1989		NE(1), TX(9)
1990		WA(6)
1991		
1992		CA(1), MD(10)
…		
1997	AR (8), TX (9)	
1998	KY (7)	
1999	LA (8)	
2000	FL (7)	
2001		
2002		
2003	PA (9)	
2004		LA (8)
…		
2012	MI (4)	

Note:
The month a law changed is listed in parentheses, where “1” denotes January, “2” denotes February, and so on. Source: Insurance Institute for Highway Safety: http://www.iihs.org/laws/default.aspx

Table 5: Estimates of the Effect of Helmet Laws on per Capita Deceased Organ Transplants and Deceased Organ Donors, by Organ

	MVA Organ Transplants	MVA Organ Donors	Non-MVA Transplants	Non- MVA Organ Donors
	(1)	(2)	(3)	(4)
Overall	3.872	0.830	0.163	0.063
	(0.956)	(0.290)	(3.380)	(0.952)
	[18.516]	[5.185]	[50.807]	[17.309]
By Organ				
Kidney	1.760		-0.699	
	(0.572)		(1.647)	
	[9.144]		[25.946]	
Liver	0.865		0.581	
	(0.276)		(1.013)	
	[3.947]		[12.302]	
Heart	0.554		-0.219	
	(0.233)		(0.441)	
	[2.576]		[5.381]	
Lung	0.454		0.221	
	(0.149)		(0.387)	
	[1.327]		[4.345]	
Pancreas	0.223		0.158	
	(0.147)		(0.306)	
	[1.453]		[2.618]	
Intestine	0.017		0.121	
	(0.018)		(0.069)	
	[0.072]		[0.215]	

Notes:
1) All estimation samples consist of 57 DSAs from 1988 to 2013. The unit of observation is a DSA-year. All models include indicators for years and DSAs and are weighted by the weights generated in the synthetic control matching procedure.
2) Bootstrapped standard errors, in parentheses, are robust to clustering within DSA over time.
3) Sample means for relevant dependent variables are listed in brackets.

Table 6: Estimates of the Effect of the Repeal of Helmet Laws on Waiting List Additions by In- Versus Out-of-Area

	All Additions	In-DSA	Out-of-DSA
	(1)	(2)	(3)
Overall	29.864	19.294	10.569
	(9.553)	(6.306)	(5.201)
	[154.807]	[110.784]	[44.023]
By Organ			
Kidney	15.667	9.508	6.159
	(7.482)	(5.698)	(2.654)
	[82.741]	[66.049]	[16.692]
Liver	5.491	5.253	0.238
	(3.409)	(1.640)	(2.460)
	[33.958]	[22.057]	[11.901]
Heart	0.396	0.636	-0.240
	(1.548)	(1.207)	(0.543)
	[13.182]	[9.301]	[3.881]
Lung	4.610	1.632	2.978
	(2.758)	(0.888)	(2.149)
	[11.596]	[4.784]	[6.812]
Pancreas	0.614	0.218	0.396
	(0.704)	(0.393)	(0.370)
	[1.632]	[1.029]	[0.603]
Intestine	0.268	0.000	0.268
	(0.327)	(0.103)	(0.243)
	[0.949]	[0.165]	[0.785]

Notes:
1) All estimation samples consist of 57 DSAs from 1992 to 2013. The unit of observation is a DSA-year. All models include indicators for years and DSAs and are weighted by the weights generated in the synthetic control matching procedure.
2) Bootstrapped standard errors, in parentheses, are robust to clustering within DSA over time.
3) Sample means for relevant dependent variables are listed in brackets.

Table 7: Estimates of the Effect of Helmet Law Repeals on Waiting List Additions by In- Versus Out-of-Area and by Multilisting Status

	No Multilistings			Multilistings		
	All Additions	In-DSA	Out-of-DSA	All Additions	In-DSA	Out-of-DSA
	(1)	(2)	(3)	(4)	(5)	(6)
Overall	15.929	12.070	3.859	13.935	7.224	6.710
	(5.597)	(4.784)	(2.034)	(5.691)	(2.825)	(3.537)
	[118.300]	[89.149]	[29.151]	[36.507]	[21.635]	[14.873]
By Organ						
Kidney	5.793	4.580	1.213	9.874	4.928	4.946
	(4.159)	(3.709)	(1.471)	(4.386)	(2.064)	(2.873)
	[61.122]	[52.510]	[8.612]	[21.619]	[13.539]	[8.080]
Liver	3.619	4.104	-0.485	1.872	1.149	0.723
	(2.882)	(1.918)	(1.371)	(1.506)	(0.641)	(0.923)
	[28.725]	[19.399]	[9.326]	[5.233]	[2.658]	[2.575]
Heart	0.472	0.765	-0.293	-0.076	-0.130	0.053
	(1.086)	(0.799)	(0.439)	(0.168)	(0.154)	(0.144)
	[11.858]	[8.513]	[3.345]	[1.323]	[0.787]	[0.536]
Lung	3.753	1.460	2.293	0.857	0.171	0.686
	(1.310)	(0.421)	(1.037)	(0.345)	(0.092)	(0.339)
	[9.689]	[4.230]	[5.459]	[1.906]	[0.554]	[1.353]
Pancreas	0.541	0.196	0.345	0.072	0.022	0.051
	(0.322)	(0.230)	(0.167)	(0.161)	(0.170)	(0.100)
	[1.083]	[0.678]	[0.405]	[0.549]	[0.351]	[0.199]
Intestine	0.325	-0.014	0.339	-0.056	0.014	-0.071
	(0.214)	(0.066)	(0.159)	(0.069)	(0.019)	(0.057)
	[0.747]	[0.136]	[0.611]	[0.202]	[0.028]	[0.173]

Notes:

1) All estimation samples consist of 57 DSAs from 1992 to 2013. The unit of observation is a DSA-year. All models include indicators for years and DSAs and are weighted by the weights generated in the synthetic control matching procedure.
2) Bootstrapped standard errors, in parentheses, are robust to clustering within DSA over time.
3) Sample means for relevant dependent variables are listed in brackets.

Table 8: Estimates of the Effect of Helmet Law Repeals on per Capita Living Organ Donors, by Relation to the Recipient

Overall	-4.421
	(1.305)
	[14.768]
By Donor's Relationship to Intended Recipient	
Parent	-0.684
	(0.206)
	[1.869]
Child	-0.493
	(0.254)
	[2.327]
Sibling	-1.205
	(0.342)
	[4.762]
Other Relative	-0.319
	(0.127)
	[0.961]
Spouse	-0.483
	(0.151)
	[1.555]
All Other Directed Donations	-1.216
	(0.384)
	[2.388]
Anonymous (Undirected)	-0.056
	(0.050)
	[0.135]

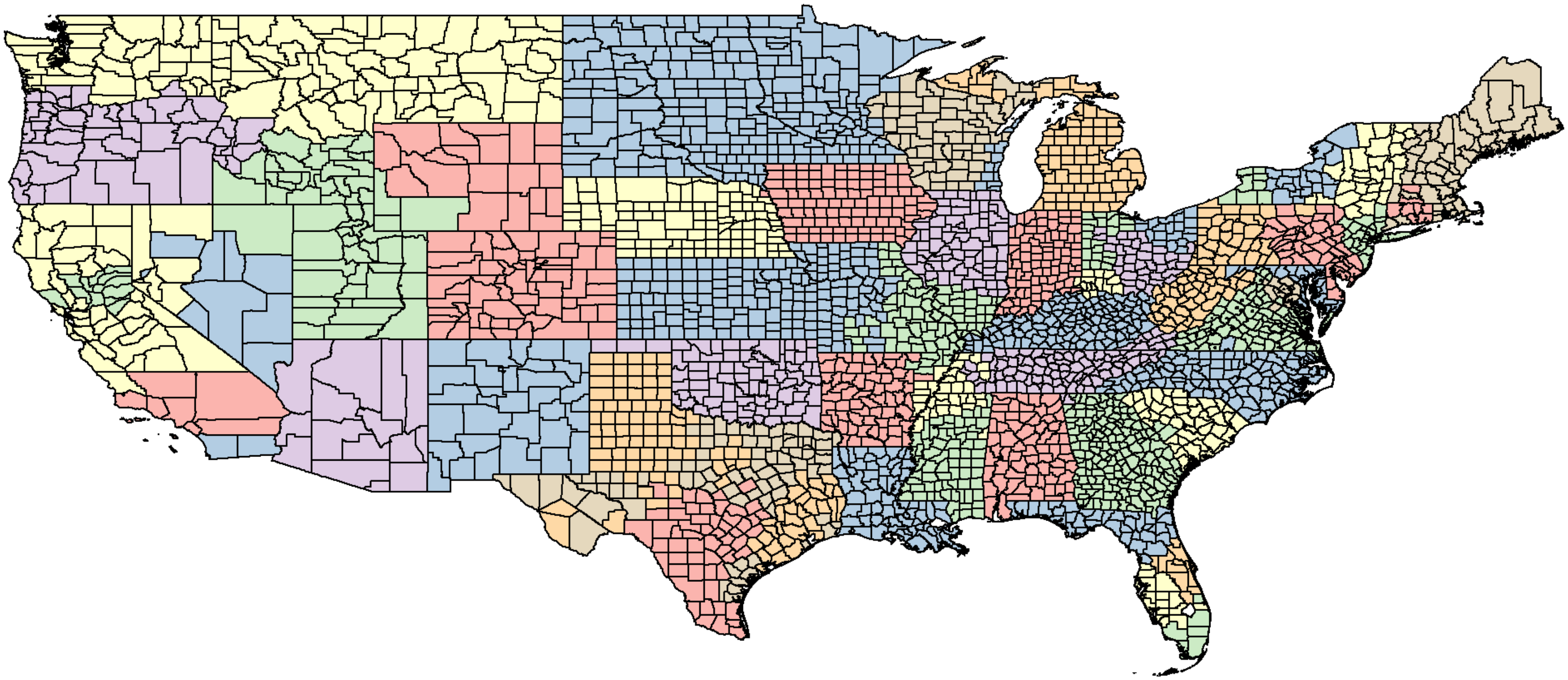
Notes:
1) All estimation samples consist of 57 DSAs from 1988 to 2013. The unit of observation is a DSA-year. All models include indicators for years and DSAs and are weighted by the weights generated in the synthetic control matching procedure.
2) Bootstrapped standard errors, in parentheses, are robust to clustering within DSA over time.
3) Sample means for relevant dependent variables are listed in brackets.

Table 9: Estimates of the Effect of Helmet Laws on Candidate Outcomes

	Received Transplant		Graft Survival	
	Within 9 months	Within 18 months	1 year	3 years
	(1)	(2)	(3)	(4)
Overall	-0.520	0.088	0.007	0.004
	(2.770)	(3.006)	(0.005)	(0.007)
	[37.098]	[47.156]	[0.880]	[0.786]
By Organ				
Kidney	-3.581	-3.214	-0.003	-0.004
	(1.733)	(2.103)	(0.005)	(0.007)
	[13.437]	[19.692]	[0.917]	[0.832]
Liver	0.974	0.984	0.022	0.021
	(2.075)	(2.008)	(0.012)	(0.014)
	[12.740]	[14.376]	[0.830]	[0.744]
Heart	-0.403	-0.253	0.034	0.033
	(0.820)	(0.841)	(0.012)	(0.013)
	[6.220]	[7.169]	[0.849]	[0.768]
Lung	2.008	2.186	0.054	0.027
	(0.568)	(0.634)	(0.028)	(0.032)
	[1.851]	[2.266]	[0.769]	[0.581]
Pancreas	0.043	0.042	0.123	0.090
	(0.369)	(0.435)	(0.034)	(0.044)
	[0.720]	[0.826]	[0.765]	[0.628]
Intestine	0.014	0.019	0.086	0.080
	(0.059)	(0.066)	(0.081)	(0.104)
	[0.292]	[0.326]	[0.647]	[0.471]

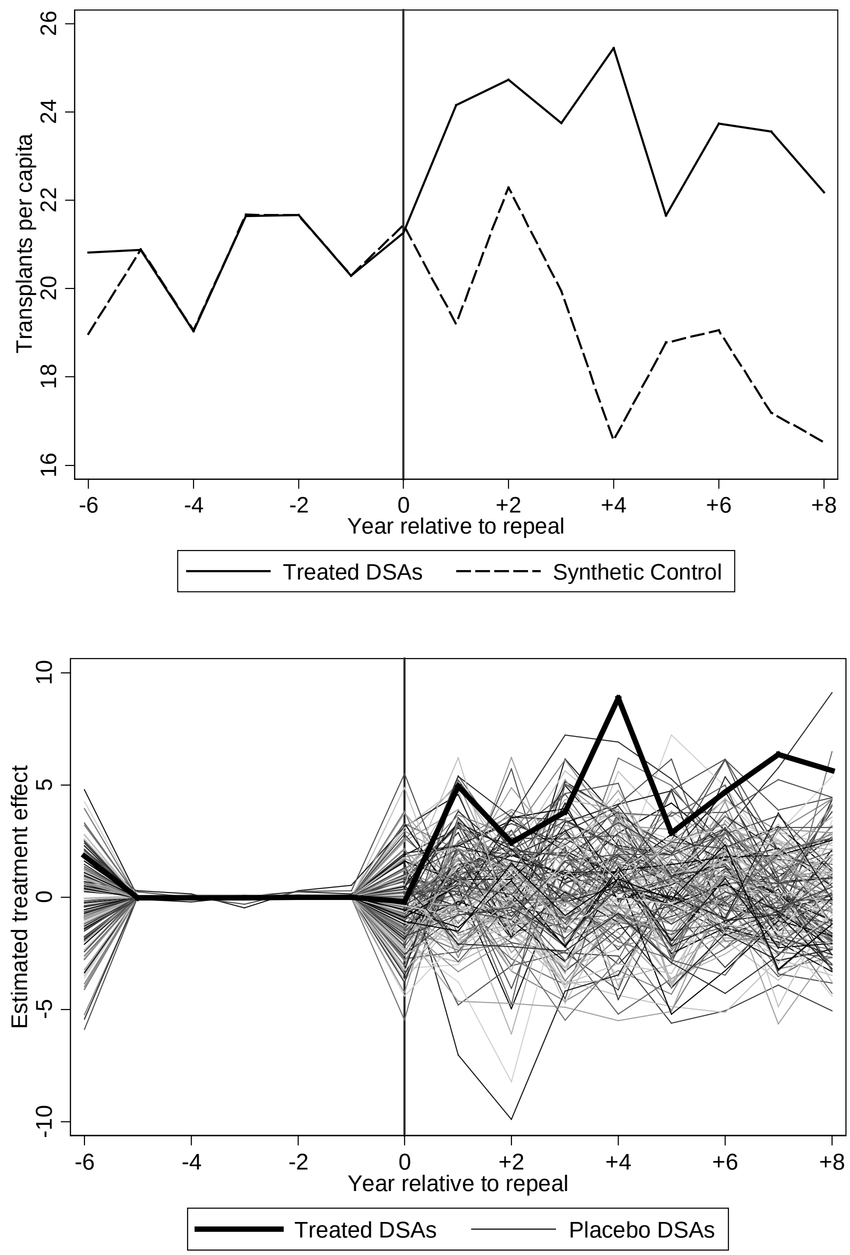
Notes:
1) All estimation samples consist of 57 DSAs from 1992 to 2013. The unit of observation is a DSA-year. All models include indicators for years and DSAs and are weighted by the weights generated in the synthetic control matching procedure.
2) Bootstrapped standard errors, in parentheses, are robust to clustering within DSA over time.
3) Sample means for relevant dependent variables are listed in brackets.

Figure 1: Donation Service Area Map of the United States



Notes: Hawaii has its own DSA, and Alaska is part of the DSA that includes Washington State. Puerto Rico also has its own DSA, but is not included in our analysis. Source: SRTR correspondences – see Online Appendix B.

Figure 2
Synthetic Control Estimates of Helmet Law Repeals on Per Capita Organ Transplants



<u>Notes</u>:
1) All estimation samples consist of 57 DSAs from 1988 to 2013.
2) In the top panel, the line labeled "Treated DSAs" is the average number of transplants per million DSA residents in the 13 aggregated treatment DSAs, by year relative to the helmet law repeal. The line labeled "Placebo DSAs" is the synthetic control group with randomly assigned repeal years and weighted as described in the text.
3) In the bottom panel, the thick line represents the actual estimated treatment effect, which is the vertical distance between the treated and synthetic control lines in the top panel. The thin lines are placebo-treatment groups generated by iteratively and randomly reassigning treatment status within the 44 control DSAs, and estimating placebo treatment effects with the synthetic control method.

Figure 3: Waiting List Participation in the Two-Market Case

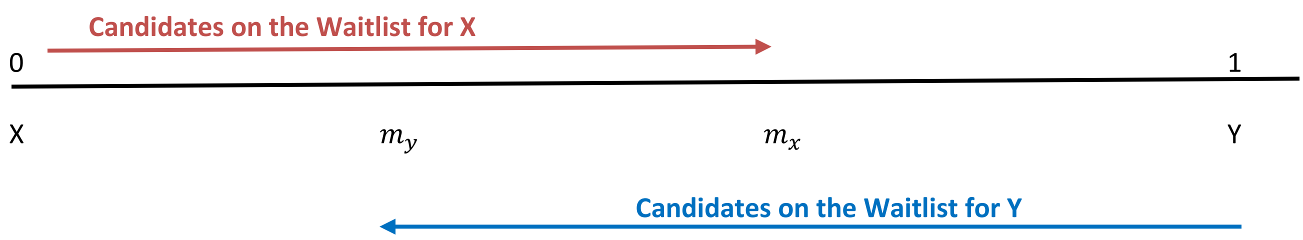


Figure 4: The Effects of a Supply shock in DSA X.

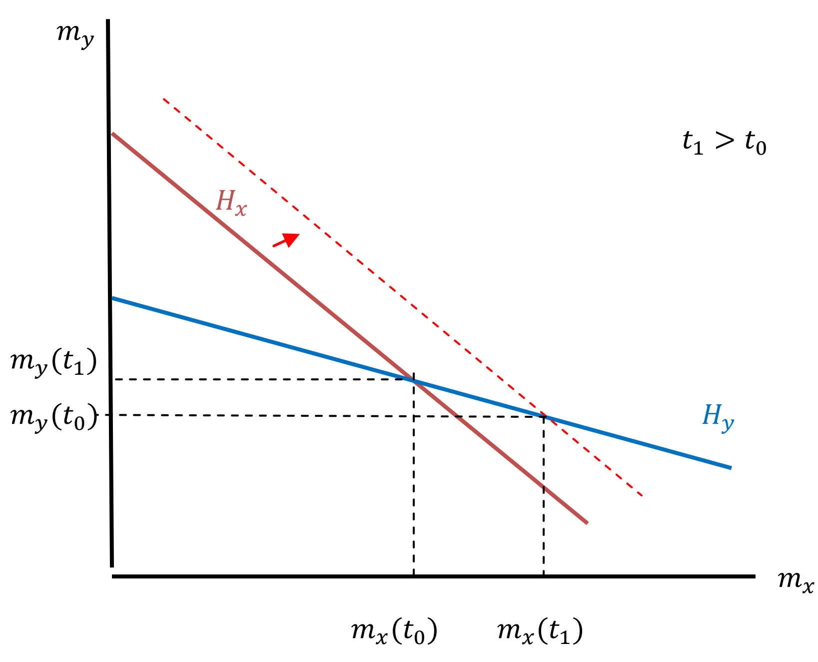
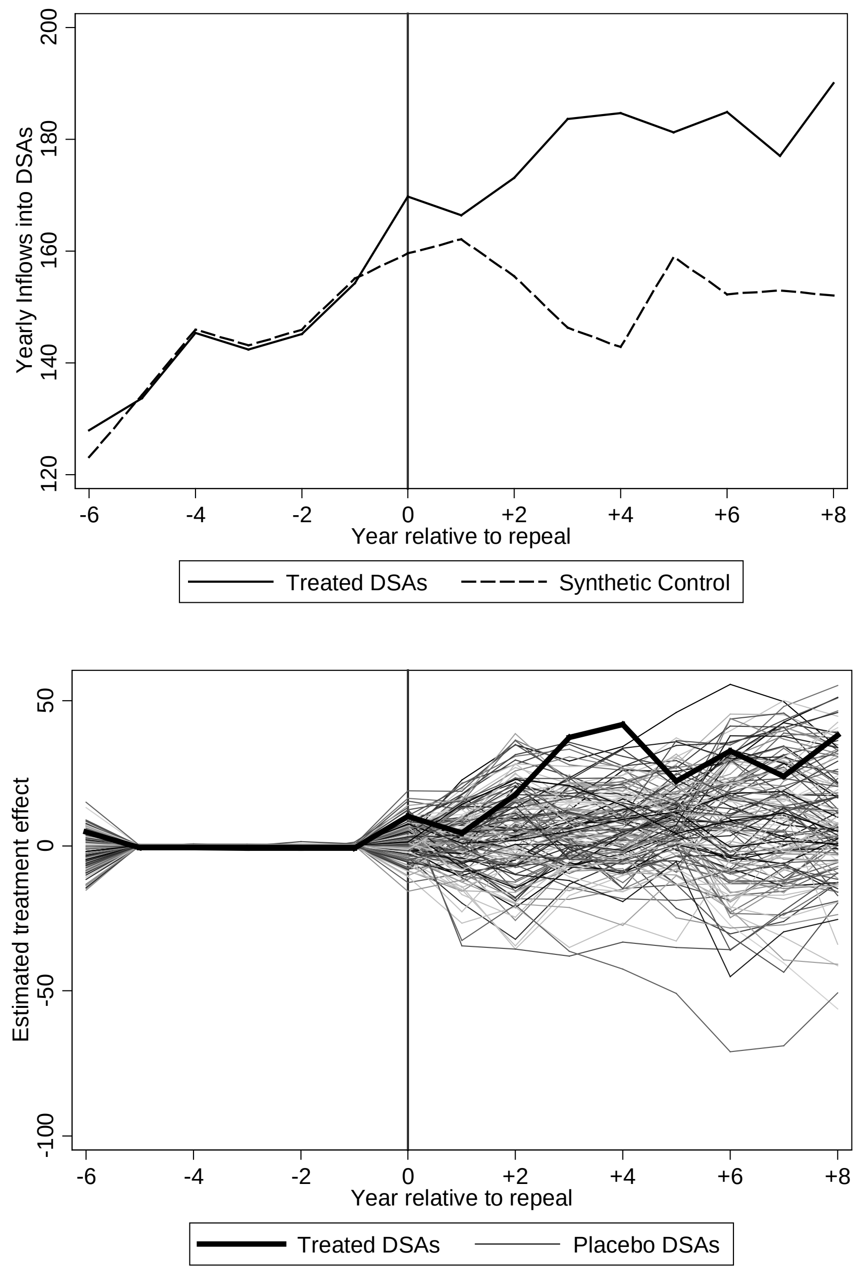


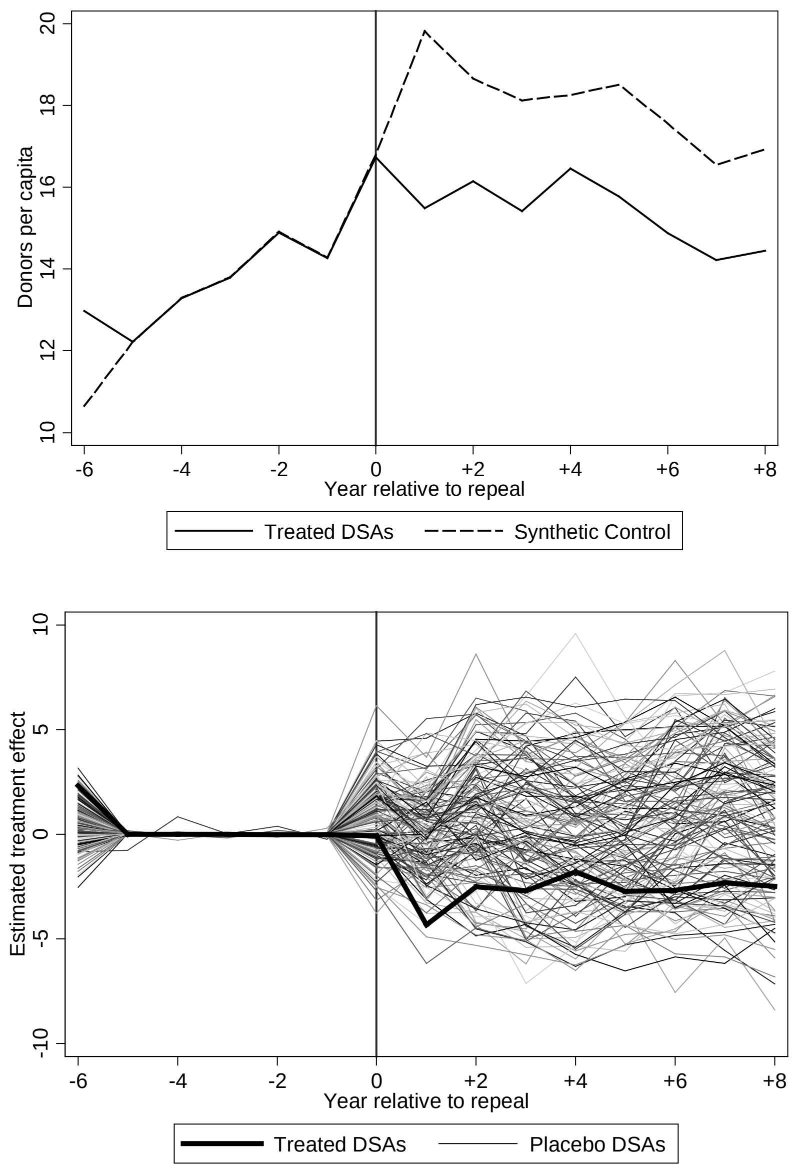
Figure 5
Synthetic Control Estimates of Helmet Law Repeals on per capita Waitlist Additions



Notes:

1) All estimation samples consist of 57 DSAs from 1992 to 2013.
2) In the top panel, the line labeled "Treated DSAs" is the average number of transplants per million DSA residents in the 13 aggregated treatment DSAs, by year relative to the helmet law repeal. The line labeled "Placebo DSAs" is the synthetic control group with randomly assigned repeal years and weighted as described in the text.
3) In the bottom panel, the thick line represents the actual estimated treatment effect, which is the vertical distance between the treated and synthetic control lines in the top panel. The thin lines are placebo-treatment groups generated by iteratively and randomly reassigning treatment status within the 44 control DSAs, and estimating placebo treatment effects with the synthetic control method.

Figure 6
Synthetic Control Estimates of Helmet Law Repeals on per capita Total Living Donors



<u>Notes</u>:
1) All estimation samples consist of 57 DSAs from 1992 to 2013.
2) In the top panel, the line labeled "Treated DSAs" is the average number of transplants per million DSA residents in the 13 aggregated treatment DSAs, by year relative to the helmet law repeal. The line labeled "Placebo DSAs" is the synthetic control group with randomly assigned repeal years and weighted as described in the text.
3) In the bottom panel, the thick line represents the actual estimated treatment effect, which is the vertical distance between the treated and synthetic control lines in the top panel. The thin lines are placebo-treatment groups generated by iteratively and randomly reassigning treatment status within the 44 control DSAs, and estimating placebo treatment effects with the synthetic control method.