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

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Vast organ shortages motivated recent efforts to increase the supply of transplantable organs, but we know little about the demand side of the market. We test the implications of a model of organ demand using the universe of US transplant data from 1987 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 in a particular region induces five transplant candidates to join that region's transplant wait list, while crowding out living-donor transplants. Even with the corresponding demand increase, positive supply shocks increase post-transplant survival rates. (*JEL* D47, I11, I18)

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 US 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 2018).

The allocation system is complex and varies by organ. It generally begins by generating a wait list of medically compatible transplant candidates in a well-defined geographic area, with priority given to the most medically needy and those waiting the longest. Geographic proximity plays a central role because organs have a limited

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window of viability between procurement and transplantation.[1] Significant shortages exist within the US system, where roughly 115,000 persons are currently awaiting a transplant. Moreover, geographic disparities in wait times are striking; for example, in 2012 the probability of receiving a liver transplant within five years of joining a wait list 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 consider numerous strategies to improve both equity and efficiency. Almost all existing and proposed policies focus on increasing the supply of organs, including educational campaigns, donor registries and consent legislation, social media outreach, coordination of paired kidney exchanges, making donor consent presumed, allowing financial exchanges for organs, and altering the organ allocation rules.[3]

Despite the multitude of efforts to improve the allocation system by focusing on supply, researchers largely ignore the demand side of the market. While it may initially seem that demand is highly inelastic for life-saving organs, there are at least two dimensions along which transplant candidates may respond to changes in market conditions. First, the allocation of deceased organs within geographic areas gives transplant candidates incentive to choose on which and on how many waiting lists to register. If persons with higher resources, independent of medical needs, are more likely to choose wait lists with shorter waiting times or to register on multiple lists, this raises a question of whether the government's allocation system meets its equity goals. Countering that argument, larger pools of transplant candidates may lead to higher quality organ matches (Roth, Sönmez, and Ünver 2004), reduce geographical inequity in wait-list times (Ata, Skaro, and Tayur 2017), and improve the efficiency of the allocation system.

A second demand side response is whether to seek a deceased-donor organ at all. Registering for a transplant is costly to the patient, and acceptance to a wait list is up to the discretion of the transplant center,[4] implying that the rate of inflows onto deceased-donor wait lists may depend on the supply of transplantable organs. For example, a shock to the supply of organs in a DSA may cause transplant candidates to substitute away from a living donor or other life-sustaining treatment like dialysis, to registering for a deceased donor. As discussed by Fernandez, Howard, and Kroese (2013) and Howard (2011), any crowd out of living donors mitigates the effectiveness, measured in quantity and potentially quality, of policies aimed at increasing the supply of deceased donors.

In this paper, we ask how transplant candidates respond to organ supply shocks within OPTN's geographic regions, which define local "markets" for organs, and

[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 2018).

[2] From http://optn.transplant.hrsa.gov/ (accessed July 9, 2017). Massie et al. (2011) provides a detailed account on disparities in waiting list outcomes across geographic regions.

[3] Studies evaluating the success of existing 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, Sönmez, and Ünver (2004, 2005); Siminoff et al. (2009); and Teltser (forthcoming). See Abadie and Gay (2006); Bilgel (2012); Becker and Elías (2007); Flavin (2016); Kessler and Roth (2012); Lacetera, Macis, and Stith (2014); Li et al. (2013); and Wellington and Sayre (2011) for discussions of proposed reforms.

[4] https://unos.org/transplantation/faqs/.

how such shocks affect the health of organ recipients. That is, does an increase in the supply of organs benefit transplant recipients, given that the demand for transplants may respond to shifts in supply?

Conceptually, the benefit of signing up for a given market's wait list 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 if new transplant candidates opt to join the wait list that experienced the shock rather than neighboring markets, or if candidates listed on multiple wait lists exit all wait lists when they receive a transplant. The overall effects of a supply shock on expected waiting times are ambiguous in all markets because of these demand-side responses. Further, the effects will vary across individuals if those who respond to the shift in incentives are those who can most easily bear the costs of doing so.

We use restricted-use data from the Scientific Registry of Transplant Recipients (SRTR). The SRTR includes the universe of all transplant candidates in the United States since 1987—nearly 1 million candidates in total—linked to detailed records of donors and transplant outcomes. We focus on the timing of state-level motorcycle helmet law changes as a source of exogenous variation in the local supply of transplantable organs. OLS and synthetic control models reveal that repeals of helmet laws increase the supply of kidneys, livers, hearts, lungs, and pancreases from donors killed in motor vehicle accidents by 16 to 30 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 five new candidates join the local wait list. With detailed zip code data, we demonstrate that candidates listed in multiple locations and candidates living outside of the local market disproportionately drive demand responses. Second, kidney transplant recipients substitute away from living-donor transplants. We estimate the largest crowd out of potential transplants from living donors who are neither blood relatives nor spouses, suggesting that these are the marginal cases in which the relative costs of living-donor and deceased-donor transplants are most influential. Taken together, these findings show that increases in the supply of organs generate demand 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 measurably decrease in response to a positive supply shock. However, for livers, hearts, lungs, and pancreases, we find evidence that an increase in the supply of deceased organs increases the probability that a transplant is successful, defined as graft survival. Among kidney transplant recipients, we hypothesize that living donor crowd out mitigates any health outcome gains resulting from increases in deceased-donor transplants.

The following section explains the institutional setting of the market for transplants and describes our data. Section II presents estimates of the relationship between helmet laws and the supply of transplantable organs. Section III presents a conceptual framework of transplant demand and estimates of candidates' responses to supply shocks. In Section IV, we consider how the supply and demand for organs interact to affect candidates' outcomes. Section V concludes.

I. Data and Institutional Details

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

Each observation in the SRTR represents a registration, so we also observe individuals who 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 recipient's case. Living donor transplant recipients were not required to register on waiting lists, but the data identify living-donor transplant recipients and their outcomes. For example, between 1987 and 2013, roughly one-third of all living donor kidney transplants were to patients who never registered on a wait list.

A. *Transplant Waiting Lists*

Patients needing a transplant from a deceased donor must register on one or more of OPTN's waiting lists. To do so, they obtain authorization from a physician associated with one of roughly 300 transplant centers in the United States, although not all transplant centers perform all types of organ transplants.[5] Each transplant center reviews a candidate's application based on its own criteria, which generally include medical and mental health conditions, the quality of the candidate's support system, the probability of surviving the transplant surgery, and the ability to follow up with post-transplant medical care.[6]

Each transplant center is located in one of 58 donation service areas (DSAs), which are crucial units in the allocation process. An Organ Procurement Organization (OPO) is the local monopoly within its DSA, responsible for coordinating and facilitating donation services between donors and transplant centers.[7] This includes evaluating potential donors, arranging for surgical removal of organs, and arranging for their distribution to wait-listed candidates. As Figure 1 shows, the borders of the DSAs broadly follow state 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 "multi-listing." Beyond the costs of requiring candidates to be able to physically arrive in time to receive a donation while the organ is viable, there may also be transplant center-specific rules on multi-listing. A transplant

[5] OPTN maintains a directory of transplant centers at http://optn.transplant.hrsa.gov/converge/members/search.asp.

[6] https://unos.org/transplantation/faqs/.

[7] For consistency, we will use DSA throughout the rest of the paper to refer to the geographic areas.

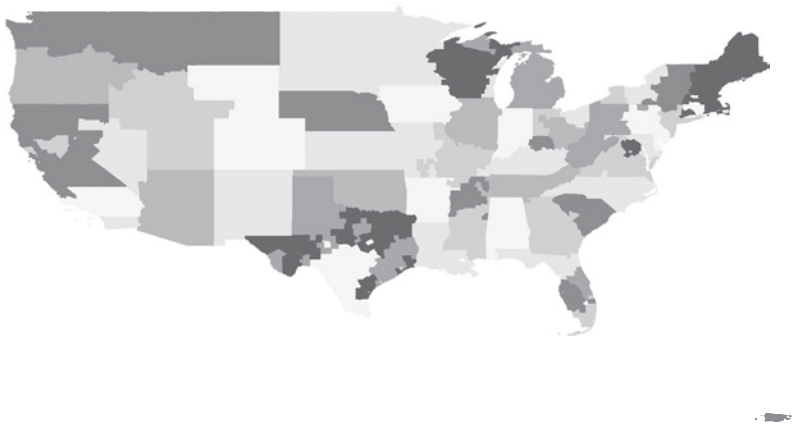

Figure 1. Donation Service Area Map of the United States

Note: Hawaii and Puerto Rico have their own DSAs, and Alaska is part of the DSA that includes Washington State.

Source: SRTR correspondences—see online Appendix C

center might require a candidate to undergo a separate evaluation, which may not be covered under insurance, and some transplant centers may refuse persons who are wait-listed at other transplant centers. Further, a patient's accrued wait time may not transfer to the new listing.[8]

The SRTR data show that multi-listing is not common, with only 6 percent of all candidates choosing to do so at a point in time (online Appendix A describes how we identify multi-listed candidates and spells in the data). However, those who multi-list 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) than candidates with a single listing (4 percent).

In recent years more than 50,000 new candidates joined transplant wait lists annually, with kidneys accounting for an increasingly large share of the inflows (roughly 65 percent in 2012 and 2013). Wait-list additions for all other organs (liver, heart, lung, pancreas, and intestines) held relatively steady since 2000, at approximately 11,000, 3,300, 2,100, 750, and 230 (see online Appendix Tables OB1-OB3 for detailed data). Annual outflows are only around 90 percent of inflows, which is consistent with total registrations increasing dramatically over time, again primarily due to kidney transplant candidates. Kidney registrations increased so dramatically because kidney candidates have a life-saving option of dialysis while awaiting a transplant, allowing them to remain on wait lists longer than other organ transplant candidates.

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

Receiving a deceased-donor transplant is the most common route off the waiting lists, accounting for almost half of all exits in 2013. When a deceased-donor organ becomes available in a given DSA, a computer system generates a pool of eligible recipients from the wait list based on blood type, other compatibility measures, and candidates' willingness to accept the quality of the organ offered (OPTN 2015).[9] Within the pool of potential matches, the computer generates a ranking of candidates based on geographic distance from the donor organ, time on the list, the ages of the donor and recipient, and urgency status. The weight given to and measurement of each of these characteristics depends on the organ.

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.[10] If the candidate's physicians accept the organ, the transplant occurs; otherwise, the OPO offers the organ to the next person on the list. The next offer may be made within the DSA or outside the DSA (to the region first and then nationally, in the case of kidneys).[11]

A candidate may also leave the transplant wait list for other reasons. In combination, death and deteriorating health (labeled "too sick or died") is the second most common reason for exiting a wait list, representing over 20 percent of all exits. In the case of kidneys and, rarely, other organs, a person might leave the wait list because they received an organ from a living donor—approximately 10 percent of candidates leave wait lists via this route. The remaining exits occur because candidates transfer to other centers, receive a single organ when they were awaiting a multi-organ transplant, or experience health improvements so that they are no longer unhealthy enough to qualify for an organ.

The statistics on inflows to and outflows from waiting lists 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 percent in New York to 86.1 percent in Arkansas (Israni, et al. 2012, 70). Similarly, "a striking (but not 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 percent in California DSAs to 67 percent in Wisconsin (Israni, et al. 2012, 13). Massie et al. (2011) reports that liver transplant candidates with equivalent MELD scores, which quantify a 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.

[9] 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.

[10] 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.

[11] 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.

B. *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. As background, in the early 1970s most states had universal helmet laws because the federal government tied state highway construction funds to such laws (Insurance Institute for Highway Safety (IIHS) 2018). By the mid-1970s, states successfully lobbied Congress to break that link, and states began repealing their universal helmet laws (IIHS 2018). By April 2018, 19 states, the District of Columbia, and Puerto Rico legally require all motorcyclists to wear a helmet, 28 states require only those under the age of 18 to wear a helmet, while three states have no motorcycle helmet laws.

Table 1 lists the timing of helmet law changes between 1988 and 2013, consisting of seven introductions and seven 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. Only Louisiana enacted a helmet law since 1995. The decline in the prevalence of helmet laws since 1995 is perhaps surprising in light of strong evidence that these laws increase helmet use and reduce fatalities (see Dee 2009). Jones and Bayer (2007) argues that helmet law repeals occurred because of motorcyclist lobbying groups' success in persuading state legislatures that motorcyclists' right to choose is paramount—and that the cost of helmet law repeals is almost entirely borne by the motorcyclists themselves.[12] We find no evidence that trends in organ donation enter helmet law debates, which validates the laws to serve as an exogenous shift in the supply of organs.

Using state-level OPTN data from 1994 to 2007, Dickert-Conlin, Elder and Moore (2011)—henceforth, DCEM—uses 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.[13] We expect that an increase in donors will affect transplants and candidate outcomes, with the effects varying by organ. While a donor can contribute multiple organs to the deceased-donor wait list, including two each of kidneys and lungs, 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.[14] These numbers are larger than the analogous ones for donors killed in all other circumstances ("non-MVA

[12] A number of sources reporting on recent state helmet law debates in Michigan, Washington, North Carolina, and Nebraska support the argument that law changes occurred because of the issue of personal freedom and also to encourage tourism in the states (Guarino 2012, Lovaas 2013, Nitcher 2018, and Campbell 2017).

[13] 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.

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

Table 1—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

donors" henceforth); for example, in 2013 each non-MVA donor contributed an average of 2.93 organs.

II. Organ Supply Shocks

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 C.

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 donors and transplants. To illustrate, consider a standard difference-in-difference specification:

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

In equation (1), d indexes the DSA, t indexes the year, ranging from 1987 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 Y_{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, and pancreas) that are transplanted from MVA donors.[15] In all cases, we measure Y_{dt} per million DSA residents using National Cancer Institute (1969–2013) county population estimates for the 50 states and the District of Columbia, and UN (various) population estimates for Puerto Rico. The

[15] 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.

Table 2—Estimates of the Effect of Helmet Law Repeals on Per Capita Organ Donors, Organ Donations, and Organ Transplants, by Organ

	MVA organ transplants (1)	MVA organ donors (2)	Non-MVA organ transplants (3)	Non-MVA organ donors (4)
Panel A. OLS estimates based on "nolawshare" measure				
Overall	3.249	0.860	−1.130	0.202
	(0.808)	(0.239)	(1.926)	(0.991)
	[17.001]	[4.851]	[49.668]	[16.844]
By organ				
Kidney	1.496		−1.109	
	(0.401)		(1.082)	
	[8.345]		[25.152]	
Liver	0.733		0.252	
	(0.212)		(0.615)	
	[3.647]		[12.223]	
Heart	0.392		−0.547	
	(0.109)		(0.264)	
	[2.393]		[5.284]	
Lung	0.417		0.241	
	(0.126)		(0.398)	
	[1.292]		[4.417]	
Pancreas	0.205		−0.073	
	(0.155)		(0.228)	
	[1.252]		[2.358]	
Panel B. Synthetic control and OLS estimates based on repeal indicator				
Overall				
Synthetic control	3.535	0.842	0.521	0.314
	{0.000}	{0.000}	{0.447}	{0.418}
OLS	3.064	0.793	−0.753	0.635
	(1.117)	(0.291)	(2.458)	(1.250)

Notes: All estimation samples consist of 58 DSAs from 1987 to 2013. The unit of observation is a DSA-year. All OLS models include indicators for years and DSAs. Standard errors of OLS estimates, listed in parentheses, are robust to clustering with DSA over time. In panel B, p-values, in braces, are obtained from permutation inference based on 10,000 placebo treatment effects in each case. Sample means for relevant dependent variables are listed in brackets.

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.

As an example of our key independent variable, $nolawshare_{dt}$, consider the DSA covering 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. Thus, in 2004, $nolawshare_{dt}$ increases from 0 to about 0.75, which represents the share of the DSA's population living in Pennsylvania. As another example, Louisiana, a self-contained DSA, is the only state to repeal and impose a universal helmet law in our data, so $nolawshare_{dt}$ increases from 0 to 1 in 2000 and decreases from 1 to 0 in 2005.

Panel A of Table 2 presents OLS estimates based on specification (1), with all observations weighted by the population in that DSA and year. The top row of column 1 shows results for all MVA transplants. The estimate implies that repealing a universal helmet law yields an average of 3.249 more transplants per million DSA residents, with a standard error of 0.808 (all standard errors are robust to within-DSA clustering over time). This is a 19 percent increase relative to the mean of 17.001 transplants per million persons, as shown in brackets.

The remaining estimates in column 1 show organ-specific treatment effects.[16] For example, the estimate for kidneys implies that helmet law repeals increase the number of kidneys transplanted by 1.496 per million DSA residents, or 17.9 percent of the sample mean [8.345]. Liver transplants increase by 0.733 per million persons (20.1 percent), heart transplants increase by 0.392 (16.4 percent), and lung transplants increase by 0.417 (34.3 percent). The estimates are positive for pancreatic transplants but are not statistically significant at standard levels.[17]

Column 2 of Table 2 shows the estimated effect of helmet law repeals on MVA organ donors, as in DCEM. The point estimate is 0.860 (with a standard error of 0.239), which represents a 17.7 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.

The estimates based on specification (1) implicitly assume that the treatment and control groups have parallel underlying trends in the dependent variables. To consider whether this assumption holds and to investigate the dynamics of the effects of helmet law changes on supply shocks, we estimate the following event-study specification:

$$Y_{dt} = \alpha_d + \delta_t + \sum_{k=-5}^{5} \gamma_k \mathbf{1}\big(t - \tau_d = k\big) + \varepsilon_{dt}, \tag{2}$$

where τ_d represents the year of a helmet law repeal in DSA d.[18] The coefficients γ_k measure average transplants and donations k years relative to a helmet law repeal, with values of $k < 0$ corresponding to pre-trends. In practice, we exclude the year before the repeal, and collapse time periods more than 5 years before and after a repeal into the "-5" and "5" periods, respectively.

Panel A of Figure 2 plots OLS estimates of γ_k and the associated 95 percent confidence intervals (estimates for individual organs are in online Appendix D). The figure shows no clear evidence of pre-trends. Moreover, relative to the DSAs in states without helmet law repeals, those with repeals experience economically and statistically significant increases in transplants beginning in the year after the repeal and persisting five years beyond.

[16] Individual results for intestinal transplants are only available upon request because they represent less than 0.4 percent of all transplants and 0.3 percent of all wait-list additions and are imprecisely estimated in all cases.

[17] Table 2 and the tables that follow include multiple outcome variables that are mechanically correlated with each other because organ-specific estimates sum to the "overall" estimates shown in the top row. This introduces the possibility of incorrectly rejecting true null hypotheses at higher rates than nominal significance levels would imply. Bonferroni corrections incorporate family-wise error rate controlling procedures by performing hypothesis tests using a significance level of α/m, where α is the chosen nominal significance level and m is the total number of hypotheses tested. If the five organ-specific estimates in column 1 are viewed as a family, the Bonferroni correction would imply that a researcher who wishes to use a nominal significance level of, say, 0.05 should reject individual null hypotheses if individual p-values are less than 0.01 ($= 0.05/5$).

[18] Our event study and synthetic control analyses (below) only consider the effects of helmet law repeals. For the majority of our analyses, reliable SRTR data became available in 1992 and only 1 of the 7 law introductions occurred after 1992. As a result, we cannot estimate pretreatment trends in outcomes for helmet law introductions, and we exclude Louisiana for the event-study and synthetic control analyses of repeals, after 2004.

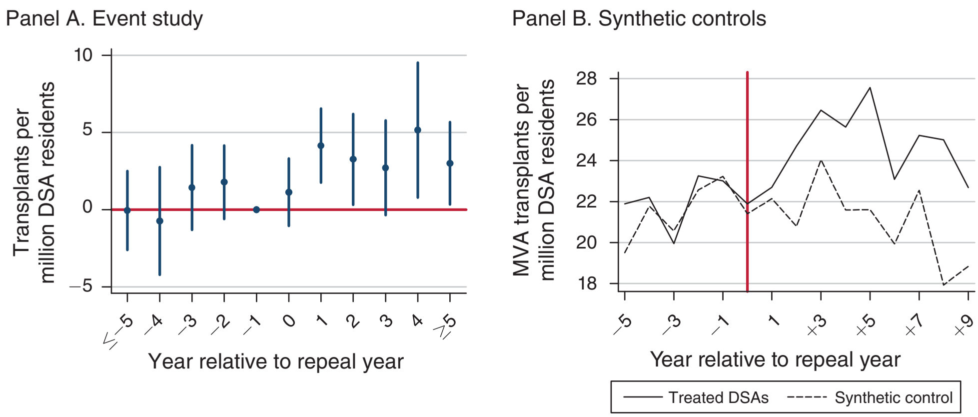

Figure 2. OLS Event Study and Synthetic Control Estimates of the Effects of Helmet Law Repeals on MVA Organ Transplants

Notes: All estimation samples consist of 58 DSAs from 1987 to 2013. The event study plots estimates as described in specification (2) in the text. In panel B, the line labeled "Treated DSAs" represents the number of transplants per million DSA residents in the 13 treatment DSAs, while the line labeled "Synthetic control" represents the number of transplants per million DSA residents in the 13 synthetic control DSAs, as described in the text.

As a complementary approach to addressing the possibility of violation of the parallel underlying trends assumption, we pursue the synthetic control method described in Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010), which allows for the role of unobserved DSA-specific factors to vary over time:

$$Y_{dt} = \mu_d \lambda_t + \gamma (repeal)_{dt} + \varepsilon_{dt}, \tag{3}$$

where $\mu_d \lambda_t$ represent DSA-specific fixed effects with time-varying coefficients. The synthetic control approach requires a dichotomous treatment variable, so we define $repeal_{dt}$ to equal one if any part of a DSA is in a state following a repeal of its helmet law, i.e., if $t \geq \tau_d$. In our Pennsylvania example above, $repeal_{dt}$ changes from 0 to 1 in 2004. Intuitively, the synthetic control approach constructs 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. We use the outcome trajectories of the synthetic control as the counterfactuals in the posttreatment period.

We apply the synthetic control approach to a setting with multiple treatment groups, following Acemoglu et al. (2016); Dube and Zipperer (2015); Osikominu, Pfeifer, and Strohmaier (2017); and Kreif et al. (2016). Specifically, we construct a synthetic control group for each of the 13 DSAs in states with helmet law repeals, denoted by $j \in \{1, \ldots, 13\}$, by calculating a set of weights W_j over the 45 control DSAs, denoted by d, that minimize the distance between the pre-repeal outcome trajectories of the treatment DSAs and the synthetic control:

$$W_j = \underset{w_d^j \in [0,1]}{\arg\min} \sum_{t=\tau_d-6}^{\tau_d-1} \left(Y_{jt} - \sum_{d=1}^{45} w_d^j Y_{dt} \right)^2. \tag{4}$$

In expression (4), the weights w_d^j sum to 1 across d for each j, the vector Y_j denotes the outcomes in treatment DSA j in each of the six years prior to a repeal, and Y_d denotes the outcomes in control DSA d over the same time period.[19]

We analyze the 13 "treatment" DSAs that experience helmet law repeals as separate events, producing 13 sets of weights W_j. We estimate the effect of each repeal, γ_j, by calculating the average difference in outcomes between the treatment and synthetic control group over the posttreatment period:

$$\hat{\gamma}_j = \frac{1}{\sum_t \mathbf{1}(t \geq \tau_j)} \sum_{t:t\geq\tau_j} \Big(Y_{jt} - \sum_{d\in\{1,\ldots,45\}} w_d^j Y_{dt} \Big). \tag{5}$$

After finding the optimal weights and estimated treatment effects for each of the 13 treated DSAs, we estimate the aggregated treatment effect as

$$\hat{\theta} = \frac{\sum_{j=1}^{13} \hat{\gamma}_j / \hat{\sigma}_j}{\sum_{j=1}^{13} 1/\hat{\sigma}_j}, \tag{6}$$

where

$$\hat{\sigma}_j = \sqrt{\sum_{t=\tau_d-6}^{\tau_d-1} \Big(Y_{jt} - \sum_{d=1}^{45} w_d^j Y_{dt} \Big)^2 / 6}. \tag{7}$$

Thus, $1/\hat{\sigma}_j$ is a measure of the closeness of the match in the pretreatment period for DSA j, and the overall estimate $\hat{\theta}$ is a weighted average of the estimated treatment effects for each of the treatment DSAs, with greater weight given to DSAs with better matches.

We use permutation tests for inference on the estimated treatment effects $\hat{\theta}$. Specifically, we randomly draw 13 placebo treatment DSAs from the set of 45 control DSAs and estimate 13 placebo treatment effects $\hat{\gamma}_j$, aggregating to an overall estimate $\hat{\theta}$ as described above. We repeat this procedure 10,000 times to calculate a distribution of placebo treatment effects and implied p-values.[20] For example, if 300 of the 10,000 placebo treatment effects are larger in absolute value than the actual estimated treatment effect $\hat{\theta}$, the implied p-value is $300/10{,}000 = 0.03$.

Panel B of Table 2 presents the synthetic control and OLS estimates for all organs, where *repeal* replaces *nolawshare* as the key independent variable. The synthetic control estimate implies that repealing a universal helmet law results in an

[19] We use only lagged values of the dependent variables to construct the synthetic controls because DCEM (2011) finds that no observable controls are powerful predictors of MVA donors. Nonetheless, as a complementary approach to our main analyses, we re-estimated our outcome models including six lags of the values of three covariates: indicators for whether a state in which a DSA was located had an organ donor registry, whether online registration was available, and whether the OPO enforced a first-person-consent paradigm (which means that health care professionals only need the potential donor's consent to recover organs). The inclusion of these covariates does not substantively affect our estimates. Given that we do not have access to controls that are powerful predictors of outcomes, we chose to match only on lagged dependent variables because doing so will maximize the chance that we control for unobserved determinants of outcomes (Kaul et al. 2018).

[20] There are $45!/(32!13!)$, or roughly 73 billion, possible groups of 13 placebo-treatment DSAs that can be drawn from the 45 control DSAs. We follow Acemoglu et al. (2016) and draw a sample (Acemoglu et al. 2016 uses 5,000 placebo treatment groups in a setting involving 561 control groups and 22 treatment groups). Using 5,000 or 20,000 placebo runs makes no substantive difference in practice for the inferences we draw below.

average of 3.535 more MVA organs transplanted per million DSA residents (the implied p-value, in braces, is less than 0.001). To facilitate a comparison between the synthetic control approach and OLS, the bottom entry in the table reports an OLS estimate based on a specification that uses the *repeal* indicator as the key independent variable. This estimate of 3.064 differs only slightly from both the synthetic control estimate and the top estimate in column 1, which uses both helmet law repeals and introductions for identification. Online Appendix B presents the full set of organ-specific synthetic control estimates in Tables OB5 to OB9.

Panel B of Figure 2 shows the effects of helmet law repeals on all transplants from MVA donors based on the synthetic control estimates. The synthetic control group closely matches the treatment group's trends in the six years up to and including the repeal year, but the two series diverge in subsequent years, implying that repeals increase MVA transplants.

In sum, the estimates in Table 2 and Figure 2 show that helmet law repeals generated an increase in the supply of transplantable organs and in the number of donors killed in MVAs, while having no effect on the number of donors from other circumstances of death. We next turn our attention to analyzing how potential transplant candidates respond to these supply shocks.

III. Wait-List Responses to the Change in the Supply of Organs

A. *Conceptual Framework of Transplant Candidate Demand*

In this section, we consider how a shock to the supply of deceased organs affects a transplant candidate's decision of whether and where to register for a deceased organ transplant. Online Appendix E presents a formal model of transplant candidates' wait-listing decisions; we summarize the model's key implications here.

We posit that candidates sign up for a given wait list if the expected benefit from doing so exceeds the cost. The benefit from registering on a given list depends on expected waiting time and expected organ quality, and overlap across lists arises if benefits exceed costs for multiple lists for a given candidate. Expected waiting time increases in the number of candidates on the list and decreases in market "thickness" (the supply of organs in a given DSA). Expected waiting time also decreases in the degree of overlap, because the "queue" for a given list moves more quickly when candidates are also signed up on another list—some of those candidates ultimately receive an organ via the other list, thereby exiting both.[21]

We further assume that organ quality in a DSA depends positively on the thickness of the market. A larger pool of organs may increase the efficiency of the allocation process for deceased-donor organs and therefore improve match quality, even holding the quality of the overall pool of organs constant (see Roth, Sönmez, and Ünver 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 also generate a direct quality change, as Dickert-Conlin, Elder, and Moore's (2011) results show that the

[21] The model in online Appendix E generates a unique equilibrium when we assume that a change in the number of persons on a candidate's own wait list has a larger effect on expected wait time than the "overlap effect."

increase in the supply of organs from helmet law repeals is concentrated in men aged 18 to 35, who may be in better pre-donation health than donors from other circumstances of death.

A positive supply shock in a DSA induces more candidates to join that DSA's wait list because the shock decreases expected waiting time while increasing expected organ quality. Because of this demand-side response, the overall effects on expected waiting time are ambiguous. Moreover, as the wait list in the DSA experiencing the supply shock grows, so does the overlap between that DSA and neighboring areas. This generates a positive externality to the neighboring DSAs by decreasing expected waiting time, thereby increasing the benefit of listing in the neighboring DSAs. We turn to testing these predictions with SRTR data.

B. *Estimates of the Effects of Supply Shocks on Wait-List Additions*

Our conceptual framework implies that an increase in the supply of organs in a given DSA affects the number of persons who register on that DSA's wait list. We test this prediction using SRTR data from 1992 to 2013; although data on wait lists began in 1987, the statistics on wait-list sizes are unreliable before 1992 as transplant programs established themselves.

In Table 3, we present estimates of the effect of helmet laws on wait-list additions in the aggregate and separately by organ for kidneys, livers, hearts, lungs, and pancreases. In column 1 of the top row, the estimate implies that repealing a universal helmet law results in an average of 17.374 more wait-list additions per million DSA residents, with a standard error of 8.015. This is an 11 percent increase relative to the mean of 157.909. The organ-specific estimates suggest that repeals increase inflows onto wait lists for kidneys (by 7 percent relative to the sample mean), livers (16 percent), and lungs (40 percent), with smaller effects on hearts and a slightly negative effect on pancreases. We caution that, with the exception of lungs, the organ-specific estimates are borderline significant or insignificant at conventional levels.

Before proceeding, we emphasize that the estimates in Table 3 capture how wait-list additions evolve in DSAs following helmet law repeals, relative to DSAs that are not in states with repeals. However, as our conceptual framework implies, an organ supply shock in a single DSA potentially increases additions onto wait lists in multiple DSAs because of spillover effects. As a result, the estimates in Table 3 may understate the effects of supply shocks on candidate behavior because the shocks also affect our control DSAs.

Because a change in a single DSA potentially affects all DSAs, there is not an obvious uncontaminated control group to analyze. Given that 94.6 percent of all candidates list in their "home" DSA or a bordering DSA only, we assume that bordering DSAs are those most likely to have spillover effects and re-estimate the models underlying Table 3 excluding all DSAs that share a border with DSAs that experienced helmet law repeals. Our results become modestly larger when we exclude bordering DSAs; for example, we estimate that repealing a universal helmet law results in an average of 20.336 more wait-list additions per million DSA residents (full results are available upon request). In sum, our conceptual framework of

Table 3—Estimates of the Effect of Helmet Law Repeals on Waiting List Additions by In- versus Out-of-Area

	All additions (1)	In-DSA (2)	Out-of-DSA (3)
Panel A. OLS estimates based on "nolawshare" measure			
Overall	17.374	9.779	7.595
	(8.015)	(5.581)	(4.796)
	[157.909]	[122.910]	[35.000]
By organ			
Kidney	8.046	2.970	5.076
	(6.732)	(5.371)	(2.721)
	[93.033]	[76.236]	[16.796]
Liver	5.170	4.384	0.786
	(3.417)	(1.593)	(2.272)
	[33.124]	[24.103]	[9.021]
Heart	0.040	0.396	−0.355
	(1.284)	(1.001)	(0.474)
	[11.778]	[9.085]	[2.693]
Lung	2.651	1.608	1.043
	(1.412)	(0.690)	(0.915)
	[6.544]	[3.970]	[2.574]
Pancreas	−0.088	−0.355	0.267
	(0.600)	(0.333)	(0.327)
	[2.003]	[1.338]	[0.665]
Panel B. Synthetic control and OLS estimates based on repeal indicator			
Overall			
Synthetic control	19.726	9.404	9.814
	{0.001}	{0.036}	{0.000}
OLS	18.647	9.805	8.842
	(7.634)	(5.746)	(4.079)

Notes: All estimation samples consist of 58 DSAs from 1992 to 2013. The unit of observation is a DSA-year. All OLS models include indicators for years and DSAs. Standard errors of OLS estimates, listed in parentheses, are robust to clustering with DSA over time. In panel B, p-values, in braces, are obtained from permutation inference based on 10,000 placebo treatment effects in each case. Sample means for relevant dependent variables are listed in brackets.

candidate behavior implies that the behavioral responses to helmet law repeals are even larger than those shown in Table 3, although the understatement is likely to be small.

Figure 3 provides insights into the dynamics of candidates' listing behavior, as well as visual evidence on the validity of the parallel pre-trends assumption underlying specification (1). The top two panels show that, across all organs, there is no evidence of differential trends in wait-list inflows prior to helmet law repeals. Additions gradually increase following helmet law repeals, which is consistent with demand responding slowly to an organ supply shock. Four years after a repeal, there are roughly 20 additional registrations per million DSA residents, relative to DSAs not in repeal states. Figure OD2 in online Appendix D2 shows that this pattern of a gradual increase in additions over time also holds for kidneys, livers, and lungs.

Columns 2 and 3 of Table 3 reveal additional information about which candidates respond to supply shocks. Using zip code data for candidates and the transplant centers at which they register, we generate separate counts of the number of wait-list

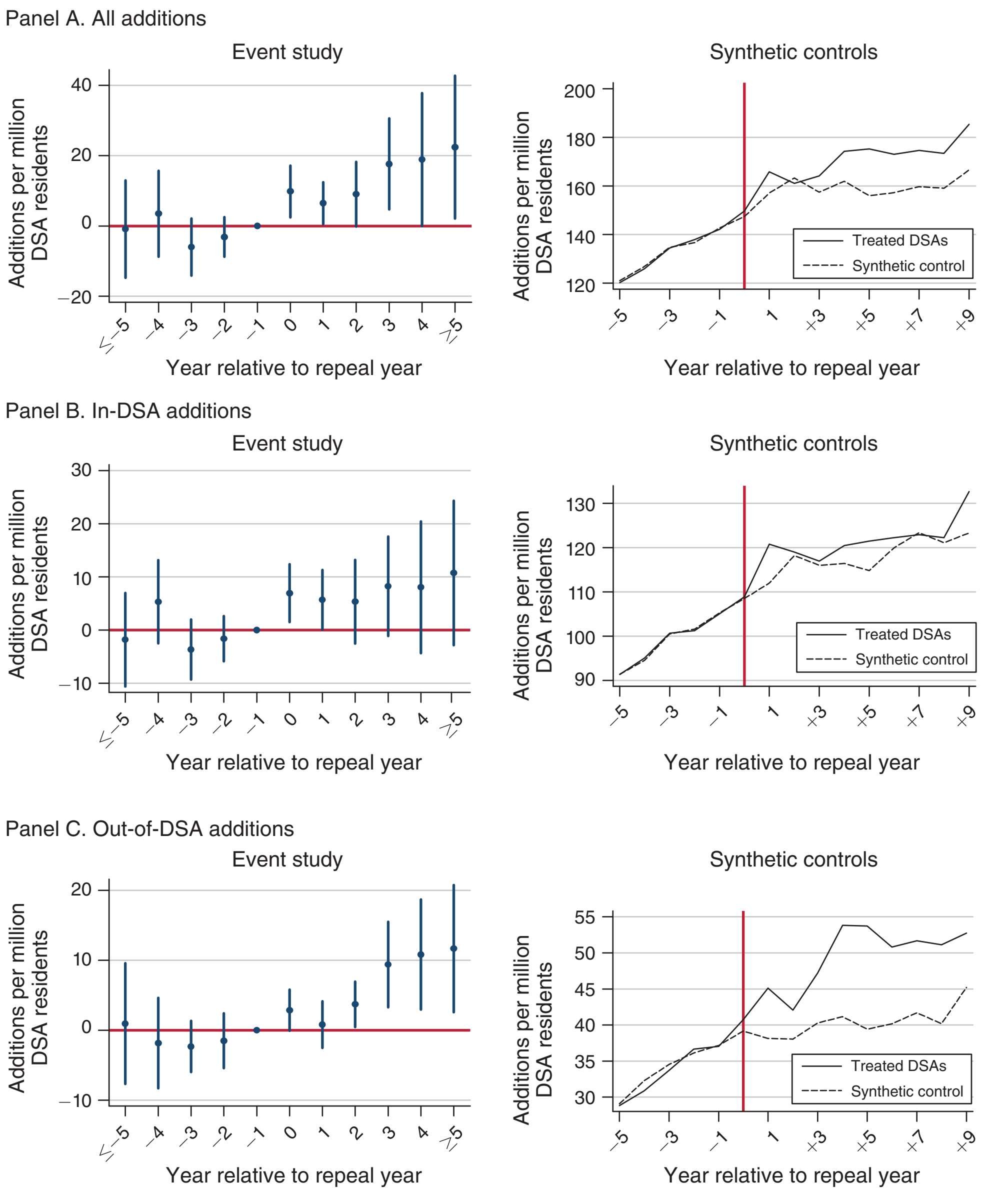

Figure 3. OLS Event Study and Synthetic Control Estimates of the Effects of Helmet Law Repeals on Waiting List Additions, In- and Out-of-Area

Notes: All estimation samples consist of 58 DSAs from 1992 to 2013. In the synthetic control graphs in the right panels, the line labeled "Treated DSAs" is the number of additions per million DSA residents in the 13 treatment DSAs, while the line labeled "Synthetic control" represents the number of additions per million DSA residents in the 13 synthetic control DSAs, as described in the text. The *y*-axis scales differ by column and panel to reflect the scale of additions by origin.

candidates who live inside and outside the DSA's boundaries. Wait-list inflows induced by repeals of helmet laws are disproportionately concentrated among out-of-DSA candidates, with approximately 43 percent $(= 7.595/17.374)$ of the marginal inflows coming from outside the DSA, compared to the baseline of roughly 22 percent ($= 35.000/157.909$) calculated from sample means. The "in-DSA" and "out-of-DSA" coefficient estimates are marginally statistically significant at standard levels. In panel B, both the synthetic control results and the OLS estimates based on the *repeal* indicator are similar to the results shown in panel A.[22]

The organ-specific estimates in the table suggest that kidney transplant candidates drive the disproportionate rise in additions from outside the DSA—63 percent of the marginal candidates come from outside the DSA. In contrast, for lungs and livers, the marginal inflows to waiting lists primarily come from within the DSA, which may reflect relatively low mobility of liver and lung patients due to health reasons or limited locational options because fewer transplant centers perform these liver and lung transplants (as of April 2018, the SRTR website lists 267 kidney transplant centers, compared to only 146 liver, 143 heart, 75 lung, and 143 pancreas transplant centers). Additions to the heart and pancreas wait lists are close to zero and small relative to the corresponding sample means.

The middle and bottom panels of Figure 3 provide evidence that the dynamic effects of helmet law repeals on wait-list additions differ across candidates living inside and outside the DSA. Specifically, in-DSA additions appear to respond immediately to repeals, both based on the event-study estimates (left panel) and the synthetic control estimates (right panel). In contrast, out-of-DSA additions respond most strongly starting three years post-repeal, increasing by roughly ten registrations per million DSA residents relative to the pre-repeal years. Although we can only speculate about the mechanisms underlying these differences, they may stem from the speed with which wait-list information disseminates from local markets to neighboring DSAs.

C. *Sources of the Inflows onto DSAs Following Supply Shocks*

The wait-list inflows shown in Table 3 represent new registrations in the DSA, but not necessarily new transplant candidates to the extent that candidates are multi-listing. Table 4 differentiates the effects of helmet law repeals on wait-list inflows separately for candidates who only list at one transplant center and those who ever multi-list. As the first three columns of Table 4 show, we estimate positive but statistically insignificant increases in wait-list additions for candidates with only one listing. For example, the OLS estimate in the top row of the "All Additions" column in panel A is 6.011 (with a standard error of 6.902), which is roughly 5 percent of the sample mean of inflows among this group. However, multi-listing candidates respond more strongly—the estimate of 11.363 (with a standard error of 5.512) in column 4 is 27 percent of the sample mean of inflows among this group. Multi-listers are more likely to register outside their DSA on average ($14.018/40.706 = 34$ percent) relative to candidates who do not multi-list (18 percent), and more than half ($6.024/11.363 = 53$ percent) of the marginal registrants among multi-listers come from outside the

[22] We generate a set of weights for each synthetic control estimate to match the pre-trends for each dependent variable, so that the estimates for in-DSA and out-of-DSA additions do not sum to the estimate for total additions.

TABLE 4—ESTIMATES OF THE EFFECT OF HELMET LAW REPEALS ON WAITING LIST ADDITIONS BY IN- VERSUS OUT-OF-AREA AND BY MULTI-LISTING STATUS

	No multi-listings			Multi-listings		
	All additions (1)	In-DSA (2)	Out-of-DSA (3)	All additions (4)	In-DSA (5)	Out-of-DSA (6)
Panel A. OLS estimates based on "nolawshare" measure						
Overall	6.011	4.440	1.571	11.363	5.339	6.024
	(6.902)	(5.562)	(2.611)	(5.512)	(2.592)	(3.639)
	[117.204]	[96.222]	[20.982]	[40.706]	[26.688]	[14.018]
By organ						
Kidney	0.000	−0.609	0.609	8.046	3.579	4.467
	(5.349)	(4.750)	(1.339)	(3.820)	(1.855)	(2.459)
	[67.063]	[58.887]	[8.176]	[25.969]	[17.349]	[8.620]
Liver	2.577	2.975	-0.398	2.593	1.409	1.185
	(2.602)	(1.538)	(1.348)	(1.885)	(0.739)	(1.260)
	[27.457]	[20.740]	[6.717]	[5.666]	[3.363]	[2.304]
Heart	0.102	0.407	−0.306	−0.061	−0.012	−0.050
	(1.071)	(0.883)	(0.376)	(0.251)	(0.164)	(0.109)
	[10.594]	[8.272]	[2.322]	[1.184]	[0.813]	[0.371]
Lung	2.356	1.426	0.930	0.295	0.182	0.113
	(1.234)	(0.665)	(0.738)	(0.307)	(0.099)	(0.229)
	[5.489]	[3.470]	[2.019]	[1.055]	[0.500]	[0.555]
Pancreas	0.075	−0.184	0.259	−0.163	−0.171	0.007
	(0.466)	(0.249)	(0.257)	(0.158)	(0.109)	(0.078)
	[1.261]	[0.860]	[0.401]	[0.742]	[0.478]	[0.264]
Panel B. Synthetic control and OLS estimates based on repeal indicator						
Overall						
Synthetic control	11.076	5.363	3.159	9.989	5.713	4.141
	{0.002}	{0.198}	{0.341}	{0.032}	{0.000}	{0.002}
OLS	7.463	5.217	2.246	11.184	4.588	6.596
	(5.854)	(4.956)	(2.440)	(5.762)	(2.909)	(3.411)
	[117.204]	[96.222]	[20.982]	[40.706]	[26.688]	[14.018]

Notes: All estimation samples consist of 58 DSAs from 1992 to 2013. The unit of observation is a DSA-year. All OLS models include indicators for years and DSAs. Standard errors of OLS estimates, listed in parentheses, are robust to clustering with DSA over time. In panel B, *p*-values, in braces, are obtained from permutation inference based on 10,000 placebo treatment effects in each case. Sample means for relevant dependent variables are listed in brackets.

DSA. As panel B shows, the synthetic control estimates are consistent with the OLS results for both single- and multi-listed candidates.

Turning to the organ-specific results, annual inflows of multi-listed kidney candidates increase by 8.046 (31 percent) following helmet law repeals, while helmet laws have no measurable effects on wait-list inflows among kidney candidates who only register at one transplant center. In contrast, the annual inflow of liver and lung transplant candidates to wait lists increases among both multi-listers and transplant candidates with a single listing, mostly from within the DSA. Given that candidates appear to respond to supply shocks on the intensive margin (where to list, conditional on listing), we hypothesize that the increases in wait-list additions among single-listed liver and lung candidates are likely to be those induced to choose a local transplant center that experienced a shock over a center outside their DSA. Again, there is no measurable response in demand, even among multi-listers, for heart and pancreas waiting lists.

Table 5—Estimates of the Effect of Helmet Law Repeals on Per Capita Living Organ Donors, by Relation to the Recipient

	All organs	Kidneys	All except kidneys
Panel A. OLS estimates based on "nolawshare" measure			
Overall	−3.599	−3.312	−0.287
	(1.482)	(1.414)	(0.246)
	[15.564]	[15.027]	[0.537]
By donor's relationship to intended recipient			
Parent	−0.395	−0.364	−0.031
	(0.203)	(0.180)	(0.060)
	[2.279]	[2.141]	[0.137]
Child	−0.535	−0.461	−0.074
	(0.271)	(0.249)	(0.063)
	[2.510]	[2.388]	[0.122]
Sibling	−0.724	−0.673	−0.050
	(0.351)	(0.346)	(0.037)
	[4.752]	[4.674]	[0.078]
Other relative	−0.253	−0.221	−0.032
	(0.110)	(0.101)	(0.035)
	[1.066]	[1.009]	[0.057]
Spouse	−0.440	−0.419	−0.020
	(0.194)	(0.196)	(0.012)
	[1.558]	[1.531]	[0.027]
Other directed donations	−1.218	−1.154	−0.064
	(0.369)	(0.367)	(0.054)
	[2.428]	[2.337]	[0.092]
Panel B. Synthetic control and OLS estimates based on repeal indicator			
Overall			
Synthetic control	−1.889	−1.630	−0.335
	{0.023}	{0.053}	{0.040}
OLS	−3.501	−3.306	−0.195
	(1.685)	(1.452)	(0.357)

Notes: All estimation samples consist of 58 DSAs from 1992 to 2013. The unit of observation is a DSA-year. All OLS models include indicators for years and DSAs. Standard errors of OLS estimates, listed in parentheses, are robust to clustering with DSA over time. In panel B, p-values, in braces, are obtained from permutation inference based on 10,000 placebo treatment effects in each case. Sample means for relevant dependent variables are listed in brackets.

There is one potentially important mechanism that could drive extensive-margin demand responses: substitution away from living-donor transplants, especially for kidneys. Roughly 34 percent of all kidney transplants involve live donors, most of whom are blood relatives (69 percent). The main cost to a candidate of substituting away from a living donor is the additional time spent waiting for a deceased-donor organ. These costs can be substantial, as over 10 percent of annual wait-list exits are due to death. However, living donation imposes obvious costs on donors, and to the extent that candidates internalize these costs, some will be induced to join a wait list as the benefits of a deceased-donor transplant increase. As a result, increases in the supply of deceased-donor organs may crowd out living donation.

Table 5 shows OLS and synthetic control estimates of the effects of helmet laws on living-donor transplants from 1992 to 2013. The first row in panel A aggregates all living-donor transplants, while the remaining rows disaggregate by the donor's relationship to the recipient. Because 96 percent of all living-donor transplants involve kidneys, we only disaggregate kidneys versus "all other organs." The OLS estimates in panel A show that the repeal of a helmet law reduces living-donor transplants by 3.599 per million DSA residents, with a standard error of 1.482. This represents a 23 percent decline from the average of 15.564 per million residents. 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 0.724 per million persons (15 percent). Similarly, donations from parents, children, other relatives, and spouses decline by 17, 21, 24, and 28 percent, respectively. The largest estimate is for "other directed donations," which are those in which the donor and recipient are acquainted but not family members, and represents a decrease of more than 50 percent relative to baseline.

Panel B of Table 5 shows that the synthetic control estimates are smaller than the corresponding OLS estimates: only 1.889 per million DSA residents, with a p-value of 0.023. Figure 4 highlights one potential reason for this discordance, as it provides the first evidence that the parallel trends assumption may not hold. Specifically, the number of living donors in DSAs with helmet law repeals appears to be trending downward in the pre-repeal periods, relative to non-repeal DSAs. Using the synthetic control method to flexibly control for pre-trends, we find that the number of living-donor transplants in treatment DSAs does not decline until four years post-repeal. The implied treatment effect is roughly three transplants per million DSA residents beginning in the sixth year following the repeal. Because the parallel trends assumption might not be met for living donors, we prefer the synthetic control estimates while noting that the 95 confidence intervals on the OLS estimates include the synthetic control point estimates.

Our estimates from Tables 3, 4, and 5 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-donor versus deceased-donor transplants play a role in the decision to sign up for *any* deceased-donor wait list.[23] We emphasize that kidney transplants drive most of the decline in living donations in Table 5, and the decline is much smaller than the overall increase in wait-list additions shown in Table 4 (17.374). This implies that even if the full decline in living donations represented additions to the deceased-donor wait list, most of the growth in wait lists involves behavior on the intensive margin.

Finally, we note that the effects on local-DSA demand for deceased organs suggested by Tables 3 and 4 are much larger than the magnitude of the supply shocks. For example, the central OLS estimates imply that helmet law repeals increase transplants by 3.249 per million DSA residents, inducing 17.374 additional candidates to join the local wait list. We might expect a large elasticity given that these additions represent persons who would have registered in other DSAs, multi-listers, candidates for whom the cost of registering was too high before the shock, and potential living-donor recipients who instead choose deceased donations. A set of transplant

[23] UNOS now requires all candidates receiving a living donation to sign up on the waiting list for a deceased donor, but this was not a requirement throughout our time period and in practice varied across transplant centers.

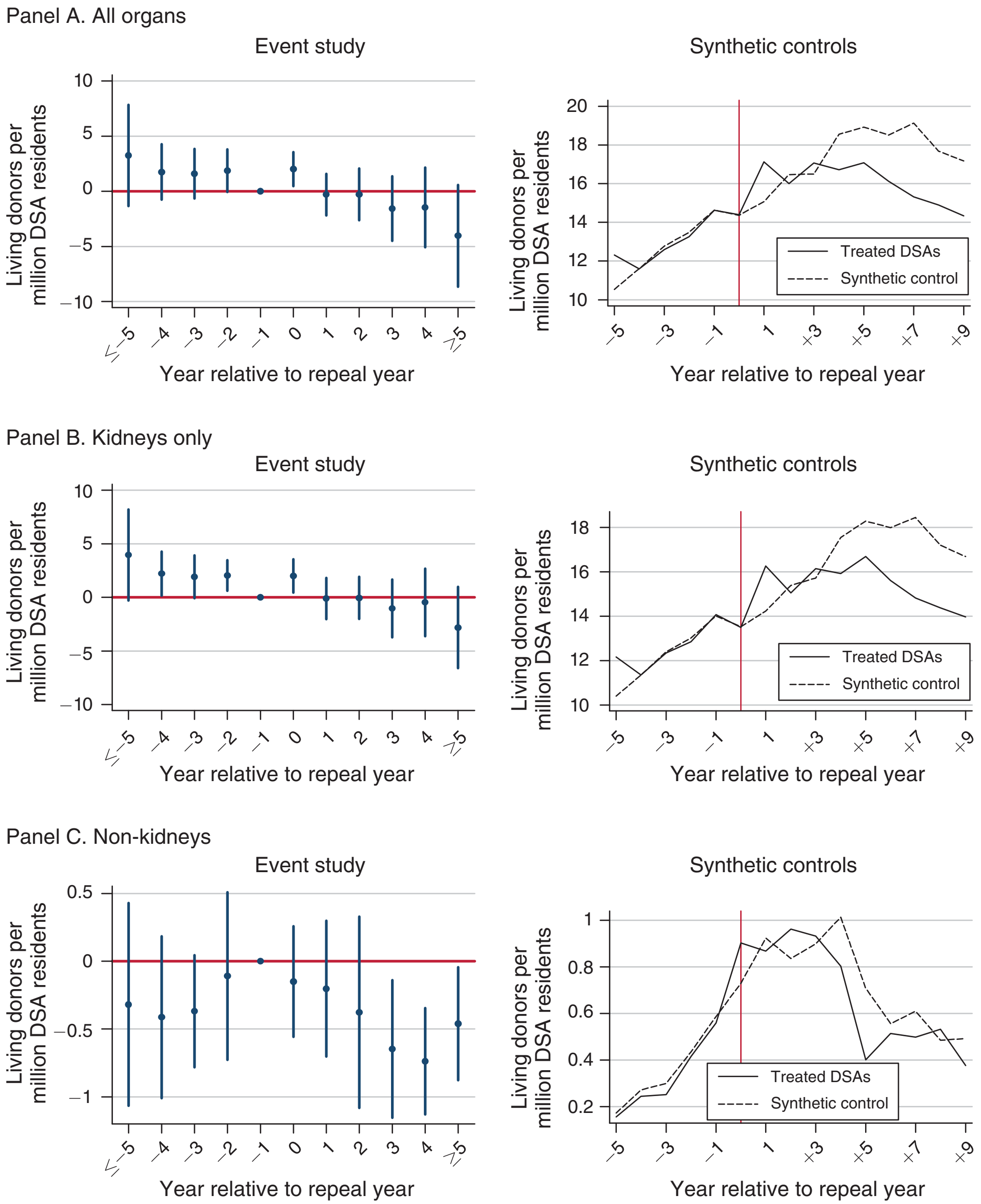

Figure 4. OLS Event Study and Synthetic Control Estimates of the Effects of Helmet Law Repeals on Total Living Organ Donors

Notes: All estimation samples consist of 58 DSAs from 1992 to 2013. In the synthetic control graphs, the line labeled "Treated DSAs" is the number of transplants per million DSA residents in the 13 treatment DSAs, while the line labeled "Synthetic control" represents the number of transplants per million DSA residents in the 13 synthetic control DSAs, as described in the text. The *y*-axis scales differ by column and panel to reflect the scale of living donors by organ.

candidates appears to be proactive in searching for an organ match, as evidenced by web pages that allow transplant candidates to search for the shortest wait lists.[24]

In addition, the patterns of wait-list additions in Figure 3 are consistent with the notion that the transplant centers affected by supply shocks drive the initial wait-list responses. Cho, et al. (2015), Halldorson, et al. (2013), Saidi, et al. (2015), Scanlon, et al. (2004), and Snyder (2010) all find evidence that transplant centers compete with one another for market share and that generating increased demand in response to a supply shock may increase market share. Figures 3 and 4 show that the response from patients outside the DSA and living donors is relatively slow, suggesting that information flows more slowly beyond the DSA borders and to living-donor transplant candidates who do not necessarily represent new transplants for the centers.

Because the effect on demand is five times as large as the supply shocks and involves some crowd out of living donors, it is not obvious that positive shocks improve average outcomes for candidates on local wait lists. We turn to this question next.

IV. Health Outcomes for Transplant Candidates

In the market for transplantable organs, an obvious and crucially important question is whether positive supply shocks improve health outcomes for those on local wait lists. The answer is not straightforward. On one hand, an increase in transplants should improve health outcomes. Apart from the mechanical increase in the quantity of transplants, research by Ata, Skaro, and Tayur (2017); Roth, Sönmez, and Ünver (2004); and DCEM (2011) suggests that expected match quality between donors and recipients improves in response to increases in market thickness and the health of the donor population. On the other hand, a central implication of the listing process is that rational agents can "offset" the local effects of supply shocks through shifts in demand. Further, if the marginal joiners to the local DSA's wait list have systematically different initial health status than inframarginal candidates, compositional changes may influence health outcomes.

The crowd out of living donors makes health predictions even less straightforward for kidneys. Evidence suggests that living-donor transplants have better post-transplant outcomes than deceased-donor transplants (Cecka 1997, Matas et al. 2001), so health outcomes may actually worsen if crowd out is sufficiently large. In sum, predictions about average health outcomes are ambiguous, especially for kidney transplant candidates.

Our measures of transplant candidate outcomes are expected waiting time until transplant and post-transplant graft survival. We measure expected waiting time by generating DSA-year counts of the number of candidates who received an organ transplant within 9 months and 18 months, respectively, of joining a wait list.[25] These counts include living-donor transplant recipients who did not join a wait list.

[24] See, for example, http://www.txmulti-listing.com/home.htm and http://www.organjet.com/services.html.

[25] We experimented with other measures of waiting time, such as median time until transplant, and with indicators that vary by organ because the distribution of waiting times vary significantly by organ. Regardless of how we code waiting time, we find little evidence of an effect of helmet law repeals.

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 measures whether the transplanted organ still functions. Transplants may fail for a number of reasons, including infections, postsurgical complications, and, most commonly, rejection by the body's immune system.[26] We create indicators for graft survival measured one and three 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 recipients after eliminating censored observations; for example, when analyzing one-year graft survival rates, our analysis sample excludes all transplants occurring less than one year before the end of our 1992 to 2013 sample period.

Panel A of Table 6 shows estimates of the effects of helmet laws from specifications relating transplant candidate outcomes to *nolawshare*, including DSA and year indicators. The estimates in columns 1 and 2 show that, overall and separately by organ, there is little evidence that the positive supply shocks generated by helmet law repeals reduce expected transplant waiting times relative to the comparison DSAs. The overall estimates are positive, consistent with a higher number of transplants within 9 or 18 months, but are not significantly different from zero. Panel B shows that the estimates from the synthetic control method and from OLS based on a repeal indicator are also positive but insignificant at standard levels, all suggesting that waiting times do not universally decrease in response to supply shocks.

The organ-specific estimates are also statistically insignificant in every case. While the negative point estimates for kidneys appear puzzling at first, the potential availability of living donors and dialysis (which are not generally available to other organ candidates) may play a role. Because these options exist, allocation of deceased-donor kidneys is based heavily on how long the candidate has been waiting, rather than on medical urgency. According to the National Institutes of Health's Renal Data System, median wait time for a first-time kidney transplant is 3.6 years.[27] As a result, the increase in available kidneys shown in Table 2 are likely allocated to candidates who have waited for a relatively long time.[28]

Columns 3 and 4 of panel A show estimates of the effects of *nolawshare* on graft survival at one year and three years, respectively. For livers, hearts, lungs, and pancreases, repeals of helmet laws significantly increase one-year graft survival rates, both statistically and practically. For example, we estimate that a helmet law repeal increases the share of transplant recipients whose transplanted liver is still functional one year post-transplant by 2.4 percentage points, relative to a baseline graft survival rate of 83.4 percent. Effects on hearts, lungs, and pancreases are even

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

[27] See https://www.usrds.org/2015/view/v2_07.aspx for a description of the kidney allocation process.

[28] Over our sample period, only 3.8 percent of kidney candidates receive a deceased-donor transplant within 9 months of joining a wait list (and only 6.0 percent receive a transplant within 18 months). In contrast, 18.6, 18.7, 27.5, and 16.4 percent of liver, lung, heart, and pancreas transplant candidates, respectively, receive deceased-donor transplants within 9 months.

TABLE 6—ESTIMATES OF THE EFFECT OF HELMET LAW REPEALS ON CANDIDATE OUTCOMES

	Transplants per million DSA residents		Graft survival rate	
	Within 9 months	Within 18 months	1 year	3 years
	(1)	(2)	(3)	(4)
Panel A. OLS estimates based on "nolawshare" measure				
Overall	2.877	5.212	0.007	0.005
	(3.858)	(3.959)	(0.004)	(0.004)
	[45.582]	[59.933]	[0.888]	[0.797]
By organ				
Kidney	−2.441	−0.765	−0.002	−0.003
	(1.630)	(1.859)	(0.006)	(0.008)
	[18.935]	[28.267]	[0.919]	[0.833]
Liver	3.312	3.579	0.024	0.021
	(2.545)	(2.566)	(0.011)	(0.012)
	[14.351]	[16.712]	[0.834]	[0.747]
Heart	−0.316	−0.266	0.033	0.029
	(0.759)	(0.839)	(0.010)	(0.015)
	[6.232]	[7.123]	[0.866]	[0.788]
Lung	1.938	1.134	0.049	0.023
	(1.249)	(1.181)	(0.022)	(0.019)
	[2.804]	[3.485]	[0.780]	[0.594]
Pancreas	0.129	0.123	0.135	0.092
	(0.226)	(0.287)	(0.051)	(0.050)
	[0.815]	[1.008]	[0.773]	[0.634]
Panel B. Synthetic control and OLS estimates based on repeal indicator				
Overall				
Synthetic control	2.158	1.628	0.007	0.003
	{0.377}	{0.675}	{0.081}	{0.273}
OLS	1.839	3.788	0.008	0.005
	(3.301)	(3.413)	(0.004)	(0.004)

Notes: All estimation samples consist of 58 DSAs from 1992 to 2013. The unit of observation is a DSA-year. All OLS models include indicators for years and DSAs. Standard errors of OLS estimates, listed in parentheses, are robust to clustering with DSA over time. In panel B, *p*-values, in braces, are obtained from permutation inference based on 10,000 placebo treatment effects in each case. Sample means for relevant dependent variables are listed in brackets.

larger at 3.3, 4.9, and 13.5 percentage points, respectively. We find no evidence of an increase in graft survival among kidney recipients. Column 4 shows estimates for three-year graft survival, which are generally similar to the one-year estimates. Figure 5 shows no evidence of differential pre-trends between treated and control DSAs in one-year graft survival. Similarly, we find little difference between the OLS and synthetic control estimates, as shown in panel B.

In sum, the estimates in Table 6 imply that positive supply shocks improve graft survival rates for liver, heart, lung, and pancreas transplant recipients. We hypothesized above that post-transplant outcomes may improve due to increases in market thickness, which results in better matches, or from changes to the composition of the wait list and/or donated organs. To address the potential importance of compositional shifts, we first rerun the graft survival regressions on a subsample that excludes all multi-listers who do not live in the transplant DSA. These multi-listers are a significant source of wait-list additions; by excluding them, we hope to

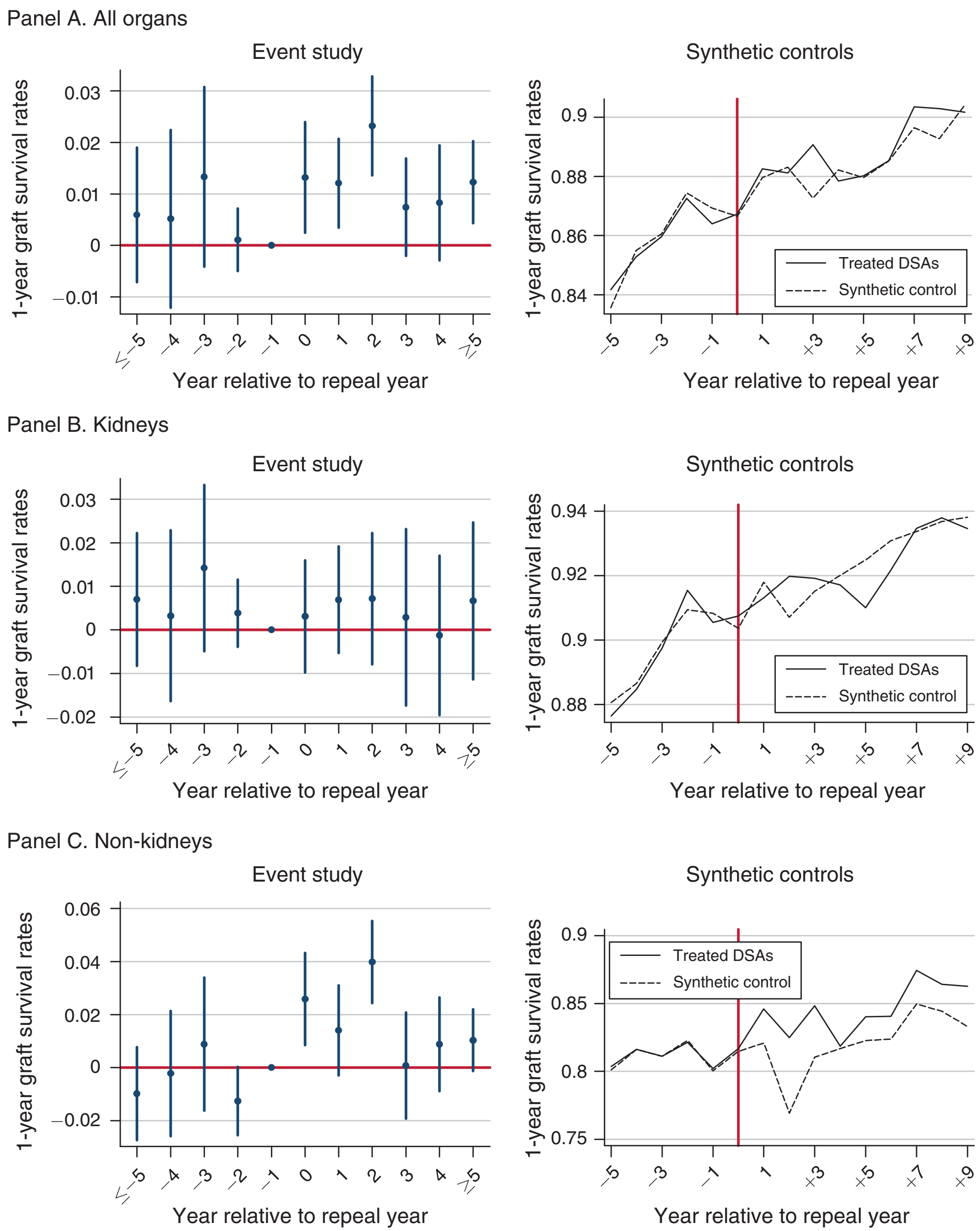

Figure 5. OLS Event Study and Synthetic Control Estimates of the Effects of Helmet Law Repeals on One-Year Graft Survival

Notes: All estimation samples consist of 58 DSAs from 1992 to 2013. In the synthetic control graphs in the right panels, the line labeled "Treated DSAs" is the number of transplants per million DSA residents in the 13 treatment DSAs, while the line labeled "Synthetic control" represents the number of transplants per million DSA residents in the 13 synthetic control DSAs, as described in the text. The *y*-axis scales differ by column and panel to reflect the scale of survival rates by organ.

isolate true health improvements from compositional shifts in the transplant recipient population. In online Appendix Table OB12, we show that most coefficient estimates become slightly larger when we exclude this group of multi-listers, which suggests that our primary results are not driven by ex ante healthier multi-listers receiving transplants.

In online Appendix Table OB13 we take a different approach to assessing the importance of compositional mechanisms by estimating the role of compositional changes in wait-listed candidates and donors. Specifically, we first estimate models relating characteristics of wait-listed candidates and donors to helmet law repeals, as in specification (1) above, and find that candidates and donors are in slightly better health along some dimensions after supply shocks; for example, candidates are 0.585 percentage points less likely to have had a previous transplant. We then ask to what extent these compositional changes can account for observed increases in graft survival rates. To do so, we estimate linear probability models of graft survival as a function of observed candidate and donor characteristics. For example, we estimate that having a previous transplant reduces 1-year graft survival by 2.440 percentage points. Together, these two estimates imply that changes in the candidate pool on this dimension would increase graft survival by 0.014 percentage points ($= 0.0244 \times 0.585$). We perform this calculation across all observable characteristics and sum the implied effects to arrive at an estimate of the overall effect of compositional changes on graft survival. The resulting estimate is small overall, 0.055 percentage points, and for each organ individually—the largest is for lungs, at 0.106 percentage points, which is only roughly 5 percent of the estimated 2.3 percentage-point effect shown in column 4. We conclude that any repeal-driven compositional effects did not meaningfully affect graft survival rates, implying that the positive health impacts of supply shocks stem from other sources, such as improvements in match quality.

One remaining puzzle is why Table 6 shows no evidence for graft survival improvements among kidney transplant candidates, in contrast to other organs. The most obvious explanation is that crowd out of living donors results in no overall change in kidney transplants—Table 2 showed that kidney transplants from MVA donors increase by 1.496 per million DSA population following repeals, while Table 5 shows that living kidney donors decline by at least 1.630. Moreover, if crowd out is sufficiently large, the overall effect of a positive supply shock on graft survival may be negative if living-donor recipients have better outcomes than do deceased-donor recipients. In our SRTR sample, one-year kidney graft survival rates are approximately 6 percentage points higher for living-donor transplants (96 percent) than for deceased-donor transplants (90 percent). Thus, a shift from living to deceased donors will decrease graft survival rates if the total number of transplants remains constant.

In summary, shocks to the local supply of organs do not appear to decrease waiting times for transplants, relative to areas that do not experience a shock, but do appear to improve post-transplant outcomes for all organs except kidneys. More efficient matches in a larger pool of donors, healthier donors, and ex ante healthier recipients are all potential mechanisms driving these improved outcomes. We leave a comprehensive answer to this question to future work, but our calculations suggest that changes in the composition of candidates and donors play a relatively minor role.

Regardless of mechanism, improved outcomes could be one reason why transplant candidates respond so dramatically following increases in the supply of organs.

V. Conclusions

By law, the allocation system in the US deceased-donor organ market operates without formal prices. Instead, waiting lists arise within defined geographic allocation regions designed to balance equity and efficiency. Conceptually, the first-order effect of increasing the local supply of organs would ostensibly raise the benefit of entering a wait list by lowering expected waiting time and increasing donor-recipient match quality. However, the ability of transplant candidates to choose where to register and whether to pursue a transplant with a living or deceased donor makes the implications of a supply shock less clear.

Using the universe of organ transplants, we find that state-level repeals of motorcycle helmet laws generate large increases in the supply of deceased organ transplants and even larger behavioral responses from the demand side of the market. For each new organ that becomes available due to a donor killed in a motor vehicle accident, roughly five new candidates join the local wait list. For all organs except kidneys, the supply shock generates increases in total transplants and in graft survival rates. The improved graft survival does not appear to arise from shorter waiting times or from compositional changes in candidates or donors. We speculate that increased thickness in the market leads to improved matches between donors and candidates, which may explain the improvements in graft survival.

The increased demand for deceased-donor transplants in response to supply shocks raises questions about whether the allocation system's geographic boundaries give rise to inefficiencies and inequities. Because our results demonstrate that the location where a candidate registers is endogenous to the supply of organs in a geographic area, a positive supply shock in one area may have differential effects on transplant candidates based on their ability to respond to changes in market conditions. Empirically, "multi-listed" candidates—those who have already joined wait lists in other geographic regions—disproportionately account for the dramatic behavioral response in wait-list additions, but we also see evidence that single-listed patients choose to join wait lists affected by a supply shock. Transplant candidates who have informational or financial advantages might be most able to capitalize on the variation in market conditions. 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.[29] While Mr. Jobs was clearly an outlier with respect to financial and informational resources, the SRTR data show that multi-listed candidates as a whole have relatively high levels of resources, as measured by educational

[29] 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.

attainment, employment rates, and private insurance coverage. These characteristics may be correlated with better access to information, such as knowledge of multi-listing websites that are dedicated to finding the DSAs with the shortest wait lists and to providing transportation to those transplant centers. Therefore, the disparities across 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. With that said, candidates listed in neighboring DSAs may also benefit from shocks if the DSA with the shock draws persons from their wait list. A key implication of our work is that the large responses in wait-list additions do not imply worse outcomes for transplant candidates.

For kidney transplant candidates, the options of dialysis and living donations complicate the answer to who benefits from a shock to the supply of kidneys. On average, we find no evidence that additional deceased-donor kidneys improve kidney candidates' waiting time or graft survival. Positive shocks crowd out the alternative life-preserving options to such an extent that we cannot find evidence that additional deceased donors benefit kidney candidates.[30]

A move toward a more national allocation system such as Spain's may 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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[30] Duranton and Turner (2011) finds comparable results in the context of transportation: highway construction does not reduce traffic congestion because the resulting increase in driving fully offsets the benefit of more highways.

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