American Economic Journal: Economic Policy 2019, 11(3): 427–453
https://doi.org/10.1257/pol.20170678

Do Kidney Exchanges Improve Patient Outcomes?†

By Keith F. Teltser*

In this paper, I estimate the number of additional transplants generated by kidney exchanges. To do this, I analyze substitution patterns between exchange transplants and other transplant outcomes. Exploiting variation in patients exposure to exchange activity across time and place, I find that 64 percent of exchange transplants represent new living donor transplants. Using the same approach, I find that an increase in the probability of receiving an exchange transplant reduces the probability of graft failure and reduces time spent waiting for a kidney. Back-of-the-envelope calculations suggest that each exchange transplant increases social welfare by $300,000 to $700,000. (*JEL* D47, I11, I12, I18)

In 2017, of the roughly 100,000 people waiting for a kidney in the United States, 4,011 died before receiving a transplant. In the same year, 35,587 people entered a waiting list for a kidney, and only 19,850 people received a kidney transplant (Organ Procurement and Transplantation Network (OPTN) 2018). Figure 1 shows the dramatic growth in the waiting list for kidneys over time, while transplants grow at a much slower pace. Addressing the increasingly unmet demand for transplantable kidneys while maintaining or increasing transplant quality requires creativity due to the National Organ Transplantation Act (NOTA) of 1984, which banned the sale of human organs.

Starting in 2000, transplant centers in the United States have worked to increase the number and quality of transplants by facilitating kidney exchanges among patients with willing but incompatible living donors. In the most basic type of exchange, a two-way *paired exchange*, patients may "swap" their willing donors when the donor from one pair is a match for the patient in another and vice versa. Paired exchanges can be extended into *donor chains*, where an altruistic donor starts a series of paired

*Andrew Young School of Policy Studies, Georgia State University, Atlanta, GA 30303 (email: kteltser@gsu.edu). Kate Ho was coeditor for this article. I would like to express my most sincere gratitude to Stacy Dickert-Conlin and Mike Conlin for their invaluable guidance on this project. I also thank Alan Leichtman, Kyoo il Kim, Christian Ahlin, Todd Elder, Soren Anderson, John Goddeeris, Daniel Litwok, Andrew Bibler, Marcelo Perraillon, Avraham Stoler, Melanie Cozad, Elizabeth Munnich, Conor Lennon, and anonymous referees for their thoughtful comments and advice. Additionally, I thank seminar participants at Michigan State University, University of Louisville, McMaster University, DePaul University, the IU/VU/UL Health Economics & Policy Conference, AEA, SEA, MEA, and APPAM for their helpful comments and discussion. I thank Jennifer Wainright at UNOS for her help with fulfilling my data request and answering follow-up questions. I gratefully acknowledge funding from Michigan State University and the University of Louisville. The data reported here have been supplied by the United Network for Organ Sharing as the contractor for the Organ Procurement and Transplantation Network. The interpretation and reporting of these data are the responsibility of the author(s) and in no way should be seen as an official policy of or interpretation by the OPTN or the US government.

†Go to https://doi.org/10.1257/pol.20170678 to visit the article page for additional materials and author disclosure statement(s) or to comment in the online discussion forum.

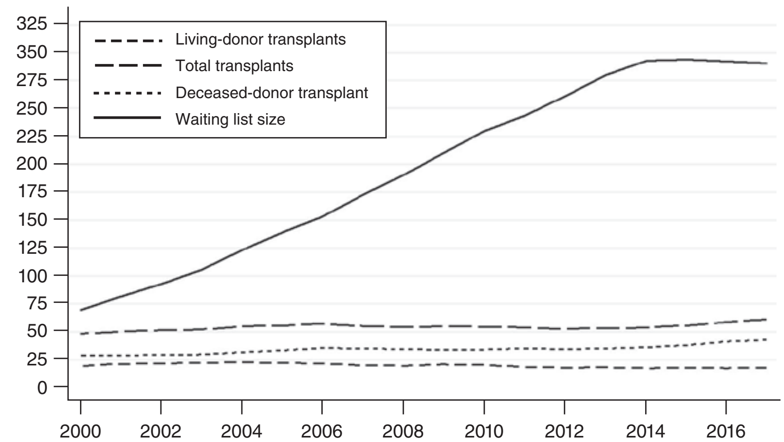

Figure 1. Kidney Transplants and Waiting List Candidates, per 1,000,000 US Residents

Source: Public OPTN data as of April 26, 2018 (http://optn.transplant.hrsa.gov)

exchanges by donating anonymously to a patient with a willing incompatible donor. Another variation is *list exchange*, where a willing donor donates to someone on the waiting list in exchange for elevated priority on the deceased donor waiting list for his or her loved one in need (Delmonico et al. 2004).

Economists have made large contributions to the development of kidney exchanges by applying existing mechanism design models to the patient-donor matching problem, simulating and comparing the effectiveness of several mechanisms, and aiding in the actual implementation of exchange programs (e.g., Roth, Sönmez, and Ünver 2004; Roth, Sönmez, and Ünver 2005b). In addition to kidney exchange, matching techniques have been applied to school choice problems (Abdulkadiroğlu, Pathak, and Roth 2005) and medical resident placement (Roth and Peranson 1999, Niederle and Roth 2008). However, the case of kidney exchange is unique in that, in addition to reducing frictions through centralized matching, it effectively enables patients to legally barter with willing living donors' kidneys. Absent kidney exchange, patients in the market for kidney transplants are entirely dependent on centrally-allocated deceased donor kidneys or transplants from known and compatible living donors. This paper is the first to examine the causal relationship between the introduction of exchange and observed patient outcomes.

Simulations from Roth, Sönmez, and Ünver (2004) demonstrate the potential of exchange to increase the number of living donor transplants, while accounting for the possibility that some patients will substitute away from *direct living* donors—those who give to known and directly compatible patients—toward exchanges. If no exchange transplant recipients substitute in this way, then every exchange transplant is a new transplant. If everyone receiving an exchange transplant substitutes in this way, then the introduction of exchange may not increase transplant quantity at all. The opposing trends in direct living, paired exchanges, and list exchanges observed from 2005 to 2017 in Figures 2, 3, and 4 are consistent with the hypothesis that at least some patients receiving kidneys via paired and list exchange substitute away from direct living donor transplants.

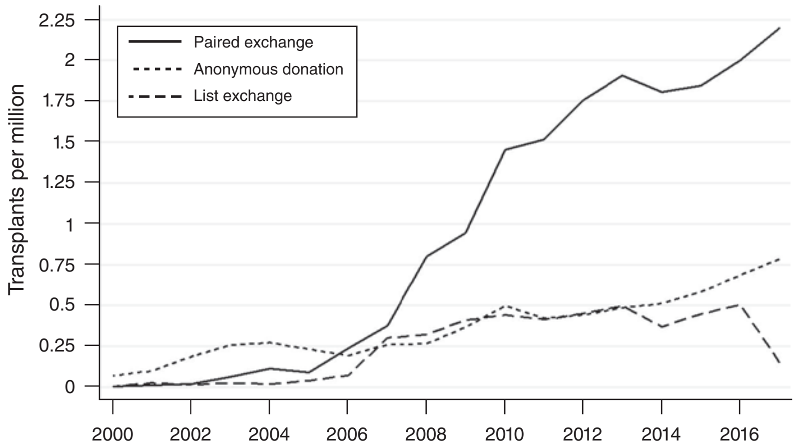

Figure 2. Transplants by Donor Type, per 1,000,000 US Population

Source: Public OPTN data as of April 26, 2018 (http://optn.transplant.hrsa.gov)

Figure 2 shows considerable growth in paired and list exchanges starting around 2005; exchanges increased from 0.6 percent of all living donor transplants in 2005 to 13.2 percent in 2017 (Organ Procurement and Transplantation Network 2018). We also see transplants from *anonymous* donors—those who altruistically give to unknown patients—growing across this period. The growth of kidney exchange may help explain this trend, since anonymous donations can facilitate more transplants when used to start donor chains. Therefore, the introduction of exchange may also incentivize anonymous donations. While Figures 3 and 4 show a clear downward trend in living donor transplants from 2005 to 2017, the "Only Direct Living" trend in Figure 4 highlights that this decline may have been even more pronounced in the absence of kidney exchange and anonymous donations.

In addition to increasing transplant quantity, kidney exchanges also have the potential to improve overall transplant quality. Holding all else equal, we would expect to see improved overall graft (i.e., transplant) survival if (i) more people receive living donations with the introduction of exchange and (ii) living donor kidneys survive longer than deceased donor kidneys.[1] Additionally, patients may substitute away from direct living donors toward willing but incompatible donors for reasons that lead to improved overall graft survival.

The presence of exchange allows patients to search for a better match, rather than having to rely on a compatible friend, relative, or the deceased donor kidney waiting list. Improving match quality is an integral part of finding suitable living donors for

[1] While there appears to be a lack of causal evidence, the transplant community generally acknowledges that living-donor kidney transplants are more successful than those from deceased donors. Calculations based on Organ Procurement and Transplant Network individual-level transplant data from 1988 to 2008 reveal that 3.2 percent of living-donor kidney grafts failed within 1 year compared to 7.9 percent of deceased-donor kidney grafts. Similarly, 16.8 percent of living-donor kidney grafts failed within 5 years compared to 29.6 percent of deceased-donor kidney grafts. In their overview of living-kidney-donation practices as of 2005, Davis and Delmonico (2005) suggests that this is partly due to reduced waiting time and time spent on dialysis for living-donor kidney recipients compared to deceased-donor kidney recipients.

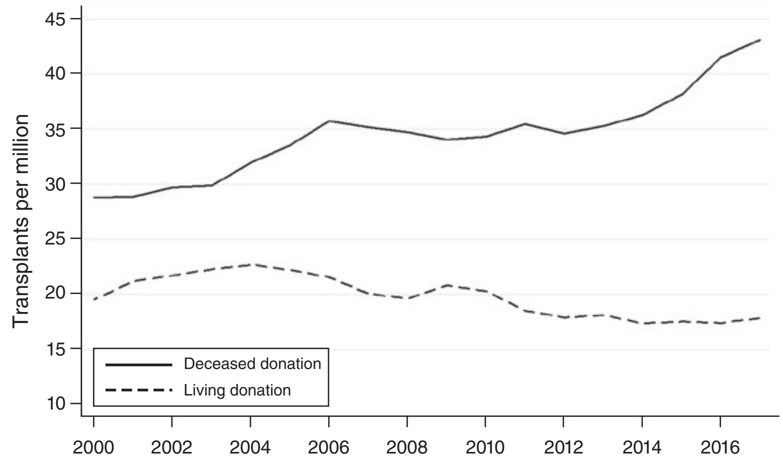

Figure 3. Transplants by Donor Type, per 1,000,000 US Population

Source: Public OPTN data as of April 26, 2018 (http://optn.transplant.hrsa.gov)

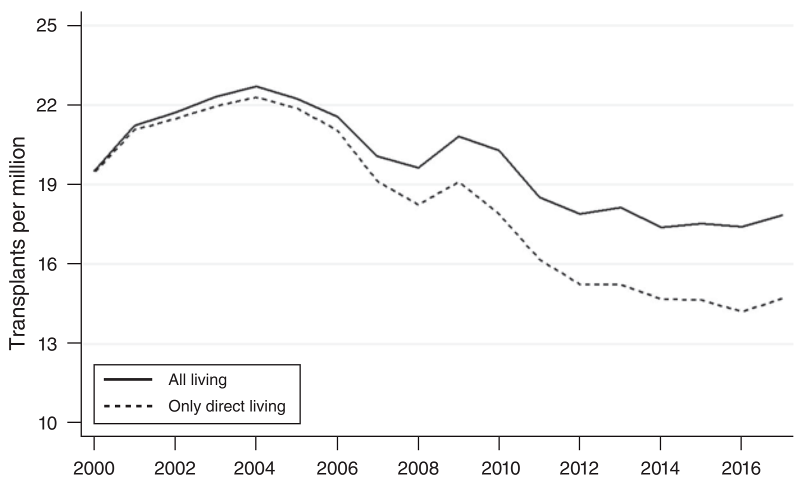

Figure 4. Transplants by Donor Type, per 1,000,000 US Population

Source: Public OPTN data as of April 26, 2018 (http://optn.transplant.hrsa.gov)

hard-to-match patients and, as we will see in Section III, exchange transplant recipients tend to be patients who are harder to match. With the compatibility restriction relaxed, we may also expect exchange to reduce the time spent searching for a suitable living donor. Moreover, if exchange increases total living donations, we would also expect to see reduced excess demand for deceased donor kidneys lead to shorter waiting times. According to the transplant literature, reductions in the number of Human Leukocyte Antigen (HLA) *mismatches*—an integer between 0 and 6 reflecting tissue-type match quality between patients and donors—and waiting list registration duration are both associated with improved graft survival (Opelz 1997, Meier-Kriesche and Kaplan 2002, Davis and Delmonico 2005).

In this paper, I first estimate the number of additional transplants generated by kidney exchanges by analyzing substitution patterns across transplant outcomes. I do this using the United Network for Organ Sharing/OPTN Standard Transplant and Analysis Research (STAR) files, which contain the universe of waiting list registrations and transplants in the United States. To identify the substitution estimates, I exploit variation in exchange activity across time and location to construct a plausibly exogenous measure of local exchange prevalence using patients' zip codes of residence, transplant center zip codes, and timing of outcomes. Second, using the same approach, I estimate the resulting improvements in graft survival, match quality, and waiting time.

In my preferred specification, I find that 64 percent of all exchange transplants represent new living donor transplants. This implies that 4,493 of the 7,021 exchange transplants performed as of March 31, 2018 (Organ Procurement and Transplantation Network 2018) would not have happened in the absence of exchange. Conditional on receiving a transplant, I find that a 1 percentage point increase in the probability of receiving an exchange transplant reduces transplant failure within 1 year by 0.21 percentage points (3 percent) and failure within 2 years by 0.24 percentage points (2 percent), relative to an average overall 1-year failure rate of 7 percent and 2-year failure rate of 12 percent. I also find a reduction in waiting list registration duration of 3.8 days (0.6 percent) that is borderline statistically significant ($p = 0.11$). These results imply that the growth in kidney exchange from 0 percent in 2000 to 3.9 percent of all transplants in 2017 (Organ Procurement and Transplantation Network 2018) reduced overall 1-year transplant failure by 0.82 percentage points (11.7 percent), 2-year failure by 0.94 percentage points (7.8 percent), and waiting list registration duration by 14.8 days (2.5 percent). I find no effect of exchange on tissue-type match quality as measured by the number of HLA mismatches.

The paper proceeds as follows. Section I provides additional background information on kidney transplantation and exchange. Section II presents a conceptual framework modeling the impact of kidney exchange on the decision to donate. Section III discusses the data and provides descriptive statistics. Section IV develops the framework for estimating the effect of exchange prevalence on observed patient outcomes. Section V presents the main results. Section VI presents back-of-the-envelope calculations of the implied cost-savings and welfare gains, and concludes.

I. Background

There are two main treatment options available to a patient experiencing kidney failure: transplantation and dialysis. Dialysis is an ongoing treatment that provides some of the blood filtering that healthy kidneys would perform. However, for those with chronic kidney disease or end-stage renal disease, dialysis is not a cure nor an attractive long-term treatment. These patients can turn to transplantation for a more permanent and flexible solution. Once a patient decides to pursue a kidney transplant, they may register on a waiting list for a deceased donor kidney and/or search for a willing living donor (National Kidney Foundation 2015).

Figure 3 shows deceased donations are the most common source of kidney transplants, accounting for 71 percent of the 19,850 kidney transplants performed in 2017 (Organ Procurement and Transplantation Network 2018). Doctors recover kidneys from eligible deceased donors, which are then allocated by organ procurement organizations (OPOs) across the United States. When a healthy kidney is recovered, the OPO generates a priority list of patients on the waiting list—based on factors such as blood type and tissue match, waiting time, and geography—and offers the kidney to the transplant team of the patient at the top of the list (United Network for Organ Sharing 2015).[2]

Blood type compatibility is the first condition that needs to be met for transplant success. In general, people with type O blood can only receive from type O donors, but they can give to any other blood type. People with type A blood can only give to type A or AB patients. People with type B blood can only give to type B or AB patients. Finally, people with type AB blood can only give to type AB patients, but can receive from donors of any blood type. However, blood type is not sufficient. The patient's level of sensitivity to foreign proteins—reflected by the Panel Reactive Antibody (PRA) score, which indicates the percentage of the blood type-compatible population with whom the patient is likely to be incompatible—is also an important determinant of compatibility.

Rather than waiting for a deceased donor kidney, patients can search for living donors within their network of family and friends. They may be particularly likely to do this if facing a long wait or they want to improve expected survival. Most living donations come from a willing compatible donor. In 2017, 82 percent of living kidney donations were direct living donations and 68 percent of these came from biological relatives or partners (Organ Procurement and Transplant Network 2018). However, finding a sufficiently healthy, willing, and compatible living donor is not always easy. Once a patient finds a potential living donor, they undergo the same compatibility tests that are used for deceased donations, as well as screenings for heart and lung disease, kidney function, and psychological wellness (United Network for Organ Sharing 2015). Although the donor's medical expenses are typically covered by the recipient's insurance or transplant center's Organ Acquisition Fund, potential donors may not be able to afford the associated travel costs, time off of work, and risk of future medical problems (United Network for Organ Sharing 2015). Moreover, while patients may be able to find healthy and willing living donors, not all will be able to find a compatible living donor within their social network.[3]

[2] Promoting deceased organ donation is one avenue toward reducing the massive shortage of kidneys. To this end, a body of literature focuses on the factors influencing the supply of deceased-donor kidneys, including analyses of presumed consent laws, traffic safety laws, and offering waiting list priority to previously registered organ donors (e.g., Abadie and Gay 2006; Dickert-Conlin, Elder, and Moore 2011; Kessler and Roth 2012; Li, Hawley, and Schnier 2013; Kessler and Roth 2014; Callison and Levin 2016; Stoler et al. 2017). However, it is also well-documented that increases in the supply of deceased-donor organs are at least partially offset by living-donor crowd-out (e.g., Sweeney 2010; Fernandez, Howard, and Kroese 2013; Anderson 2015; Dickert-Conlin, Elder, and Teltser forthcoming).

[3] Some argue in favor of financially compensating organ donors as a way to reduce the shortage. Among a body of economics research focusing on this topic (e.g., Adams, Barnett, and Kaserman 1999; Byrne and Thompson 2001; Becker and Elias 2007; and Wellington and Sayre 2011), recent work focusing on policy efforts to offset the costs of donating yields mixed results. In particular, Lacetera, Macis, and Stith (2014) finds that state tax and paid

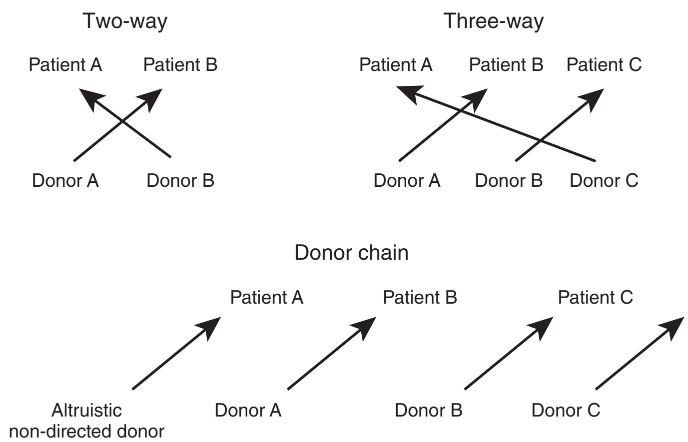

Figure 5. Two-Way and Three-Way Exchange, and Donor Chain Diagrams

Kidney exchange offers a promising solution by facilitating transplants for patients who can find incompatible willing living donors. As discussed in the introduction, such arrangements include paired exchanges, list exchanges, and donor chains. Paired exchanges can occur in a closed cycle of two or more incompatible patient-donor pairs, or as part of a donor chain where a non-directed living donor—one who is not giving on behalf of a loved one in need—gives to a recipient who has a willing incompatible donor. That recipient's willing incompatible donor then gives to a patient in a second incompatible pair. This process continues until no more matches are found, a recipient's willing incompatible donor backs out, or the final donor gives to someone on the deceased donor waiting list. Figure 5 depicts diagrams of a two-way exchange, three-way exchange, and donor chain.

Exchange arrangements are generated by matching incompatible patient-donor pairs who have signed up with an exchange registry. Registries may be managed by a single transplant center, such as the Johns Hopkins University Incompatible Kidney Transplant Program, or by a consortium of transplant centers where centers share a registry, such as the National Kidney Registry and Alliance for Paired Donation. In the early 2000s, exchange programs matched incompatible pairs manually. That changed in 2005, when Roth, Sönmez, and Ünver helped the New England Paired Kidney Exchange implement computerized matching algorithms (Hanto et al. 2010). As we can see in Figures 2 and 6, centers across the United States rapidly adopted this new technology. Today, exchange programs use computerized matching to maximize some mix of quality and quantity, though each program implements its own unique objective function. For example, the algorithm that the Alliance for Paired Donation uses gives highest priority to patients with high PRA scores, patients who previously donated, patients under five years old, and to matches with zero HLA mismatches (Alliance for Paired Kidney Donation 2015).

time-off incentives do not appear to increase living kidney donations, while Schnier et al. (2018) finds that efforts to reimburse donors' travel-related expenses via the National Living Donor Assistance Center significantly increase living kidney donations.

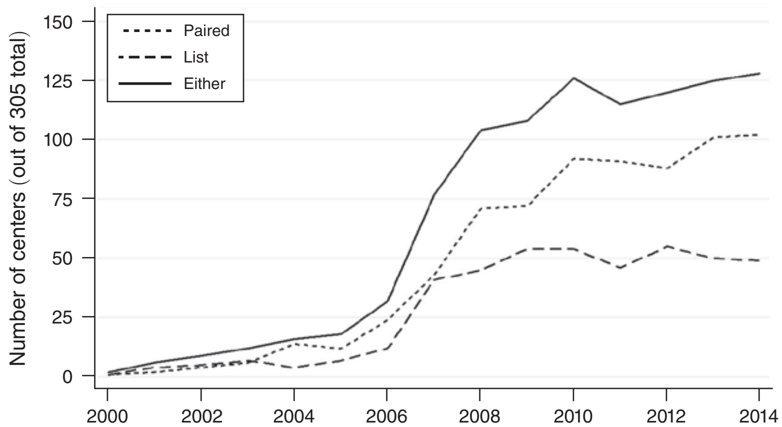

Figure 6. Centers Performing at Least One Paired or List Exchange, or Either

Source: OPTN STAR data as of December 31, 2014

To date, economic research on kidney exchange primarily consists of important theoretical work on matching and simulations of patient outcomes.[4] A representative set of simulations from Roth, Sönmez, and Ünver (2004) suggests that one additional transplant via exchange reduces direct living donations by 0.48.[5] This implies that 52 percent of exchange transplants represent *new* living donor transplants that would not have occurred in the absence of exchange, and that 48 percent represent patient-donor substitution toward exchange away from direct living donation. The representative set of simulations also yields a post-introduction reduction of average HLA mismatches from 4.83 to 3.85 for those receiving a living donor transplant.

While the simulations yield valuable baseline estimates, we must be careful not to rely only on those results. First, the simulations use a fixed set of patient-donor pairs, meaning that they do not allow for possible changes in the number and composition of patient-donor pairs in response to the introduction of exchange. That is, the presence of exchange may induce additional patient-donor pairs to join the transplant market. In reality, patients may also substitute *across* potential living donors when opting for exchange instead of direct living donation, rather than using the same would-be direct living donor to engage in an exchange. In fact, this is quite likely to be the case since few compatible patient-donor pairs participate in

[4] See, for example, Roth, Sönmez, and Ünver (2004, 2005a, 2005b, 2007); Roth et al. (2006); Ünver (2010); Ashlagi et al. (2011); Sönmez and Ünver (2015); Andersson (2015); and Chun, Heo, and Hong (2017).

[5] The researchers simulate fixed pools of 30, 100, and 300 unrelated patient/donor pairs randomly generated to closely reflect Organ Procurement and Transplantation Network population statistics. They assume that patients' preferences are determined by maximizing the probability of a successful transplant, given certain constraints. The representative simulations cited here use 100 pairs and are based on the assumption that 40 percent of patients would prefer waiting list priority to their incompatible willing donor's kidney, which allows for the possibility of list exchange. I calculate (Own Donor TXs With Exchange − Own Donor TXs Without Exchange)/(Exchanges), where the total number of transplants from one's own donor is 22.81 with exchange, 54.79 without exchange, and the number of exchanges is 66.16. This gives us a substitution estimate of −0.48 and yields the following interpretation: of the 66.16 exchanges performed, 31.98 (or 48 percent) of the patients involved would have received a living kidney donation otherwise and 34.18 would not. For reference, see table 3 of Roth, Sönmez, and Ünver (2004).

kidney exchange arrangements.[6] Second, those switching from compatible living donation to exchange in the simulations are driven only by reductions in the number of HLA mismatches and donor age. In practice, other factors may affect the substitution decision (e.g., relationship-based preferences) such that patients are willing to accept an older donor or more HLA mismatches.

To my knowledge, there is no research estimating the transplant quantity gains generated by exchange using observational data. However, several papers in the transplant literature focus on quality by comparing exchange and direct living transplant survival rates. For example, Segev et al. (2008) finds no statistically significant difference in survival rates between these two groups, even when controlling for observables. Mierzejewska et al. (2013) reports the same findings when comparing average survival rates, despite exchange recipients being more sensitized on average. This is consistent with the findings of Delmonico (2004) and Gjertson and Cecka (2000) that the number of HLA mismatches has little to no effect on graft survival, but goes against the earlier findings of Opelz (1997). In any case, these survival comparisons suggest that patients are not made worse off by kidney exchanges, implying that quantity gains may be welfare-improving. However, such comparisons are descriptive and therefore invite further empirical research on the impact of kidney exchange on patient outcomes.

II. Conceptual Framework

While a patient ultimately has the ability to accept or reject a donation, his or her transplant outcome fundamentally depends on the underlying set of available willing living donors. Developing a simple model of donor behavior can therefore help us understand how the introduction of exchange affects patients' observed transplant outcomes. An expansion in a patient's pool of potentially willing and suitable living donors may improve the likelihood of receiving a kidney, improve transplant match quality, and reduce transplant waiting time. As this pool expands, however, there is also greater ability for potential donors to free ride on other potential donors in the pool. In particular, if donor utility is a function of patient transplant outcomes, some willing compatible potential donors may no longer be willing once the compatibility constraint is relaxed and patients' outside options improve.

Consider the following model of the decision to donate for an individual, L, with a loved one in need of a kidney, k. Individual L's general indirect utility is given by the following:

$$U_L(Y) = B_k(Q(Y)) + \alpha_L S_{-k}(Q(Y)) - C(Y), \tag{1}$$

where $B_k(Q(Y))$ is the benefit L derives from patient k's outcome, α_L is a nonnegative, donor-specific altruism parameter, and $S_{-k}(Q(Y))$ represents the total surplus L generates for other patients. Further, $Q(Y)$ is the expected quality of the

[6] For example, according to the National Kidney Registry's first quarterly report of 2017, compatible patient-donor pairs opting for exchange rather than direct living donation only accounted for 65 of the 1,477 exchange transplants facilitated by the National Kidney Registry from 2013 to March 2017 (National Kidney Registry 2017).

transplant outcome, which is a function of L's donation decision Y. The function $C(Y)$ represents the costs of donating, which may include travel, uncovered medical expenses, time off work, and health risks. I assume that B_k is an increasing function of $Q(Y)$ and that donating via exchange is prohibitively costly when exchange has yet to be formally introduced. I also assume that no spillover surplus is generated when L does not donate via exchange, or $S_{-k}(Q^N(Direct)) \approx S_{-k}(Q^N(None)) = 0$. Note, however, that there may actually be some spillover surplus generated by a direct living donation. If registered, k is removed from the deceased donor waiting list after the transplant. All else equal, which may not be the case given evidence of offsetting demand-side responses to positive organ supply shocks (Dickert-Conlin, Elder, and Teltser forthcoming), this slightly reduces waiting time for those "behind" k on the list.

Donor L's expected utility when she donates directly is given by

$$U_L^x(Direct) \;=\; B_k(Q^x(Direct)) - C^x(Direct). \tag{2}$$

When she donates via exchange, her utility is

$$U_L^x(Exch) \;=\; B_k(Q^x(Exch)) + \alpha_L S_{-k}(Q^x(Exch)) - C^x(Exch). \tag{3}$$

When she does not give at all, her reservation utility is

$$U_L^x(None) \;=\; B_k(Q^x(None)). \tag{4}$$

The superscript x indicates the absence $(x = N)$ or presence $(x = E)$ of formal kidney exchange. Since the pool of possible donors available to k expands following the introduction of exchange, prospective donor L should rationally expect that patient k's outcome, when L does not donate, improves following the introduction of exchange (i.e., $Q^E(None) \geq Q^N(None)$). From this starting point, I present the following proposition.

PROPOSITION 1: *If the introduction of exchange does not affect the costs nor the benefits to L of direct donation, then L is less likely to choose direct donation over no donation post-introduction. See online Appendix A.1 for the proof.*

In addition to showing a crowd-out effect of exchange on direct donations, Proposition 1 suggests that, after the introduction of exchange, direct donors may be higher quality matches and/or yield better expected transplant outcomes, on average, compared to direct donors prior to the introduction of exchange. A direct donor who is marginal, such that $U_L^N(Direct) \geq U_L^N(None)$ and $U_L^E(Direct) < U_L^E(None)$, is crowded out when her direct donation no longer improves k's expected outcome enough to overcome the cost of donating. Thus, marginal direct donors are either relatively low quality or face high costs of donating.

It is straightforward to show that the probability that L chooses to give via exchange rather than directly or not at all is higher after exchange is introduced. This is driven by the assumption that donating via exchange is prohibitively costly when transplant centers have yet to formally implement an exchange program. The ability to generate surplus for other patients in need through an exchange mechanism provides additional incentive for prospective donors to give via exchange rather than directly or not at all. Note that a donor switching from giving directly toward exchange will not, by itself, change the number of living donations.[7] Therefore, to show that exchange will result in a net increase of living kidney donations, it is sufficient to show that the gain in living donor transplants via exchange outweighs the loss of living donations due to the crowd-out of direct donations.

PROPOSITION 2: *Suppose again that the introduction of exchange does not affect the costs nor the benefits to L of direct donation, i.e.,* $C^E(Direct) = C^N(Direct)$ *and* $B_k(Q^E(Direct)) = B_k(Q^N(Direct))$. *Then a representative prospective donor L is more likely to become a living kidney donor if the introduction of exchange increases the net utility of donating via exchange, relative to not donating, by a larger magnitude than it increases L's reservation utility, i.e.,* $[U_L^E(Exch) - U_L^E(None)] - [U_L^N(Exch) - U_L^N(None)] > U_L^E(None) - U_L^N(None)$. *See online Appendix A.2 for the proof.*

Given a large enough reduction in the cost of donating via exchange, the condition given in Proposition 2 will hold trivially. But even in the extreme and unrealistic case of zero cost reduction, the condition would hold if the introduction of exchange increases the marginal benefits of donating via exchange, relative to no donation, by a larger magnitude than it increases L's reservation utility. This stronger condition is still relatively weak; L's net expected utility will weakly increase if the formal introduction of exchange substantially increases the thickness of the market.[8]

Comparing L's post-introduction utility from donating via exchange to donating directly, note that L is more likely to donate via exchange rather than directly when she is a relatively poor direct match for k. This implies an increase in transplant quality for direct donation recipients, as some marginal quality direct donors will substitute toward exchange in order to obtain a higher quality of transplant for their loved one in need. As the cost differential between donating directly donating via exchange approaches zero, L will choose exchange rather than direct donation if there is any gain in total benefit derived from giving via exchange rather than direct donation. Also, depending on L's altruism parameter and the amount of

[7] For instance, suppose two patients have donors who give directly before exchange is introduced. After introduction, suppose they both switch to exchange. If these pairs are matched with each other in a two-way exchange, there is no net gain in living-donor transplants. A net gain can only occur if at least one exchange-transplant recipient would not have received a living-donor kidney in the absence of exchange.

[8] An increase in market thickness would lead to a substantially higher chance of finding a quality match for k and increasing the surplus of other patients $-k$. Given a large enough increase in market thickness, net expected utility would remain unchanged only if L is not a suitable exchange donor. In this case, she is also highly unlikely to be a suitable direct donor, so we would expect exchange introduction to have no effect on L's donation decision. Therefore, if L is a suitable exchange donor, then net expected utility would strictly increase with a large enough increase in market thickness.

expected surplus generated by L's donation via exchange, L may prefer to donate via exchange rather than directly even though it could imply a worse outcome for k.

Taken together, the results from Propositions 1 and 2 suggest (though not unambiguously) that the introduction of exchange should increase the quantity of living donor transplants and weakly improve the quality of direct living donor transplants. This comes with an important caveat: while not formally modeled, there is likely more uncertainty about the quality of a kidney obtained via exchange than one from a well-known direct donor. Accordingly, the larger the uncertainty and the more risk-averse potential donors and patients are, the less substitution there will be away from direct living donation toward exchange or no donation. Similarly, higher levels of uncertainty and risk aversion imply smaller direct living donor transplant quality gains.

Additionally, we should not expect to see a change in deceased donor transplants following the introduction of kidney exchanges. Such a change would require donor registration rates, rates of consent among next-of-kin after death, or the number of recovered kidneys deemed transplantable to respond to exchange. None of these seem likely given the size of the waiting list and the fact that exchange is still a small share of total transplants despite recent growth in utilization. Moreover, because the waiting list is sufficiently long, there should always be someone willing and able to accept a suitable deceased donor kidney. Therefore, we may see the allocation of deceased donor organs naturally shift toward areas with less exchange activity, but this would not have an effect on the overall number of deceased donor transplants.

Next, the model can be extended to account for increases in anonymous donations. Suppose individual A does not have a loved one in need of a kidney but cares about the surplus her donation generates for unknown patients, such that she would get the following utility from donating anonymously:

$$U_A^x(Anon) \;=\; S_i(Q^x(Anon)) + S_{-i}(Q^x(Anon)) - C^x(Anon), \tag{5}$$

where S_i is the surplus generated by A's anonymous donation to an immediate recipient i, S_{-i} is the surplus generated for additional patients via a donor chain, and $C^x(Anon)$ is the cost of donating. Her utility is zero when she does not donate:

$$U_A^x(None) \;=\; 0. \tag{6}$$

I assume zero spillover surplus in the absence of exchange: $S_{-i}(Q^N(Anon)) = 0$. Note that the altruism parameter, α, is dropped as A cares equally about all potential beneficiaries.

PROPOSITION 3: *If the cost of donating anonymously is unaffected by the introduction of exchange, i.e.,* $C^E(Anon) \;=\; C^A(Anon)$, *then individuals without a loved one in need of a kidney will be more likely to donate anonymously to start a* (*sufficiently long*) *donor chain and less likely to donate anonymously to a single patient following the introduction of exchange. See online Appendix* A.3 *for the proof.*

Individuals will be less likely to donate anonymously to a single individual for essentially the same reason donors with a loved one in need are less likely to give directly. The introduction of exchange reduces the surplus generated by *A*'s donation to *i*, since it improves *i*'s expected outside option, while the quality of *A*'s transplant for *i* should not be affected by the existence of exchange. When *A* donates anonymously in order to start a donor chain, the surplus generated by helping even one additional person receive a transplant via exchange is very likely to at least offset the reduction in surplus experienced by patient *i*. Since the average donor chain length includes more than four patients (Melcher et al. 2013), the additional surplus is very likely to outweigh the reduction in surplus experienced by *i*. If all anonymous donations are steered toward donor chains, their donations have the potential to help more patients receive transplants and we would therefore expect that individuals are more likely to donate anonymously after exchange is introduced. While I can test for the net effect on anonymous donations in my empirical analyses to follow, I am unable to test whether increasing exchange prevalence leads to a reduction in single anonymous donations and an increase in chain-initiating anonymous donations, since I do not observe that information.

III. Data

In the following analysis, I begin with individual-level data extracted on December 31, 2014, from the Standard Transplant Analysis and Research (STAR) file, which is available by request from the United Network for Organ Sharing. The data contain 788,106 observations of kidney waiting list registrations and transplants that occurred from 1988 to 2014. Of these observations, 398,984 are registrations that resulted in transplants and living donor transplants that occurred without an associated waiting list registration. I have information on the outcome of each registration including: transplant, death, transfer to a different center, or still waiting as of December 31, 2014. I restrict my analysis to outcomes resulting in either transplant or death while waiting, as these include all the well-defined registration outcomes.[9]

Donor type and living donor relationship are the key variables I use to determine whether a transplant is direct living, deceased, anonymous, or exchange.[10] Note that I can only connect donors to their actual recipients. Therefore, for exchanges, I cannot connect donors to the loved one on whose behalf they are donating. Also, I cannot observe whether an anonymous donor's kidney is used to start a donor chain. Nonetheless, these data are rich. I observe variables including blood type, level of sensitization to foreign proteins, race, education, previous transplant status, age, gender, registration date, transplant date, HLA mismatches, additional medical information, donor characteristics, and transplant follow-up information from which graft survival is calculated. Additionally, I obtained zip code information for

[9] This means that I do not include patients who are still waiting, became too sick to transplant, transferred to different centers, etc. Note also that patients may have multiple waiting list registrations. Patients with multiple registrations who died while waiting are only counted once. For a transplant recipient with multiple registrations, I use only the registration associated with their actual transplant outcome.

[10] Kidney transplants are coded with one of the following donor relationships: sibling, twin, child, parent, other relative, significant other, miscellaneous unrelated donor, paired exchange, list exchange, anonymous, or deceased.

Table 1—Frequency of Registration Outcomes

	2000–July 2014		2007		2013	
Outcome	Observations	Percent	Observations	Percent	Observations	Percent
Exchange	4,103	1.39	202	0.96	753	3.52
Anonymous	1,528	0.52	97	0.46	176	0.82
Direct living	82,844	27.99	5,720	27.04	4,786	22.37
Deceased	145,408	49.13	10,591	50.08	11,164	52.19
Died on WL	62,064	20.97	4,540	21.47	4,512	21.09
Total	295,947		21,150		21,391	

Note: Includes all transplants where a donor relationship is observed, and deaths of those registered on the deceased-donor waiting list.

Source: OPTN STAR data as of December 31, 2014

patients and transplant centers via special request to the United Network for Organ Sharing.

I restrict my analysis to data from January 2000 to July 2014. There is a large increase in the quality of reporting for the donor relationship variable in 2000.[11] Due to lags in data processing, August through December 2014 are incomplete with respect to donor relationship at the time of my extract. Table 1 presents the frequency of each well-defined registration outcome across the sample period, as well as snapshots of 2007 and 2013 to provide some additional insight on changes over time. Here we see that anonymous donations (0.5 percent) and exchanges (1.4 percent) account for a small but growing fraction of all observed outcomes, while direct living donations (28 percent) decline, deceased donations (49 percent) increase slightly, and deaths while waiting (21 percent) stay relatively constant.

Overall, exchange transplant recipients appear to be harder to match, on average. They are the most sensitized to foreign proteins according to PRA score, which takes on a value between 0 and 100 and reflects the proportion of the blood type-compatible population with whom one is likely to be incompatible. In particular, exchange recipients have an average calculated PRA score of 22, compared to recipients of deceased donor kidneys at 20, anonymous at 17, and direct living at 9 (see online Appendix Table B1). Exchange transplant recipients also tend to be older and receive organs from older donors, which suggest that they tend to be in a more desperate position compared to those receiving direct living donations. Taken together, these statistics suggest that patients may pursue exchanges only after exploring more conventional options. If true, this would imply that most exchange transplants represent new living donor transplants.

Turning to summary statistics of transplant quality (see online Appendix Table B2), graft survival is slightly higher for exchanges but similar across all living donor transplants for both 1 and 2 years at 96–97 percent and 93–94 percent, respectively.[12]

[11] From 1988 to 1999, there are an average of 77 unreported donor relationships per year compared to 1 per year from 2000 to 2013.

[12] Graft survival is defined for observations with a non-missing graft survival time in the OPTN STAR data. It takes on a value of zero if the patient died before one or two years, or if there is a reported graft failure within one or two years. It takes on a value of one if the graft survival time exceeds one or two years, or if the patients' last known

Ex ante tissue type match quality, measured by number of HLA mismatches, tends to be worse in exchange and anonymous transplants (4.31) relative to deceased and living donor recipients (3.88 and 3.16, respectively). Finally, recipients of direct living donations have the shortest waiting list registration durations, roughly 237 days, followed by exchange at 468 days, anonymous at 654 days, and deceased donation at 813 days.[13] While the overall picture here suggests that exchange recipients are harder to match, a comparison of survival across living donation methods suggests that exchange methods are able to overcome such difficulties.

IV. Estimation

The first goal of this paper is to estimate the number of new transplants generated by kidney exchanges. At first glance, a duration (e.g., competing risk) model may seem most appropriate for this setting. However, the validity of such an approach is threatened by selection bias and duration measurement issues. First, I am unable to measure search/waiting duration for the relatively large (33 percent) and nonrandom subset of patients who receive living donor transplants without initially registering on a deceased donor waiting list.[14] Second, duration would be systematically under-measured if a substantial portion of patients only register on the waiting list after (unsuccessfully) searching for a living donor.

To avoid these issues, I aggregate the individual-level data to obtain totals of each type of registration outcome, as well as various patient characteristics, by zip code of residence, and month and year of the observed outcome. To create a balanced panel of zip code-month-year observations, I replace missing registration outcome totals and patient characteristic totals with zero to reflect the lack of any observed registration outcomes. I then use this panel to estimate a linear model of the relationship between time-varying local exchange activity and the frequency of direct living, anonymous, deceased donations, and deaths while waiting.

Consider the following structural model:

$$Y_{zt} = \lambda E_{zt} + X_{zt}\beta + \alpha_z + \gamma_t + \eta_z t + \zeta_{sy} + \varepsilon_{zt}, \tag{7}$$

where the dependent variable is the frequency of non-exchange registration outcome Y, in zip code z, in month-year t.[15] The variable E is the number of exchange

status is alive with a functioning kidney. The assumption is that these "lost" individuals would have returned to the system or they would have a death date reported through the Social Security Death Master File if their graft failed or they died. In order to ensure adequate time has passed for follow-up data, I restrict the analysis of one-year graft survival to transplants occurring on or before December 31, 2012, and December 31, 2011 for two-year graft survival.

[13] Note, roughly one-third of living donor kidney recipients never register for the waiting list. In these cases, registration duration is set to zero.

[14] Almost 26 percent of direct living, 6 percent of exchange, and 3 percent of anonymous transplants occurred without an associated waiting list registration, based on OPTN STAR data as of December 31, 2014. In fact, I find that patients receiving living-donor transplants in areas with higher levels of exchange activity are less likely to register on the deceased-donor waiting list beforehand.

[15] Note that I do not normalize the included measures by zip code population for two reasons. First, census population information is only available by zip code tabulation area, which do not perfectly correspond to zip codes. Second, this information is only available decennially. The natural approach would be to normalize by 2010 population, but this is unnecessary when also including time-invariant zip code fixed effects.

transplants received by patients residing in zip code z in period t; X is a vector of characteristics of patients experiencing a well-defined registration outcome in zip code z and period t including race, gender, blood type, education, previous transplant status, PRA score, and age at listing.[16] Zip code fixed effects, α_z, control for any unobserved heterogeneity across zip codes where patients live that are correlated with local kidney exchange activity such as affluence, quality of nearby health care institutions, and proximity to research institutions. Month-year fixed effects, γ_t, control for nationwide transplantation trends and national-level policy shocks. Zip code-specific linear time trends, $\eta_z t$, account for local trends in transplant quantity and quality that could be correlated with local kidney exchange activity such as demand for kidney transplants, technological progress, quality of local medical facilities, and demographic composition. State-year fixed effects, ζ_{sy}, control for state-level policy shocks that may affect the supply of living and deceased donor transplants, such as incentives for living donors, traffic safety laws, and the Uniform Anatomical Gift Act. Finally, ε_{zt} is the idiosyncratic error term.

The naïve OLS estimator of λ is likely to be biased by reverse causality and selection issues. Patients who are sicker and less likely to find living donor transplants may be more likely to seek out exchange transplants. Those patients may also be more likely to experience worse transplant quality outcomes, thereby leading to biased estimates of the quality effects as well. Therefore, I use an instrumental variables approach to estimate the structural parameters of interest. I estimate the following first-stage specification:

$$E_{zt} = \phi Activity_{\bar{z}t} + X_{zt}\beta + \alpha_z + \gamma_t + \eta_z t + \zeta_{sy} + \varepsilon_{zt}, \tag{8}$$

along with the reduced-form specification:

$$Y_{zt} = \theta Activity_{\bar{z}t} + X_{zt}\beta + \alpha_z + \gamma_t + \eta_z t + \zeta_{sy} + \varepsilon_{zt}, \tag{9}$$

where $Activity_{\bar{z}t}$ is a measure of exchange activity at transplant centers near zip code z in month t. I discuss the proposed instrument, *Activity*, further in Subsection IVA.

We can think of both θ and ϕ as difference-in-differences estimators, where *Activity* measures time- and location-varying treatment intensity. Rather than focus on each individual θ, the main focus of the estimation results will be the structural parameter λ given by the ratio θ/ϕ. A one unit increase in the number of exchange transplants near zip code z in period t results in a change of θ/ϕ in the frequency of outcome Y. This ratio, which is equivalent to the Wald IV estimator and can be estimated directly using two-stage least squares, yield the substitution estimates of interest.

Next, I turn to the estimation of transplant quality. Here, I estimate how the probability of receiving an exchange affects the quality of transplant

[16] Patient characteristics enter the regressions as subgroup counts. For age, the groups are 0–5, 6–17, 18–34, 35–54, and 55+. For PRA score, the groups are 0–10, 10–20, . . . , 90–100, and missing.

outcomes, conditional on receiving a transplant, using individual-level data. Consider the following structural model:

$$(10) \qquad Y_{izt} \;=\; \pi E_{izt} + X_i\beta + \alpha_z + \gamma_t + \eta_c t + \zeta_{sy} + \varepsilon_{izt},$$

where each observation now represents one transplant, Y is the quality outcome of interest, including one-year graft survival (binary), two-year graft survival (binary), the number of HLA mismatches (0–6), and waiting list registration duration (days). Now, E is a binary indicator for whether transplant i is an exchange transplant. The other main difference is the inclusion of county-specific, instead of zip code-specific, linear time trends to avoid overfitting the data.[17]

The first stage specification is given by the following linear probability model:

$$(11) \qquad E_{izt} \;=\; \psi Activity_{\tilde{z}t} + X_i\beta + \alpha_z + \gamma_t + \eta_c t + \zeta_{sy} + \varepsilon_{izt}.$$

The reduced-form specification is

$$(12) \qquad Y_{izt} \;=\; \delta Activity_{\tilde{z}t} + X_i\beta + \alpha_z + \gamma_t + \eta_c t + \zeta_{sy} + \varepsilon_{izt}.$$

Thus, a 1 percentage point increase in the probability of receiving an exchange transplant results in change of $\delta/\psi \;=\; \pi$ in quality outcome Y.

A. *Measuring Activity*

In practice, I define *Activity* as the number of exchanges that occurred at transplant centers within 50 miles of zip code z in month-year t. From this measure, I subtract the number of exchange transplants received by patients residing in zip code z in month t that occurred at transplant centers within 50 miles.[18] This measure is similar to other distance-based instruments such as distance from nearest hospital (Chandra and Staiger 2007) and nearby college openings (Currie and Moretti 2003).

Since patients and donors must be able to travel to transplant centers for testing and eventual transplant procedures, this proposed measure of *Activity* crucially reflects patient access to exchange with respect to cost, salience, and the existence and intensity of local transplant center participation.[19] Moreover, this measure also exploits the network externalities inherent in paired exchange, since they must be

[17] Overfitting is a concern in the quality analyses because each observation now represents an individual transplant, and roughly 48 percent of zip codes have 3 or fewer observed transplants across the sample period.

[18] I use GIS mapping software along with the zip codes of patients and transplant centers to determine which transplant centers are within 50 miles of the centroid of each observed patient zip code. I then aggregate over these nearby centers to determine how many transplants via kidney exchange occurred each month within the 50 mile radius.

[19] Since there is a wide range of participation in and promotion of kidney exchange across transplant centers and within transplant centers across time, we need a more precise measure of local exchange activity than a simple indicator of transplant center kidney exchange adoption. For example, a transplant center in Dallas joined the Alliance for Paired Donation in late 2010 and only performed one exchange transplant (in mid-2013) by the end of 2014. Meanwhile, a transplant center in Phoenix, also part of the Alliance for Paired Donation, performed its first exchange transplants in late 2009 and performed 47 exchange transplants total by the end of 2014 (OPTN STAR data as of December 31, 2014).

Table 2—Patient Distance to Transplant Center of Operation

Percentile	All	Exchange	Anonymous	Direct living	Deceased
10	4.12	5.63	4.38	4.85	3.74
20	7.30	9.79	7.34	8.49	6.65
30	11.09	13.79	10.76	12.62	10.16
40	16.05	21.00	14.66	18.07	14.82
50	24.01	29.75	21.11	26.10	22.49
60	36.07	43.71	31.89	38.45	34.53
70	56.21	65.36	49.59	58.74	54.45
80	86.93	103.21	81.10	93.05	83.40
90	146.22	193.37	182.88	163.57	137.81
Observations	231,796	4,070	1,514	82,019	144,193

Source: OPTN STAR data as of December 31, 2014

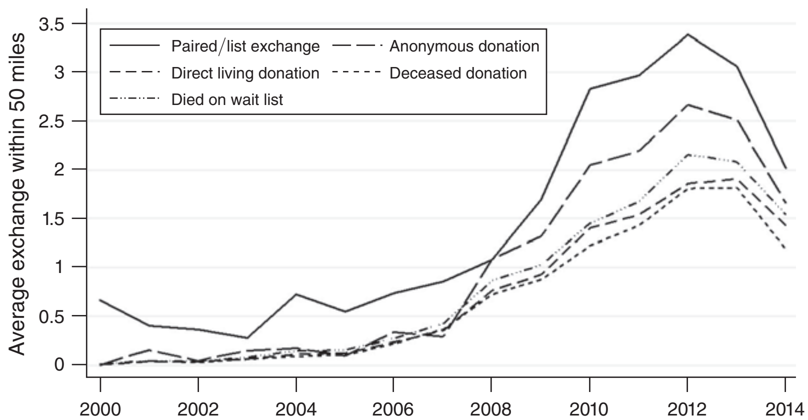

Figure 7. Number of Exchanges within 50 Miles, Excluding Own

Source: OPTN STAR data as of December 31, 2014

performed across two or more patient-donor pairs. Unsurprisingly, I find *Activity* to be strongly correlated with the number of patients receiving exchange transplants in a given zip code and month.

I use 50 miles as the default radius based on the percentiles presented in Table 2 and my prior on the distance most patients would be willing and able to travel to a transplant center. Most patients who receive transplants do so within 50 miles of their home zip code—between 60 and 70 percent overall. Figure 7 shows the average monthly number of exchanges performed within 50 miles for individuals in the sample over time and observed registration outcome. We see that this number ranges from 0 to 3.5 and tends to be higher for recipients of exchanges and anonymous donations, which supports the strength of the instrument. Since choice of 50 miles is admittedly somewhat arbitrary, I show in online Appendix C that the results are robust to the use of 30 and 75 mile radii.

To be valid, *Activity* must satisfy the exclusion restriction. That is, conditional on controls, it can only affect non-exchange quantity and quality outcomes through its effect on the number of exchange transplants. As discussed earlier, zip code and month fixed effects control for any national trends and time-invariant differences across locations in the dependent variables, location-specific linear time trends control for significant pre-trends in the outcomes of interest, and state-year fixed effects control for any correlated state-level policy shocks. Thus, the main threat to the exogeneity of *Activity* is whether transplant centers adopt and promote exchange as a transplant option in response to local idiosyncratic nonlinear trends in demand for exchange and/or transplant quantity and quality. To address this threat, I test whether local shocks to the outcome variables of interest predict future kidney exchange activity and find no clear evidence to support this concern. I present and discuss these results in more detail in online Appendix C.

Anecdotal evidence lends additional support, suggesting that the presence of a "champion"—a leader or small group of people motivated to implement new technology—is the driving force behind effective exchange adoption and promotion. For example, Garet Hil created the National Kidney Registry, a paired exchange consortium, after his daughter had to endure a "difficult and extensive donor search" (National Kidney Registry 2015). Additionally, centers with active exchange programs appear to be those with the resources necessary for such an undertaking.[20] Conversations with a prominent nephrologist who initiated the paired kidney donation program at the University of Michigan support the importance of these two criteria. While the latter may raise the concern that centers with sufficient resources to start or participate in exchange programs tend to be in areas with systematically different patient outcomes, the included set of time and location controls should alleviate this concern.

A second concern is that patients may endogenously move from areas of low exchange activity to areas of higher exchange activity in pursuit of an exchange transplant. While I cannot perfectly observe moving behavior, I do observe zip code of residence at the time of registration and at the time of transplant among patients who register on the deceased donor waiting list. Using this information, I analyze whether exchange activity near a patient's most recent zip code of residence predicts a change in zip code, whether exchange activity near a patient's original zip code predicts a change in zip code, and whether the *Activity* differential between a patient's original and most-recent zip code is correlated with the type of transplant received. The results, which I discuss further in online Appendix C, suggest that patients do not decide to change their zip code of residence based on local exchange activity.

V. Results

In this section, I present the main results from estimating the effect of exchange on transplant quantity and quality via OLS and using an instrumental variables approach. I address the primary concerns about the validity of the

[20] University hospitals are likely candidates to have a champion and the resources needed; 13 of the 20 most active kidney exchange centers are at university medical centers based on the number of exchanges performed between January 2000 and July 2014. The most active centers include Johns Hopkins Hospital, Methodist Specialty and Transplant Hospital, University of Michigan Medical Center, Northwestern Memorial Hospital, University of Maryland Medical System, and UCLA Medical Center (OPTN STAR data as of December 31, 2014).

Table 3—Estimating Substitution Patterns

	Exchange (first stage)	Direct living	Anonymous	Deceased	Died on wait list
Mean of dependent variable	[0.00089]	[0.018]	[0.00033]	[0.031]	[0.013]
Panel A. OLS estimates					
Exchange (count)	–	−0.32	−0.0070	−0.48	−0.19
	–	(0.0037)	(0.00057)	(0.0039)	(0.0034)
Panel B. Reduced form and IV estimates using Activity					
Nearby exchanges (excluding own)	0.00087	−0.00037	0.000064	−0.00038	−0.00018
	(0.000059)	(0.000097)	(0.000025)	(0.00012)	(0.00010)
Wald IV estimates	–	−0.43	0.073	−0.44	−0.20
	–	(0.11)	(0.029)	(0.13)	(0.12)
Observations	4,594,450	4,594,450	4,594,450	4,594,450	4,594,450
Number of zip codes	26,254	26,254	26,254	26,254	26,254

Notes: Clustered standard errors are in parentheses (at zip code level). Regressions include month-year fixed effects, zip code fixed effects, zip code-specific linear time trends, and state-year fixed effects. They also include controls for age at listing, previous transplant status, PRA score, blood type, gender, ethnicity, and education.

instrument, *Activity*, and also show the robustness of these main results to alternate choices of specification, estimation sample, *Activity*, and location-by-time control variables in online Appendix C.

A. *Quantity Estimates*

Table 3 presents the estimates of the effects of kidney exchange prevalence on the frequency of other registration outcomes.[21] The OLS estimates are presented in panel A, and the first-stage, reduced-form, and Wald IV estimates that exploit *Activity* as a plausibly exogenous measure of exchange prevalence are presented in panel B. The first column of panel B presents the first-stage estimate (ϕ): the effect of nearby exchange activity in the month of a patient's registration outcome on the probability that the patient receives a kidney via exchange. The estimated $\hat{\phi} = 0.00087$, relative to the sample average of 0.00089 exchange transplants per zip code month, implies that one additional exchange transplant within 50 miles of a patient increases the number of exchange transplants observed in a given zip code month by 98 percent. This estimate is highly significant with a t-statistic of 14.7, further supporting the importance of proximity to exchange activity with respect to obtaining a transplant via exchange.

The second through fifth columns present the substitution estimates of interest. The first row of panel B contains the reduced-form estimates (θ). The second row of panel B and first row of panel A contain, respectively, the Wald IV and OLS structural parameters of interest (λ). The second column reduced-form estimate implies that one additional nearby exchange transplant results in a statistically

[21] Note: All of the linear regression models in this paper are estimated using the Stata command reghdfe to accommodate the inclusion of several high-dimensional fixed effects. This command implements the estimator developed in Correia (2017).

significant reduction in the frequency of direct living donor transplants by 0.00037 (2.1 percent) relative to an average of 0.018. The substitution ratio of interest, $-0.00037/0.00087 = -0.43$, estimated directly via 2SLS and presented in the second row of panel B, implies that 43 percent of exchange transplant recipients would have received a direct living donor transplant in the absence of exchange. The corollary to this is that 57 percent would not have received a direct living donor transplant in the absence of exchange. Compared to the OLS substitution estimate of -0.32, this approach yields a larger estimate of substitution away from direct living donor transplants and contributes to a more conservative estimate of the net living donor transplant gains attributable to exchanges.

The third column reduced-form estimate implies that one additional nearby exchange transplant increases the frequency of anonymous donations by 0.000064 (19 percent) relative to an average of 0.00033. The corresponding substitution estimate of interest implies an *increase* of roughly 0.07 anonymous donations for every exchange transplant, as opposed to the OLS estimate of -0.007 that implies a small anonymous donation crowd-*out* effect. This increase in anonymous donations is a new finding; prior simulations rely on fixed pools of representative patient-donor pairs and therefore cannot account for an increase in donors from outside of the selected pool.

The fourth column reduced-form estimate implies that one additional nearby exchange transplant decreases the frequency of deceased donor transplants by 0.00038 (1.2 percent) relative to an average of 0.031. This implies substitution away from deceased donor transplants toward exchange transplants at a rate of 44 percent, compared to the OLS estimate of 48 percent. However, as discussed in Section II, it is likely that any estimated substitution here is explained by the allocation of deceased donor kidneys being shifted toward areas with less kidney exchange activity and does not affect the overall number of deceased donor organ transplants. Finally, the fifth column shows a statistically significant relationship between exchange and death on the waiting list; one additional nearby exchange transplant reduces deaths on the waiting list by 0.00018 (1.4 percent) relative to an average of 0.013. The substitution estimate implies that 20 percent of exchange transplant recipients would have died while waiting, which is nearly identical to the OLS estimate of 19 percent.

The direct living and anonymous estimates (columns 2 and 3) are key to determining the number of new living donor transplants that would not have occurred in the absence of exchange. The Wald IV estimates imply that 64 percent $(1 - 0.43 + 0.07)$ of exchange transplants represent new living donor transplants. The OLS estimates imply a nearly identical 67.3 percent $(1 - 0.32 - 0.007)$, though the differences in the underlying estimates call attention to the potential bias of OLS due to selection and reverse causality.[22]

[22] Suppose instead that I were to estimate the substitution parameters of interest via OLS using individual-level data and a linear probability model, where the key independent variable of interest is an indicator for whether a patient actually received an exchange transplant. With this approach, which is analogous to my approach to estimating transplant-quality effects, we would worry about selection and reverse causality because actual exchange transplant recipients appear to be sicker and harder to match. In this setting, such worries persist when aggregating to the zip code-month level. This is due to the fact that, even in the aggregated data, the number of direct living transplants (anonymous donations) is 0 in 96 percent (99.9 percent) of the observations that drive identification (i.e., those where the number of exchange transplants is greater than 0). In practice, this means that the OLS substitution

Table 4—Estimating Quality Effects

	Exchange (first stage)	Graft survival > 1 years	Graft survival > 2 years	HLA mismatches	Registration duration (days)
Mean of dependent variable	[0.018]	[0.93]	[0.88]	[3.64]	[604]
Panel A. OLS estimates					
Exchange (binary)	–	0.028	0.041	0.70	−214
	–	(0.0040)	(0.0058)	(0.022)	(9.34)
Panel B. Reduced form and IV estimates using Activity					
Nearby exchanges (excluding own)	0.0064	0.0013	0.0015	−0.00014	−2.45
	(0.00052)	(0.00057)	(0.00085)	(0.0034)	(1.54)
Wald IV estimates	–	0.21	0.24	−0.022	−384
	–	(0.093)	(0.13)	(0.54)	(240)
Observations	225,268	198,644	182,257	223,518	224,869
Number of zip codes	18,462	17,689	17,173	18,422	18,449

Notes: Clustered standard errors are in parentheses (at zip code level). Regressions include month-year fixed effects, zip code fixed effects, county-specific linear time trends, and state-year fixed effects. They also include controls for age at listing, previous transplant status, PRA score, blood type, gender, ethnicity, and education. The non-death-censored graft survival variables assume transplant survival for those whose last known status is alive with a functioning kidney transplant. Excludes patients who experienced a non-transplant outcome. One-year graft survival excludes 2013–2014 data; two years excludes 2012–2014. Waiting list registration duration is set to zero for the living-donor transplant recipients who do not register on the deceased-donor waiting list. Note that the results are not sensitive to this decision; dropping those patients instead yields a reduced-form estimate of −2.35 (1.58) and a Wald IV estimate of −375 (251).

B. *Quality Estimates*

Because OLS estimates of the impact of exchange on graft survival, HLA mismatches, and waiting list registration duration are also likely to be biased by selection issues and reverse causality, I identify these effects using *Activity* and present my preferred estimates in panel B of Table 4. The first column presents the first-stage parameter estimate, $\hat{\psi}$, from equation (11): one additional nearby exchange transplant increases the probability that a patient, conditional on experiencing a well-defined registration outcome, receives an exchange transplant by 0.0064 (36 percent) relative to an average of 0.018.

The reduced-form estimate, $\hat{\delta}$, in the second column suggests that one additional nearby exchange transplant increases the probability of one-year graft survival by 0.0013 percentage points. Thus, a 1 percentage point increase in the probability of receiving an exchange transplant increases 1-year graft survival by $\hat{\pi}_{1yr} = 0.21$ percentage points relative to an average of 93 percent, which translates directly into a 0.21 percentage point (3 percent) reduction in the average 1-year failure rate of 7 percent. Similarly, the third column reduced-form estimate suggests that one additional nearby exchange transplant increases the probability of 2-year graft survival by 0.0015 percentage points. This implies that a one percentage point increase in the probability of receiving an exchange transplant increases 2-year

estimates are very similar to their respective non-exchange outcome shares (see Table 1). The estimated effect on direct living transplants is −0.32, while direct living transplants comprise 28.4 percent $(27.99/(100 - 1.39))$ of all the well-defined non-exchange outcomes. These numbers are −0.007 and 0.53 percent for anonymous donations. Using a plausibly exogenous instrument such as *Activity* solves this problem.

graft survival by 0.24 percentage points relative to an average of 88 percent, i.e., a 0.24 percentage point (2 percent) reduction in the average 2-year failure rate of 12 percent. Compare this to the OLS estimates in panel A, which imply only a 0.03 percentage point (0.4 percent) reduction in the one-year failure rate and a 0.04 percentage point (0.3 percent) reduction in the two-year failure rate.[23]

The fourth column shows the effect of increasing exchange prevalence on HLA mismatches, one possible mechanism through which graft survival could improve (Opelz 1997). In contrast to the OLS estimate suggesting a one percentage point increase in the probability of receiving an exchange transplant *increases* HLA mismatches by 0.007 (0.70×0.01), the IV estimate implies that exchange has a very small negative and statistically insignificant effect on the number of HLA mismatches. Recall that Roth, Sönmez, and Ünver (2004) finds large reductions in HLA mismatches as exchanges are introduced; this is partially driven by patients choosing exchange over direct donation on the basis of HLA mismatches and donor age only, which does not appear to hold in reality. While exchange may enable patients to find closer matches, patients may also be willing to accept a slightly worse match instead of having to rely on a compatible family member, for example, who may be a much closer match. Moreover, if most of those receiving kidney exchanges are harder-to-match individuals and would not have received a transplant otherwise, then we would expect their transplants to put upward pressure on the average number of HLA mismatches.

The fifth column shows the effect of increasing exchange prevalence on registration duration, another mechanism through which graft survival could improve (Meier-Kriesche and Kaplan 2002). An additional nearby exchange transplant reduces registration duration by 2.45 days, though this result is just outside of the range of statistical significance at the 10 percent level. The magnitude of this estimate is, however, economically significant. It implies that a 1 percentage point increase in the probability of receiving an exchange transplant reduces registration duration by $384 \times 0.01 = 3.84$ days (0.6 percent) relative to an average of 604 days. This is larger in magnitude than the OLS estimate of 2.14 days (214×0.01), but does not appear to be statistically distinguishable. Part of this positive effect is likely driven by the net increase in living donor transplants, where waiting time is shorter than for a deceased donor transplant. It is also possible that reduced search frictions and reduced excess demand for deceased donor kidneys contribute to this effect, though there is no clean way to isolate these different components.

Note that these estimates of transplant quality are based on the subset of patients who receive a transplant. Because some of these recipients would not have received a transplant in the absence of exchange, it is possible that a change in the composition of recipients leads me to underestimate the beneficial effects of exchange on transplant quality. It is also possible that there is selection in who receives an exchange transplant, such that the results do not reflect the effects of exchange on the health outcomes of

[23] Graft failure is defined as failure of the transplanted kidney itself or the death of the transplant recipient. Note that the positive IV survival estimates are not sensitive to the exclusion of patients who die within one or two years with a functioning graft, nor dropping all patients who die within one or two years. Thus, they appear to reflect actual transplant quality improvements rather than compositional changes among transplant recipients.

transplant candidates more broadly. While imprecise, I present estimation results in online Appendix Table B3 that suggest an increase in exchange prevalence increases the probability that a patient receives a transplant within two years and four years, reduces the probability that they die within two years and four years, and reduces the probability that they still need a kidney (conditional on surviving) two years and four years following their initial deceased donor waiting list registration.

VI. Conclusion

On August 2, 2018, 94,932 candidates were waiting for a kidney (Organ Procurement and Transplantation Network 2018). The growing shortage of transplantable organs has driven economists, transplant practitioners, and lawmakers to develop creative solutions. The innovation of transplantation among patients with incompatible willing donors via exchange has grown in prevalence in recent years, facilitated by single-center registries and consortia of transplant centers using computer-optimized matching mechanisms.

Analyzing the extent to which exchange improves patient outcomes is the most direct way of evaluating efforts to introduce and promote this mode of transplantation. This paper is the first to tackle such an evaluation using administrative data on waiting list registrations, transplants, and follow-up visits. To identify the quantity and quality effects of interest, I construct and exploit a plausibly conditionally exogenous measure of time-varying local exchange activity using patient and transplant center location data.

The findings of this paper clearly illustrate the welfare gains that are possible when applying theoretical work on matching and mechanism design to real-world problems, particularly in markets where money cannot facilitate exchange. In particular, the preferred specifications imply that 43 percent of exchange transplant recipients would have received a direct living transplant in the absence of exchange, which turns out to be quite similar to the 48 percent substitution rate simulated by Roth, Sönmez, and Ünver (2004). The corollary is that 57 percent would not have received a direct living transplant. Combined with the estimated additional 0.07 additional anonymous altruistic living donations for each additional exchange transplant, this implies that 64 percent of exchange transplants represent new living donor transplants. Through June 30, 2018, there have been 7,271 transplants performed via exchange (Organ Procurement and Transplantation Network 2018). The results of this paper suggest that 4,653 of those represent living donor kidney transplants that would not have happened in the absence of exchange.

In addition to yielding many new living donor transplants, the evidence also shows that the increasing prevalence of exchange has a significant impact on transplant quality outcomes. Conditional on receiving a transplant of any kind, a 1 percentage point increase in the probability of receiving a transplant via exchange is shown to reduce 1-year transplant failure by 3 percent, reduce 2-year failure by 2 percent, and reduce registration duration by 3.8 days (0.6 percent). To put these estimates in context, exchange transplants grew from 0 percent of all transplants in 2000 to 3.9 percent in 2017 (Organ Procurement and Transplant Network 2018). These results are in line with what we would expect given that exchanges increase the number of living donor transplants performed. However, contrary to simulations (e.g., Roth, Sönmez, and Ünver 2004), there appears to be no effect on tissue type match quality.

The net increase in social welfare from a single living donor transplant ranges from an estimated \$473,000 (Schnier et al. 2018, based on Matas and Schnitzler 2004) to \$1.1 million (Held et al. 2016) depending on the gain in quality-adjusted life-years (QALY), value of a QALY, and the cost savings of living donor transplantation compared to continued dialysis. The cost savings alone range from roughly \$125,000 in 2014 US dollars (based on Matas and Schnitzler's \$94,579 in 2002 US dollars) to \$195,000 (Held et al. 2016), 75 percent of which represents savings to taxpayers (Held et al. 2016). A high-end estimate of the additional cost of facilitating an exchange transplant is \$6,000 based on the fees to join and use the services of the National Kidney Registry (Melcher et al. 2012).

The estimated cost reductions and net social welfare gains are substantial. Focusing only on cost savings, every exchange transplant reduces health care costs by an estimated \$74,000 to \$120,000, amounting to a total of \$520 to \$843 million, 75 percent of which accrues to US taxpayers. Considering net social welfare, every exchange transplant generates a net benefit of \$300,000 to \$700,000,[24] amounting to a total of \$2.1 to \$4.9 billion. However, caution is required when considering the cost reduction and welfare estimates as they do not include costs or benefits incurred by living donors.

All else equal, increasing the total number of transplants through the channel of living donation via exchange slows the growth of deceased donor kidney waiting lists. Moreover, as new living donor transplant recipients leave waiting lists earlier, the average waiting time for deceased donor kidneys also falls. These factors contribute to an increase in overall average graft survival, meaning patients who receive transplants live longer with a functioning kidney before passing away or having to search for another transplant.

As Roth, Sönmez, and Ünver (2004) shows, the proportion of patient-donor pairs who are able to be matched via exchange increases with the number of registered pairs. Moreover, there is substantial room for growth in kidney exchange by alleviating agency problems and the existing fragmentation of kidney exchange registries (Agarwal et al. 2018). These considerations, combined with my findings, should encourage existing kidney exchange programs, prospective kidney exchange programs, and policymakers to further promote exchange as a transplant option. To the extent that transplant programs, patients, and potential donors are constrained by the costs of participating in kidney exchange, or do not fully internalize the benefits, subsidies funded by the cost savings could increase participation and reduce fragmentation.

REFERENCES

Abadie, Alberto, and Sebastien Gay. 2006. "The Impact of Presumed Consent Legislation on Cadaveric Organ Donation: A Cross-Country Study." *Journal of Health Economics* 25 (4): 599–620.

Abdulkadiroğlu, Atila, Parag A. Pathak, and Alvin E. Roth. 2005. "The New York City High School Match." *American Economic Review* 95 (2): 364–67.

[24] Sample calculation: $(\$473{,}000 \times 0.64) - \$6{,}000 = \$296{,}720$ per exchange transplant.

Adams, A. Frank, III, A.H. Barnett, and David L. Kaserman. 1999. "Markets for Organs: The Question of Supply." *Contemporary Economic Policy* 17 (2): 147–55.

Agarwal, Nikhil, Itai Ashlagi, Eduardo Azevedo, Clayton R. Featherstone, and Ömer Karaduman. 2018. "Market Failure in Kidney Exchange." NBER Working Paper 24775.

Alliance for Paired Kidney Donation (APKD). 2015. "Matching Algorithm." http://paireddonation.org/about-us/algorithm/ (accessed on October 14, 2015).

Anderson, Drew M. 2015. "Direct and Indirect Effects of Policies to Increase Kidney Donations." https://www.aeaweb.org/conference/2016/retrieve.php?pdfid=862.

Andersson, Tommy, and Jörger Kratz. 2015. "Pairwise Kidney Exchange with Blood-Group Incompatibility." Lund University Department of Economics Working Paper 2015:2.

Ashlagi, I., D.S. Gilchrist, A.E. Roth, and M.A. Rees. 2011. "Nonsimultaneous Chains and Dominos in Kidney-Paired Donation—Revisited." *American Journal of Transplantation* 11 (5): 984–94.

Becker, Gary S., and Julio Jorge Elias. 2007. "Introducing Incentives in the Market for Live and Cadaveric Organ Donations." *Journal of Economic Perspectives* 21 (3): 3–24.

Byrne, Margaret M., and Peter Thompson. 2001. "A Positive Analysis of Financial Incentives for Cadaveric Organ Donation." *Journal of Health Economics* 20 (1): 69–83.

Callison, Kevin, and Adelin Levin. 2016. "Donor Registries, First-Person Consent Legislation, and the Supply of Deceased Organ Donors." *Journal of Health Economics* 49: 70–75.

Chandra, Amitabh, and Douglas O. Staiger. 2007. "Productivity Spillovers in Health Care: Evidence from the Treatment of Heart Attacks." *Journal of Political Economy* 115 (1): 103–40.

Chun, Youngsub, Eun Jeong Heo, and Sunghoon Hong. 2017. "Kidney Exchange with Immunosuppressants." http://www.fas.nus.edu.sg/ecs/events/seminar/seminar-papers/18-03-20.pdf.

Correia, Sergio. 2017. "Linear Models with High-Dimensional Fixed Effects: An Efficient and Feasible Estimator." http://scorreia.com/software/reghdfe/cite.html.

Currie, Janet, and Enrico Moretti. 2003. "Mother's Education and the Intergenerational Transmission of Human Capital: Evidence from College Openings." *Quarterly Journal of Economics* 118 (4): 1495–1532.

Davis, Connie L., and Francis L. Delmonico. 2005. "Living-Donor Kidney Transplantation: A Review of the Current Practices for the Live Donor." *Journal of the American Society of Nephrology* 16 (7): 2098–2110.

Delmonico, Francis L. 2004. "Exchanging Kidneys—Advances in Living-Donor Transplantation." *New England Journal of Medicine* 350 (18): 1812–14.

Delmonico, Francis L., Paul E. Morrissey, George S. Lipkowitz, Jeffrey S. Stoff, Jonathan Himmelfarb, William Harmon, Martha Pavlakis, et al. 2004. "Donor Kidney Exchanges." *American Journal of Transplantation* 4 (10): 1628–34.

Dickert-Conlin, Stacy, Todd Elder, and Brian Moore. 2011. "Donorcycles: Motorcycle Helmet Laws and the Supply of Organ Donors." *Journal of Law and Economics* 54 (4): 907–35.

Dickert-Conlin, Stacy, Todd Elder, and Keith Teltser. Forthcoming. "Allocating Scarce Organs: How a Change in Supply Affects Transplant Waiting Lists and Transplant Recipients." *American Economic Journal: Applied Economics*.

Fernandez, Jose M., David H. Howard, and Lisa Stohr Kroese. 2013. "The Effect of Cadaveric Kidney Donations on Living Kidney Donations: An Instrumental Variables Approach." *Economic Inquiry* 51 (3): 1696–1714.

Gjertson, David W., and J. Michael Cecka. 2000. "Living Unrelated Donor Kidney Transplantation." *Kidney International* 58 (2): 491–99.

Hanto, Ruthanne L., S. Saidman, Alvin E. Roth, and F. Delmonico. 2010. "The Evolution of a Successful Kidney Paired Donation Program." *Transplantation* 90: 940.

Held, P.J., F. McCormick, A. Ojo, and J.P. Roberts. 2016. "A Cost-Benefit Analysis of Government Compensation of Kidney Donors." *American Journal of Transplantation* 16 (3): 877–85.

Kessler, Judd B., and Alvin E. Roth. 2012. "Organ Allocation Policy and the Decision to Donate." *American Economic Review* 102 (5): 2018–47.

Kessler, Judd B., and Alvin E. Roth. 2014. "Don't Take 'No' for an Answer: An Experiment with Actual Organ Donor Registrations." NBER Working Paper 20378.

Lacetera, Nicola, Mario Macis, and Sarah S. Stith. 2014. "Removing Financial Barriers to Organ and Bone Marrow Donation: The Effect of Leave and Tax Legislation in the US." *Journal of Health Economics* 33: 43–56.

Li, Danyang, Zackary Hawley, and Kurt Schnier. 2013. "Increasing Organ Donation via Changes in the Default Choice or Allocation Rule." *Journal of Health Economics* 32 (6): 1117–29.

Matas, Arthur J., and Mark Schnitzler. 2004. "Payment for Living Donor (Vendor) Kidneys: A Cost-Effectiveness Analysis." *American Journal of Transplantation* 4 (2): 216–21.

Meier-Kriesche, Herwig-Ulf, and Bruce Kaplan. 2002. "Waiting Time on Dialysis as the Strongest Modifiable Risk Factor for Renal Transplant Outcomes: A Paired Donor Kidney Analysis." *Transplantation* 74 (10): 1377–81.

Melcher, M.L., D.B. Leeser, H.A. Gritsch, J. Milner, S. Kapur, S. Busque, J.P. Roberts, et al. 2012. "Chain Transplantation: Initial Experience of a Large Multicenter Program." *American Journal of Transplantation* 12 (9): 2429–36.

Melcher, Marc L., Jeffrey L. Veale, Basit Javaid, David B. Leeser, Connie L. Davis, Garet Hil, and John E. Milner. 2013. "Kidney Transplant Chains Amplify Benefit of Nondirected Donors." *JAMA Surgery* 148 (2): 165–69.

Mierzejewska, Beata, Magdalena Durlik, Wojciech Lisik, Caitlin Baum, Paul Schroder, Jonathan Kopke, Michael Rees, and Stanislaw Stepkowski. 2013. "Current Approaches in National Kidney Paired Donation Programs." *Annals of Transplant* 18: 111–23.

National Kidney Foundation (NKF). 2015. National Kidney Foundation. http://www.kidney.org/ (accessed July 13, 2015).

National Kidney Registry (NKR). 2015. National Kidney Registry. http://www.kidneyregistry.org/about_us.php (accessed October 27, 2015).

National Kidney Registry (NKR). 2017. *Paired Exchange Results Quarterly Report*. March, 2017. http://www.kidneyregistry.org/pages/p410/NKR_Quarterly_Report_Q1_2017.php.

Niederle, Muriel, and Alvin E. Roth. 2008. "The Effects of a Centralized Clearinghouse on Job Placement, Wages, and Hiring Practices." NBER Working Paper 13529.

Opelz, Gerhard. 1997. "Impact of Hla Compatibility on Survival of Kidney Transplants from Unrelated Live Donors." *Transplantation* 64 (10): 1473–75.

Organ Procurement and Transplantation Network (OPTN). 2018. Organ Procurement and Transplantation Network. http://optn.transplant.hrsa.gov/ (accessed April 27, 2018).

Roth, Alvin E., and Elliott Peranson. 1999. "The Redesign of the Matching Market for American Physicians: Some Engineering Aspects of Economic Design." *American Economic Review* 89 (4): 748–80.

Roth, Alvin E., Tayfun Sönmez, and M. Utku Ünver. 2004. "Kidney Exchange." *Quarterly Journal of Economics* 119 (2): 457–88.

Roth, Alvin E., Tayfun Sönmez, and M. Utku Ünver. 2005a. "Pairwise Kidney Exchange." *Journal of Economic Theory* 125 (2): 151–88.

Roth, Alvin E., Tayfun Sönmez, and M. Utku Ünver. 2005b. "A Kidney Exchange Clearinghouse in New England." *American Economic Review* 95 (2): 376–80.

Roth, Alvin E., Tayfun Sönmez, and M. Utku Ünver. 2007. "Efficient Kidney Exchange: Coincidence of Wants in Markets with Compatibility-Based Preferences." *American Economic Review* 97 (3): 828–51.

Roth, A.E., T. Sönmez, M.U. Ünver, F.L. Delmonico, and S.L. Saidman. 2006. "Utilizing List Exchange and Nondirected Donation through 'Chain' Paired Kidney Donations." *American Journal of Transplantation* 6 (11): 2694–2705.

Schnier, Kurt E., Robert M. Merion, Nicole Turgeon, and David Howard. 2018. "Subsidizing Altruism in Living Organ Donation." *Economic Inquiry* 56 (1): 398–423.

Segev, Dorry, Lauren Kucirka, Sommer Gentry, and Robert Montgomery. 2008. "Utilization and Outcomes of Kidney Paired Donation in the United States." *Transplantation* 86 (4): 502–10.

Sönmez, Tayfun, and M. Utku Ünver. 2015. "Enhancing the Efficiency of and Equity in Transplant Organ Allocation via Incentivized Exchange." https://ideas.repec.org/p/boc/bocoec/868.html.

Stoler, Avraham, Judd B. Kessler, Tamar Ashkenazi, Alvin E. Roth, and Jacob Lavee. 2017. "Incentivizing Organ Donor Registrations with Organ Allocation Priority." *Health Economics* 26 (4): 500–510.

Sweeney, Matthew. 2010. "Does the Public Provision of Kidneys Crowd Out Living Kidney Donation? A Regression Discontinuity Analysis." https://ecommons.cornell.edu/handle/1813/30691.

Teltser, Keith. 2019. "Do Kidney Exchanges Improve Patient Outcomes?: Dataset." *American Economic Journal: Economic Policy*. https://doi.org/10.1257/pol.20170678.

United Network for Organ Sharing (UNOS). 2015. United Network for Organ Sharing Transplant Living. http://www.transplantliving.org/before-the-transplant/about-organ-allocation/matching-organs (accessed July 13, 2015).

Ünver, M. Utku. 2010. "Dynamic Kidney Exchange." *Review of Economic Studies* 77 (1): 372–414.

Wellington, Alison J., and Edward A. Sayre. 2011. "An Evaluation of Financial Incentive Policies for Organ Donations in the United States." *Contemporary Economic Policy* 29 (1): 1–13.