May 2019

The Economic Analysis of Kidney-Exchange Networks

Roksana Ghanbariamin
Clemson University, roxana.ghanbari@gmail.com

THE ECONOMIC ANALYSIS OF KIDNEY-EXCHANGE NETWORKS

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Economics

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by
Roksana Ghanbariamin
May 2019

Accepted by:
Dr. Patrick Warren, Committee Chair
Dr. Robert Fleck
Dr. F. Andrew Hanssen
Dr. Devon Gorry

Abstract

This dissertation investigates the effects of the largest national kidney-exchange network, National Kidney Registry (NKR), on the speed of finding a transplant and the quality of donors in participant hospitals. It also examines the effect of surgeons in the network-adoption decision of hospitals.

The prohibition of monetary transactions for human organs under U.S. law generates a shortage of kidneys available for transplant. In 2017, about 100,000 patients were waiting on the long wait-lists to receive a kidney for transplant. Creation of distinct kidney-exchange networks that find compatible matches between patients who each have willing but incompatible living kidney donors reduced this shortage.

This dissertation uses the data from the scientific registry of transplant recipients and the National Kidney Registry data on the list of participant hospitals by year. The first chapter estimates the change in the probability of receiving a transplant conditional on wait-time for patients after a hospital adopts the NKR network. Using survival analysis accounting for the competing risks, I find that the probability of finding a transplant from a living donor increases by 0.25 percentage points in hospitals participating in the network. This positive effect is mainly driven from the additional indirect-living transplants that these networks can accommodate through exchange transplants.

The second chapter investigates how the quality of living donors changes as the use of the NKR network expands. I use the variation in the period before and after the adoption of NKR by hospitals and run a difference-in-differences method. Further, I use a Coarsend Exact Matching to correct for the imbalance between treatment and control groups. My

finding suggests that the quality of living donors as measured by age, body mass index, and blood type decreases in participant hospitals. Specifically, I show that living donors in NKR affiliated hospitals are on average 8 months older, have 0.19 points higher body mass indexes, and are 3.8 percent less likely to have an O blood-type.

The final chapter analyzes the fragmentation in the participation of hospitals in these networks. We (with Bobby W. Chung) investigate the influence of surgeons in expanding the use of the NKR by hospitals. We find that hospitals that are connected through mutual surgeons are more likely to adopt the NKR network. Specifically, we find that one more adoption by connected hospitals increases the probability of the focal hospital to adopt by about 4 percentage points. This trend shows a diminishing magnitude as the number of connected hospitals increases. This effect is stronger for surgeons that have performed a larger number of transplant surgeries and for hospitals that have more than one mutual surgeon.

Dedication

To my mother, **Marjan** - You are always the greatest inspiration of my life, yesterday, today, and tomorrow.

Acknowledgments

I owe a great deal to several people who helped me complete this dissertation, but the role of my advisor professor Patrick Warren has been unique. He is one of the advisors who not only provides invaluable comments on the context of his students' work but walks side-by-side of them in all the ups and downs of the Ph.D. journey. I will always remember his encouragement after my first presentation, his patience when I struggled, and his tireless guidance at every setback. I am also much indebted to professor Robert Fleck for his thoughtful comments on my papers and his unlimited support. I am also grateful to my other committee members professors Andrew Hanssen and Devon Gorry whom I have benefited tremendously from their depth of academic advice. Together, they created a scholarly family in the economics department of Clemson University for me to belong to when I needed most.

Coming to Clemson and pursuing my Ph.D. would not have happened if it was not for the support of my Master's advisor professor Glenn Jenkins. He proved to be an inexhaustible source of wisdom and generosity. Without his belief in me, constant guidance, and support all my efforts could have been in vain. I am also thankful to professors William Dougan, Arnold Harberger, Thomas Hazlett, the participants of Industrial Organization Seminars of Clemson University and the Wednesday Warren Workshops for helpful comments and suggestions that constantly improved the quality of my work.

I cannot thank my family enough for their love and understanding, and for helping me widen my personal view of the world. My mother, Marjan, is always ready to listen to

all the detailed stories that I have to tell over our weekly video calls. She has never ceased believing in me, even when I have no faith in myself. But above all, her determination taught me what it means to have big dreams and to fight for them. I also cherished the love of my beloved sister, Delaram, and brother, Ramin. They have, as always, given me courage and endless support in my most challenging moments by being there when I needed someone to talk and laugh with.

Finally, I would like to thank my Clemson family. Even though I was miles away from my family and childhood friends in a foreign country, I never felt lonely having them beside me in all the tough moments. I specifically want to thank: Steven, for being the best friend one can ask for, and for challenging me the most and encouraging me the most at the same time. Majid and Neda - for their warmhearted friendship and for making me feel like a part of their family. Liuna - for bearing me as her office mate, especially at times when we agreed on nothing. Kelsey - for all the moments we shared at Wednesday Warren Workshops and for letting me be one of Sebastian's aunts. Kimmie and Lisa - for transforming the economic department to a second home for us.

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Chapter 1

The Effect of the National Kidney Registry on the Probability of Receiving a Transplant

1.1 Introduction

A kidney transplant is the preferred method of treatment for End-Stage Renal Disease (ESRD) patients. It increases the life expectancy of the recipients of transplants by ten years on average (Wolfe et al. 1999; APD 2018). A transplant is also much less costly than dialysis, the alternative treatment. Each kidney transplant for a Medicare beneficiary saves the government about $270,000 in present value (Wolfe et al. 1999; Held et al. 2016). Between the increase in life expectancy and the costs saved, each transplant generates $1.1 million in social value (Held et al. 2016). However, there is a significant shortage of kidneys available for transplant. In 2018, approximately 110,000 patients were waiting on the wait list for a kidney transplant (OPTN 2018).

The growing difference between quantity supplied and quantity demanded for transplantable kidneys, and the hefty cost of dialysis precipitated the search for a solution to alleviate the shortage of kidneys. Creation of kidney-exchange networks, which provide

a market that enables patients with living but incompatible donors to swap donors, was the solution proposed by Roth et al. (2004). The previous literature has focused on expanding the number of transplants from creating a large pool of available patient-donor pairs in kidney-exchange networks.[1] However, the literature lacks an empirical evaluation of the magnitude of the effect of national kidney-exchange networks in expanding the number of transplants.

This paper is the first to empirically investigate the causal effect of the adoption of the largest national network, the National Kidney Registry (NKR), by a hospital on the probability of receiving a transplant conditional on wait-time for patients. I use a survival analysis estimation to capture the effect of hospitals' decision on joining NKR on the probability of receiving a transplant for patients. Furthermore, to account for the existence of other events, other than receiving a transplant, that a patient can experience waiting on the wait-list, I use a survival analysis with competing risks following Hinchliffe and Lambert (2013) and Royston and Parmar (2002).

My results suggest that NKR participation increases the probability of receiving a living transplant conditional on wait-time by 0.25 percentage points. The extra number of living transplants that are generated are mainly due to the expansion of the indirect living transplants through exchange transplants. Furthermore, the results provide some evidence for substitution between deceased transplants and living transplants.

1.2 Institutional Background

For an ESRD patient, a kidney transplant is the preferred method of treatment compared to dialysis, due to its higher life expectancy and lower cost. The life expectancy of the recipients of a transplant is on average ten years higher than patients on dialysis

[1]The original idea started with Roth et al. (2004) and Roth et al. (2005) who introduced the idea of emerging national kidney-exchange networks. Ashlagi and Roth (2014) focused on expanding the original model, to an alternative that provides incentives for hospitals to register all of their patient-donor pairs in these national networks. Agarwal et al. (2018) estimated the additional number of transplants from merging all kidney-exchange networks into the largest national network in the United States. Teltser (2018) evaluated the additional number of transplants created from kidney exchanges using differences in the patient's local exchange activity over time.

(Wolfe et al. 1999; APD 2018). In addition, 7% of the annual budget of Medicare is spent on ESRD patients, the majority of which is used to finance dialysis cost (Agarwal et al. 2018). A kidney transplant for a Medicare beneficiary saves the government about $270,000 in present value (Wolfe et al. 1999; Held et al. 2016). These cost savings are even more substantial for a privately insured patient (Irwin et al. 2012).[2].

Before 2004, the only option for an ESRD patient with a willing but incompatible living donor was waiting on the deceased-donor list for a cadaver kidney. The shortage of transplantable kidneys, created from the prohibition against monetary compensation of human organs by United States law, generates the need for creative solutions to make better use of the incompatible living donors.[3] The introduction of kidney exchanges provided the opportunity of donor swapping for incompatible patient-donor pairs (Roth et al. 2005). In addition to the extra number of transplants created by making better use of incompatible living donors, a transplant from a living donor has a higher quality. A transplant from a living donor has on average 12 years higher graft survival rate, compared to a transplant from a deceased donor (APD 2018).

Initially, kidney exchanges were managed by single hospitals within the population of incompatible patient-donor pairs in that hospital. The need for a thick marketplace constituting a larger pool of patients and donors emerged across hospital kidney-exchange programs, starting from small, local networks, and expanding to three national ones. Today, there are numerous single-hospital programs, several multi-hospital ones, and three major national pairing organizations each with some hospital participants in the United States.

The leading national pairing organization in the U.S. is the National Kidney Registry (NKR). The NKR was the first major network to organize living-donor kidney exchanges nationwide since 2007 effectively. Medical-compatibility and some recipients' preferences

[2] "Typical patients covered by commercial insurance can expect to become Medicare primary well before they receive a kidney transplant. If these patients are transplanted preemptively before starting dialysis, there is a net benefit to the commercial payer of $250,000 to $400,000 for cost avoidance during the 33 months Medicare is the secondary payer, and to Medicare, the net benefit will be over $100,000 for the average of 16 months Medicare would become primary before transplantation." (Irwin et al. 2012)

[3] According to 42 U.S. Code §274e "It shall be unlawful for any person to knowingly acquire, receive, or otherwise transfer any human organ for valuable consideration for use in human transplantation if the transfer affects interstate commerce."

regarding their donors is the base of pairing in this network. The NKR runs the matching on a daily basis. Match-runs maximize the number of potential transplants, after giving priority to some hard-to-match patients. Once a match was accepted, the NKR imposes a strict timetable and sets forth rigid guidelines for the transportation of kidneys between hospitals. The NKR charges hospitals roughly 4,000 dollars per transplant to cover operational expenses, in addition to the annual membership fee (Ellison 2014). The number of exchange transplants grew gradually as hospitals' adoption of NKR expanded following its introduction in 2007 (Figure 1.1), and there are about a hundred hospitals that are currently participating in this network. The NKR is still the leading network in accommodating across-hospital kidney-exchange transplants (Figure 1.2), and as of July of 2018, they have facilitated about 2,800 kidney transplants (NKR 2018).

The other national networks are the Alliance for Paired Donation and Kidney Paired Donation Pilot Program of United Network for Organ Sharing which started operating in 2007 and 2010, respectively.[4] Despite a large number of hospital participants in these two networks, the total number of transplants they have facilitated together is about one-fifth of the number of transplants in the NKR.[5] This is mainly due to their stricter matching criteria, and their weaker reputation compared to the NKR. As Figure 1.2 shows, these two national networks together with all the other local networks constitute a small part of across hospitals exchange transplants. Therefore, the focus of my analysis is on the NKR for the remainder of this paper.

[4]The United Network for Organ Sharing is the private, non-profit organization that manages the organ transplant system of the United States under contract with the federal government.

[5]A large number of hospitals participating in the other two national networks are mainly because these networks are free of charges. Hospitals' participation in these three networks are not mutually exclusive, but the other two networks facilitated a very small number of across hospital exchange transplants, overall.

1.3 Empirical Framework

1.3.1 Single-Risk Survival Analysis

In the single-risk survival model, T is defined as the number of months a patient remains on the wait list for a kidney transplant. The event of interest is receiving a deceased or a living transplant. All patients start their search for a kidney at $t = 0$, irrespective of calendar time. The probability density function of T, $f(t)$, gives the probability that the event of interest has occurred by time t. The hazard function, $h_i(t)$, is defined as the conditional probability that a patient, who has remained on the wait list for a period from 0 to t, receives a transplant in the interval of $(t, t + dt)$, and it is defined by

$$h_i(t) = \lim_{dt \to 0} \frac{Pr(t \leq T_i < t + dt | T_i \geq t)}{dt}. \tag{1.1}$$

The hazard rate is modeled as a function of exogenous individual-level covariates x capturing the corresponding increase or decrease in risk associated with each of the characteristics. Thus, the hazard function is

$$h_i(t|x_i) = h_0(t) exp(\beta' x_i), \tag{1.2}$$

where the baseline hazard function $h_0(t)$ describes the risk of the hazard for an individual with $x_i = 0$. The model can be written in terms of the cumulative hazard function as

$$H_i(t|x_i) = \left\{ \int_0^t h_0(u) du \right\} exp(\beta' x_i) = H_0(t) exp(\beta' x_i). \tag{1.3}$$

One common approach to estimate the above model is to make an assumption about the functional form of the baseline hazard function. I use a flexible parametric version of the Cox model introduced by Royston and Parmar (2002), which uses a cubic spline function of log time to model the logarithm of the baseline cumulative hazard function. Thus, (1.3)

can be written as

$$lnH_i(t|x_i) = lnH_0(t) + \beta' x_i = s(ln(t)) + \beta' x_i. \tag{1.4}$$

The idea of spline smoothing of the baseline hazard distribution was originally suggested by Efron (1988). Natural cubic spline functions, $s(z)$, are cubic splines that are bounded to be linear at the endpoint knots k_{min} and k_{max}. In addition, m internal knots can be specified between the two endpoints $k_{min} < k_1 < .... < k_m < k_{max}$, and the complexity of the model depends on the number of such nodes. The natural cubic spline of $z = log(t)$ can be written as

$$s(z) = \gamma_0 + \gamma_1 z + \gamma_2 \upsilon_1(z) + ... + \gamma_{m+1}\upsilon_m(z), \tag{1.5}$$

in which the υ_j also known as the basis function is determined for $j = 1, ..., m$ using

$$\upsilon_j(z) = (z - k_j)_+^3 - \eta_j(z - K_{min})_+^3 - (1 - \eta_j)(z - K_{max})_+^3, \tag{1.6}$$

$$and,$$

$$\eta_j = \frac{k_{max} - k_j}{k_{max} - k_{min}}, (z - a)_+^3 = max(0, (z - a)^3).$$

Since the derivative of cubic spline function is well-defined, the hazard function is easy to calculate. Specifically, to test the hypothesis that the probability of receiving a transplant conditional on wait-time varies between patients who are in an NKR hospital, and the non-NKR ones, I specify the hazard function as

$$lnH_{ihy}(t|\mathbf{X}) = s(ln(t)) + NKR_{hy}\beta_1 + X_{ihy}\beta_2 + POP_{hy}\beta_3 + \tau_y + \sigma_h, \tag{1.7}$$

where NKR is a dummy variable equal to one if the patient was listed in an NKR affiliated hospital after the adoption day of the hospital, and zero otherwise. The set of regressors in X_{ihy} includes personal controls since patients have different probabilities of finding a transplant based on their medical and demographic characteristics. I use the patient's

age, gender, race, education, body-mass index (BMI), Panel Reactive Antibody (PRA), O blood-type dummy, and a dummy for patients under Medicare as control variables. Furthermore, to account for the differences in the number of patients each hospital receives, I use the United States Bureau of the Census data to include a control for the population of the state where the hospital is located in over time, POP_{hy}. Finally, all estimates include a vector of hospital dummies, σ_h, that control for mean differences in the hazard rate across hospitals, and year dummies, τ_y, that control for the changes in the hazard rate over time common to all hospitals.

In single-risk survival analysis, subjects are followed until either they experience the event of interest or are censored. In other words, we observe only the minimum of T and C, where C is the censoring time. This setup assumes that the censoring mechanism is non-informative, and anyone in the censored population should have the same likelihood function. More specifically, the censored individual should acquire no information regarding the expectation of survival of that observation. (Rodriguez 2007)

Competing-risk arises when individuals are at risk of experiencing more than one type of event, in which the occurrence of one of them might preclude the incidence of others. The existence of competing-risk violates the above assumption because some of the censored population that experience a competing-risk convey information regarding the survival of those observations. Estimating the difference in the transplant rate without accounting for competing-risk can result in biased estimation, and the direction of bias depends on the frequency of the different types of competing events in the treatment group. For example, if the censored observations in NKR hospitals have a higher rate of death while waiting, single-risk survival estimation would result in an upward bias in the probability of receiving a transplant in NKR affiliated hospitals.

1.3.2 Competing-Risk Survival Analysis

In survival analysis, subjects are often at risk of more than one mutually exclusive event, and the incident of one of them may prevent the event of interest from ever happening.

For example, the probability of being removed from the wait list due to receiving a transplant depends upon the removal rate due to death while waiting, and removal due to other reasons. Figure 1.3 depicts the difference in hazard definition between single-risk and competing-risk survival analysis models.

When competing risks are present, one should consider both the survival time and the event type ($k = 1, ..., K$). The cause-specific cumulative incidence function for cause k is defined as $F_k(t) = Pr(T \leq t, cause = k)$, which describes the probability of receiving a transplant by time t accounting for the competing events. The cause-specific hazard function for cause k, $h_i^k(t)$, is defined as the conditional probability that a patient, who has not experienced any of the competing events in the period of 0 to t, gets a transplant in the interval of $(t, t + dt)$. Thus, the cause-specific hazard is defined by

$$h_i^k(t) = \lim_{dt \to 0} \frac{Pr(t \leq T_i < t + dt, cause = k | T_i \geq t)}{dt}. \tag{1.8}$$

Based on equation (1.8), the cause-specific hazard for event k depends on the cause-specific hazard of all the other $K - 1$ events and requires separate models for each event. The problem with fitting separate models for each cause is that it does not allow the inclusion of shared parameters. Hinchliffe and Lambert (2013) use the flexible parametric model introduced by Royston and Parmar (2002) to fit one model for all events simultaneously, which enables one to estimate the direct effect of covariates on the cause-specific cumulative incidence function of event k without the need to model the other events. They transform the data set by stacking it in a format where each individual has k rows of data, one for each event, so each patient is at risk of experiencing any of the events.[6] This will allow one to incorporate both covariates that are shared across events, and covariates that vary for each event. To test the difference in the probability of receiving a transplant in NKR and

[6]Table 11 in the Appendix demonstrates how the data should look after they have been expanded.

non-NKR hospitals in the presence of competing risks, I specify the hazard function as

$$\begin{aligned} lnH^k_{ihy}(t|\mathbf{X}) = &\sum_{j=1}^{4} C_j(ln(t)) + \sum_{j=1}^{4} \beta_j C_j(ln(t)) \times NKR_{hy} + \\ &\sum_{j=1}^{4} \delta_j C_j(ln(t)) \times X_{ihy} + \sum_{j=1}^{4} \theta_j C_j(ln(t)) \times POP_{hy} + \tau_y + \sigma_h, \end{aligned} \tag{1.9}$$

where $\sum_{j=1}^{4} C_j(ln(t))$ are the four cause indicators depicted in Table 4. I fit a stratified model with four baselines by including the four cause indicators as both main effects and time-dependent effects. The interaction between NKR and the cause indicators captures the distinct treatment effect for each of the four causes. More specifically, it captures the effect of NKR on the probability of experiencing any of the four events. Also, by including the interaction of each of the cause indicators with covariates, I allow for each covariate to vary by each cause separately. Finally, year and hospital fixed effects are shared across the four events.

1.4 Data Description

This study used data from the Scientific Registry of Transplant Recipients (SRTR). The SRTR data system includes data on all donor, wait-listed candidates, and transplant recipients in the US, submitted by the members of the Organ Procurement and Transplantation Network (OPTN). The Health Resources and Services Administration (HRSA), U.S. Department of Health and Human Services provides oversight to the activities of the OPTN and SRTR contractors. Each registration provides detailed medical and demographic characteristics of the individual patients, their registration date, their status on the wait list, including removal from the waiting list if applicable, the removal reason, and the removal date. I merge patients data with the data from the NKR network on the list of hospitals in the network by adoption year.

I restrict my analysis to all the patients registered beginning in January 2000 through

September 2017. Observations before 2000 are omitted due to the poor reporting quality of the variables of interest. I drop individuals who were removed due to improvement in the candidate's condition, refusing transplant, closure of their hospital, transfer to kidney and pancreas waiting list, receiving a transplant in another country, and removal by error or other unknown reasons. Additionally, I drop patients who have a removal code but do not have a registration or removal date, as the wait-time duration is unknown for them. Table 1.1 reports the summary statistics of transplant wait-time.

The duration is the number of months a patient stays on the transplant wait list, and the event of interest is receiving a transplant. Individuals are tracked from 1 to 60 months, the mean and median wait-time of patients are 24.74, and 19.9 months, respectively. They are either removed from the waiting list in this period or are still waiting on the list.[7] Removal can be due to receiving a transplant (from a deceased or a living donor) or due to death on the wait list, getting too sick for a transplant, being transferred to another hospital, getting a transplant in another hospital, and losing track of the patient. There are 505,686 observations in the dataset, from which 227,951 (45.07%) receive a transplant.

I use the described data to test whether the probability of receiving a transplant, conditional on wait-time, is different between patients who are registered in NKR affiliated hospitals and the non-affiliated ones.

1.5 Results

The baseline hazard model is estimated using a cubic spline function with four knots.[8] The number of knots is selected using the Akaike Information Criterion (AIC) (Royston and Parmar 2002).[9] Table 1.3 reports the result of estimating (1.7) using the flexible parametric proportional-hazard model.[10] The hazard rate for the group of patients

[7]For patients who are still waiting, I consider the last day of the data as their last follow-up date.

[8]The results are not sensitive to the selection of the number of knots. I provide a robustness check for results using a different number of knots for the baseline hazard in Table 10 in the Appendix.

[9]Table 9 in the Appendix depicts the differences in the AIC between assigning a different number of knots for the baseline hazard function.

[10]The correct choice of spline function for the baseline hazard gives an estimate which is very close to Cox model estimation. I provide an estimation of equation (1.7) using a Cox model in Table 1.3 for comparison.

in NKR affiliated hospitals indicates that controlling for the characteristics of patients, those that are listed in NKR hospitals have a higher probability of receiving a transplant, but this difference is not statistically significant. The result in Table 1.3 relies on the assumption that anyone who was listed on the waiting list and did not receive a transplant is in the censored population with the same likelihood function. However, the censored population in the single-risk estimation consists of patients who died or got too sick for a transplant, patients who were transferred to another hospital, and patients who got a kidney transplant in another hospital.

I exploit the information on reasons for removal from the wait list to allow for estimating a cause-specific hazard model. Table 1.4 shows the hazard rates estimated from (1.9). According to the results, patients who were listed in NKR affiliated hospitals, compared to non-NKR ones have higher probabilities of transplant, death (or getting too sick) while waiting, and receiving a transplant in another hospital, but none of these are statistically significant. However, patients listed in hospitals that adopted NKR are 0.34 percentage points less likely to be transferred to another center.

The target of the NKR, and kidney-exchange networks in general, is expanding the use of incompatible living donors. Therefore, I extend the estimation further to capture the difference in the rate of transplants from living and deceased kidney-donors in NKR and non-NKR affiliated hospitals, separately. Table 1.5 reports the result of this estimation, indicating that patients who were listed in NKR affiliated hospitals are 0.25 percentage points more likely to receive a transplant from a living donor. The coefficient on the deceased transplants indicates that patients in NKR affiliated hospitals have a lower probability of receiving a transplant from a deceased donor as well. Nonetheless, this coefficient is not statistically different from zero at 10% confidence interval. These results are suggesting that there is some degree of substitution from deceased-donor transplants to living-donor ones after the adoption of the NKR by a hospital.

Furthermore, to capture the effect of NKR on exchange transplants, I expand the competing events by dividing living donors into the exchange, and direct-living transplants.

Table 1.6 and Figure 1.4 report the result of this estimation. According to Table 1.6, NKR increases the probability of receiving an exchange and direct-living transplant by 1.90 and 0.11 percentage points, respectively. This difference is more pronounced in Figure 1.4. While there is a substantial difference in the rate of exchange transplants between NKR and non-NKR affiliated hospitals, the difference in transplants from direct-living and deceased donors are small, and not statistically significant at 5%.

The findings in this section confirm that participation in the NKR network by a hospital increases the probability of receiving a transplant from a living-donor for its patients. Furthermore, most of this increase comes from the tremendous growth in the probability of obtaining an exchange transplant, where patients can swap their incompatible living donors. While there is no significant improvement in the probability of receiving a transplant in NKR hospitals, the substitution from deceased-donor transplants to living-donor ones can improve the quality of transplants for patients listed in NKR hospitals. In the following section, I investigate the effect of the adoption of this exchange platform on the quality of donors that patients bring into these hospitals.

1.6 Conclusion

The number of kidney-exchange transplants grew gradually after the introduction of the National Kidney Registry (NKR) in 2007, increasing the pool of patient-donor pairs willing to participate in an exchange. With the expansion of hospitals' use of NKR, the questions that arise are how effective is this network in expanding the number of transplants. This paper analyzes the effects of hospitals' adoption of NKR network on the probability of receiving a transplant conditional on wait-time using variation in NKR adoption by different hospitals and years.

This study uses the unique data set of the Scientific Registry of Transplant Recipients (SRTR) merged with NKR data on participant hospitals. The data allow me to identify the hospitals' participation status in the NKR in each year, subsequent medical

and demographic characteristics of patients and donors, the registration date, status on the wait list including reasons for removal, and the removal date of patients in these hospitals.

The estimates suggest that hospitals NKR participation increases the probability of receiving a living transplant for their patients. This larger number of transplants are accommodated by expanding the use of incompatible patient-donor pairs through exchange transplants. One of the surprising findings of this study is that participation in NKR does not have a significant effect in increasing the probability of receiving a transplant overall, but it induces substitution from the deceased kidney transplant to a living one. A relatively lower quality living donor is preferred to a transplant from a deceased donor, due to their higher graft survival rate.

Table 1.1: Summary Statistic of Transplant Wait Time by NKR Participation

	Total	NKR	Non-NKR
Mean Waiting Time (Months)	24.74	22.74	25.52
Median Waiting Time (Months)	19.9	17.83	20.8
Maximum Follow-up (Months)	60	60	60
Number of Patients	505,686	141,365	364,321
Number of Hospitals	287	98	189
Mean of Removal Due to:			
Transplants	0.451	0.349	0.490
Living-Transplants	0.154	0.146	0.157
Deceased-Transplants	0.297	0.203	0.334
Death or too Sick for Transplants	0.164	0.131	0.177
Transferred Patients	0.042	0.023	0.049
Transplants Elsewhere	0.056	0.046	0.059
Exchange Transplants	0.015	0.024	0.012
Direct-Living Transplants	0.139	0.122	0.145

Note: The sample includes every patient who was registered on the wait list to receive a transplant between January 2000 to July 2017.

Table 1.2: Summary Statistic of Competing Events by NKR Participation

	Total	NKR	Non-NKR
Number of Removal Due to:			
Transplants	227,951	49,282	178,669
Living-Transplants	77,719	20,571	57,148
Deceased-Transplants	150,232	28,711	121,521
Death or too Sick for Transplants	82,968	18,576	64,392
Transferred Patients	21,022	3,265	17,757
Transplants Elsewhere	28,323	6,550	21,773
Exchange Transplants	7,580	3,340	4,240
Direct-Living Transplants	70,139	17,231	52,908

Note: The sample includes every patient who was registered on the wait list to receive a transplant between January 2000 to July 2017.

Table 1.3: Probability of Receiving a Transplant

	Cubic Spline Model	Cox Model
NKR	1.0653	1.0653
	(0.045)	(0.045)
Patient's Age	0.9895***	0.9895***
	(0.001)	(0.001)
Body Mass Index	0.9780***	0.9780***
	(0.001)	(0.001)
O Blood-Type	0.7115***	0.7116***
	(0.007)	(0.007)
Panel Reactive Antibody	0.9911***	0.9911***
	(0.000)	(0.000)
Female	1.0905***	1.0905***
	(0.007)	(0.007)
Black	0.6883***	0.6884***
	(0.012)	(0.012)
Other Ethnicity	07153.***	0.7154***
	(0.013)	(0.013)
College Education	1.0745***	1.0745***
	(0.011)	(0.011)
Medicare	0.9036***	0.9037***
	(0.011)	(0.011)
State Population/1000	0.9658	0.9658
	(0.022)	(0.022)
Observations	498,544	498,544
Year FE	Yes	Yes
Hospital FE	Yes	Yes

Notes: Exponentiated coefficients (hazard ratios) are reported with corresponding standard errors. The probability of receiving a transplant is calculated using a single-risk hazard function by fitting a cubic spline function for the baseline hazard. I also provide the estimation using a Cox model for robustness check. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and *, respectively. Standard errors are in parentheses and are clustered at the hospital level.

Table 1.4: Probability of Being Removed from the Transplant Wait List (Competing Risks)

	All Transplants	Died or too Sick for Transplant	Transferred Elsewhere	Transplant Elsewhere
NKR	1.0463	1.0422	0.6610***	1.1004
	(0.040)	(0.054)	(0.077)	(0.106)
Patient's Age	0.9891***	1.0406***	0.9873***	0.9935***
	(0.001)	(0.001)	(0.001)	(0.001)
Body Mass Index	0.9771***	0.9900***	0.9899***	0.9772***
	(0.001)	(0.001)	(0.002)	(0.002)
O Blood-Type	0.7152***	0.9042***	0.9386***	0.8352***
	(0.006)	(0.008)	(0.016)	(0.013)
Panel Reactive Antibody	0.9912***	0.9971***	0.9946***	0.9948***
	(0.000)	(0.000)	(0.001)	(0.000)
Female	1.0921***	1.0125	1.1002***	1.0167
	(0.007)	(0.011)	(0.021)	(0.016)
Black	0.6586***	0.8872***	0.7679***	0.6453***
	(0.015)	(0.017)	(0.055)	(0.035)
Other Ethnicity	0.7110***	0.7661***	0.8742**	0.8089***
	(0.016)	(0.022)	(0.058)	(0.046)
College Education	1.0915***	0.8942***	1.1909***	1.7825***
	(0.013)	(0.011)	(0.062)	(0.109)
Medicare	0.9141***	1.3578***	0.7856***	1.0515
	(0.011)	(0.022)	(0.031)	(0.036)
State Population/1000	0.9745	0.9887	0.9997	0.9834
	(0.018)	(0.019)	(0.020)	(0.017)
Observations		498,544		
Year FE		Yes		
Hospital FE		Yes		

Notes: Exponentiated coefficients (hazard ratios) are reported with corresponding standard errors. The results are reported by expanding the data and fitting one model for all k events simultaneously. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and *, respectively. Standard errors are in parentheses and are clustered at the hospital level.

Table 1.5: Probability of Being Removed from the Transplant Wait List(Competing Risks)

	Living Transplants	Deceased Transplants	Died or too Sick for Transplant	Transferred Elsewhere	Transplant Elsewhere
NKR	1.2585***	0.9369	1.0423	0.6614***	1.1008
	(0.078)	(0.051)	(0.054)	(0.079)	(0.106)
Patient's Age	0.9802***	0.9944***	1.0406***	0.9872***	0.9934***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Body Mass Index	0.9813***	0.9758***	0.9900***	0.9899***	0.9772***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
O Blood-Type	0.7854***	0.6841***	0.9041***	0.9386***	0.8352***
	(0.007)	(0.009)	(0.008)	(0.016)	(0.014)
Panel Reactive Antibody	0.9851***	0.9934***	0.9971***	0.9946***	0.9948***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Female	1.133***	1.0693***	1.0127	1.1004***	1.0170
	(0.012)	(0.009)	(0.011)	(0.021)	(0.017)
Black	0.3699***	0.8302***	0.8888***	0.7690***	0.6463***
	(0.012)	(0.024)	(0.018)	(0.055)	(0.035)
Other Ethnicity	0.5277***	0.8361***	0.7664***	0.8741**	0.8091***
	(0.017)	(0.027)	(0.022)	(0.057)	(0.046)
College Education	1.4752***	0.9357***	0.8943***	1.1904***	1.7820***
	(0.029)	(0.013)	(0.011)	(0.062)	(0.109)
Medicare	0.5476***	1.1594***	1.3581***	0.7853***	1.0513
	(0.011)	(0.017)	(0.022)	(0.032)	(0.036)
State Population/1000	0.9765	0.9697*	0.9859	0.9971	0.9808
	(0.018)	(0.017)	(0.018)	(0.019)	(0.016)
Observations			498,544		
Year FE			Yes		
Hospital FE			Yes		

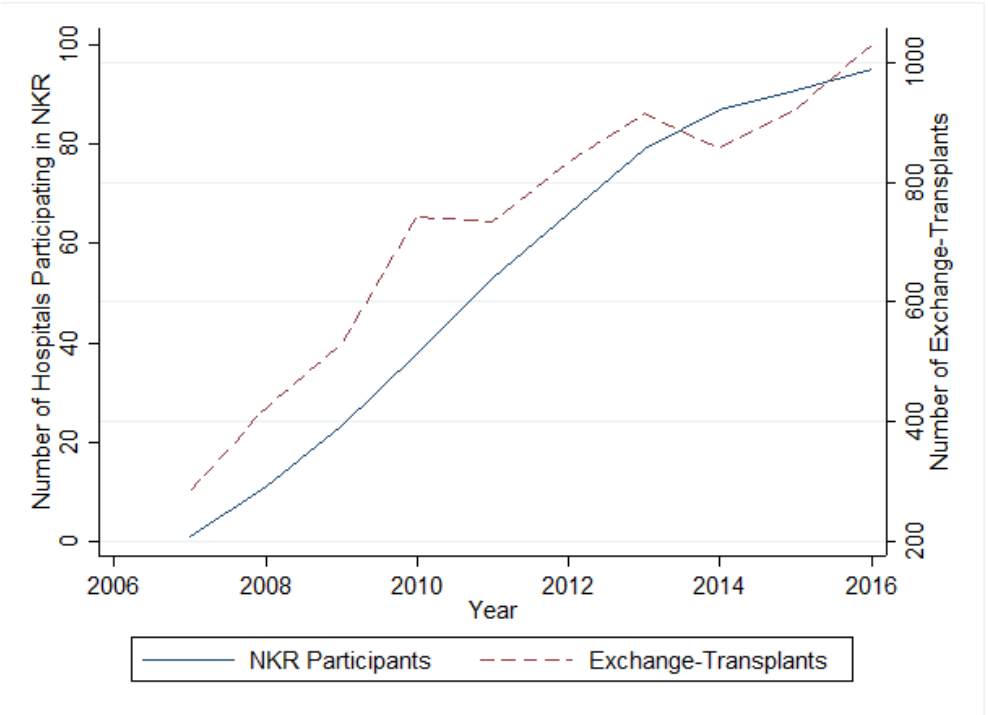
Notes: Exponentiated coefficients (hazard ratios) are reported with corresponding standard errors. The results are reported by expanding the data and fitting one model for all k events simultaneously. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and *, respectively. Standard errors are in parentheses and are clustered at the hospital level.

Table 1.6: Probability of Receiving Different Types of Transplants

	Exchange Transplant	Direct-Living Transplant	Deceased-Donor Transplant
NKR	2.9072***	1.1135*	0.9387
	(0.307)	(0.067)	(0.051)
Patient's Age	0.9816***	0.9802***	0.9944***
	(0.001)	(0.001)	(0.001)
Body Mass Index	0.9885***	0.9806***	0.9757****
	(0.003)	(0.001)	(0.001)
O Blood-Type	0.6398***	0.8041***	0.6841***
	(0.020)	(0.011)	(0.009)
Panel Reactive Antibody	0.9974***	0.9829***	0.9934***
	(0.001)	(0.000)	(0.000)
Female	1.1687***	1.1302***	1.0694***
	(0.034)	(0.012)	(0.011)
Black	0.3353***	0.3751***	0.8301***
	(0.018)	(0.012)	(0.024)
Other Ethnicity	0.5867***	0.5218***	0.8359***
	(0.072)	(0.033)	(0.033)
College Education	1.7791***	1.4439***	0.9357***
	(0.034)	(0.021)	(0.013)
Medicare	0.5958***	0.5424***	1.1592***
	(0.039)	(0.020)	(0.015)
State Population/1000	0.9678	0.9792	0.9710*
	(0.021)	(0.018)	(0.018)
Observations		498,544	
Year FE		Yes	
Hospital FE		Yes	

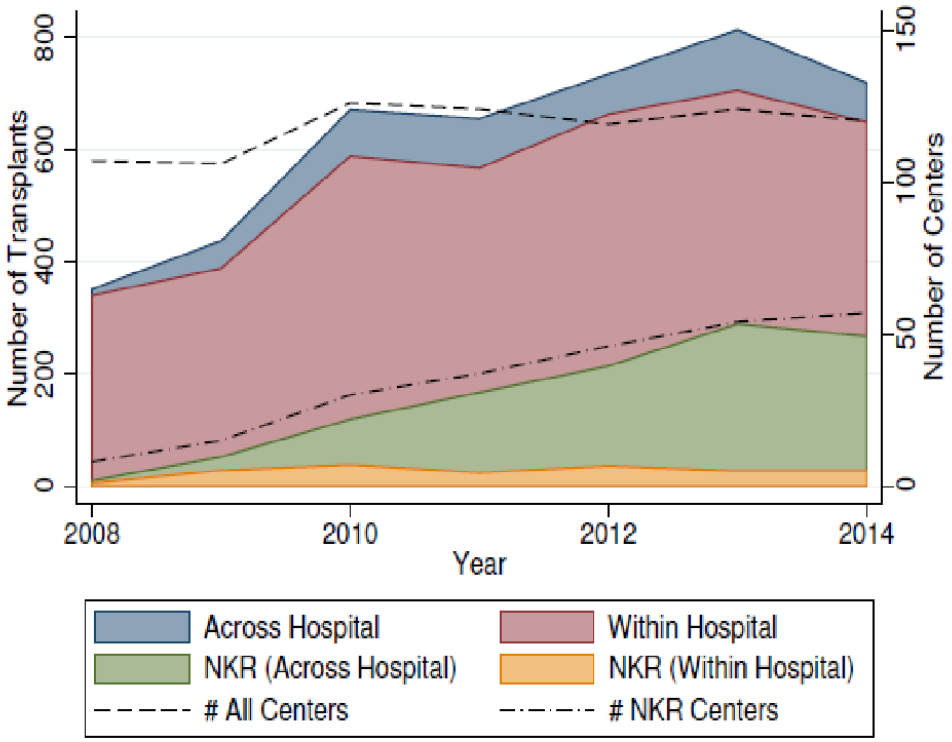
Notes: Exponentiated coefficients (hazard ratios) are reported with corresponding standard errors. The results are reported by expanding the data and fitting one model for all k events simultaneously. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and *, respectively. Standard errors are in parentheses and are clustered at the hospital level.

Figure 1.1: NKR Adoption and Exchange-Transplant Trends



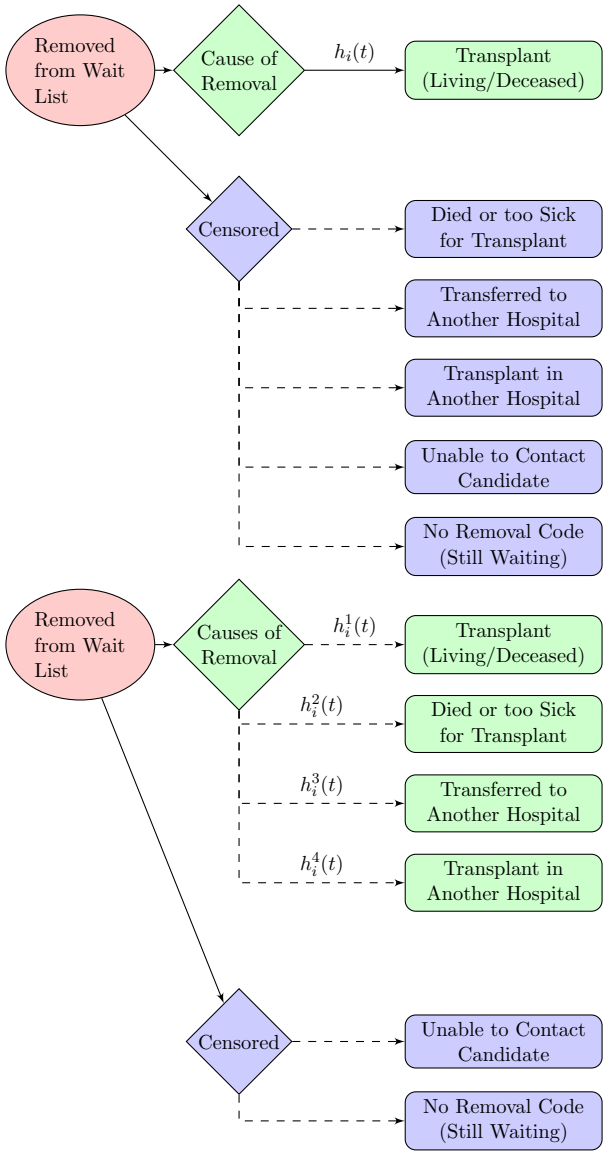
Notes: The NKR was introduced in 2007. From 2007 the number of hospitals that participate in this network increased every year, and at the same time, the number of exchange transplants increased as well.

Figure 1.2: NKR Adoption and Exchange-Transplant Trends



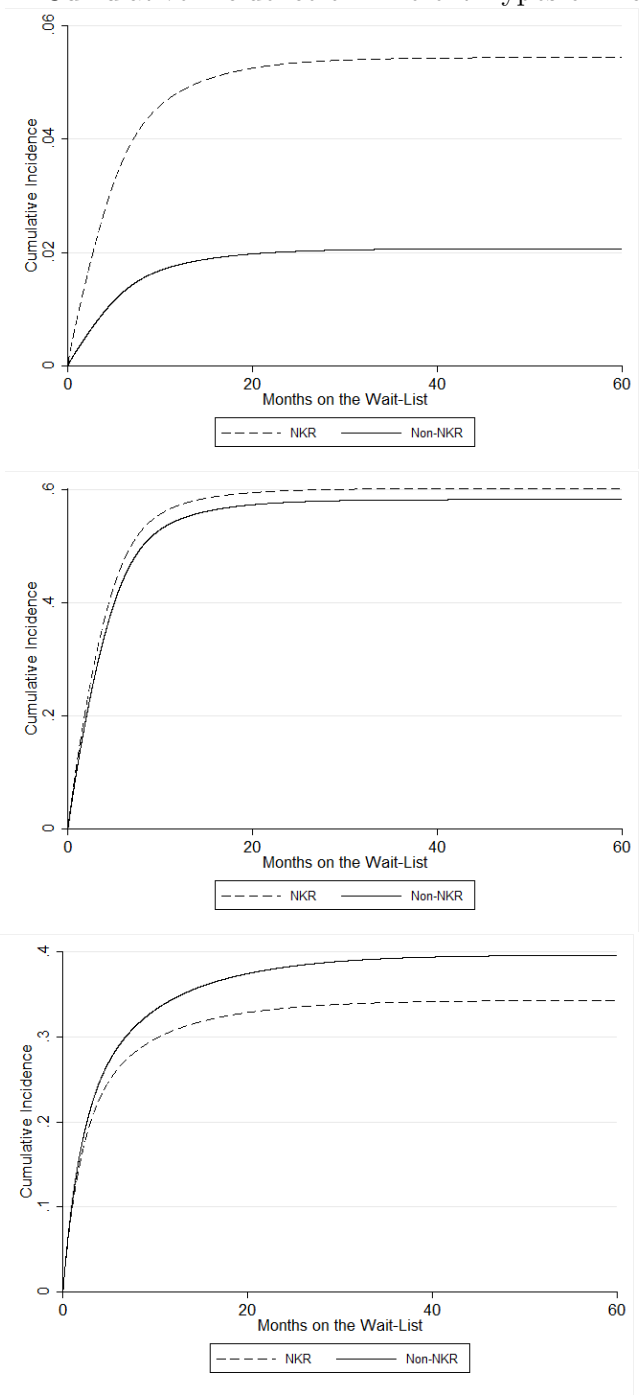
Notes: See Agarwal et al. (2018).

Figure 1.3: Hazard Definition Difference Between Survival Analysis Models



Notes: This figure depicts the difference in hazard definition between single-risk and competing-risk survival analysis models, respectively. In the presence of competing risks, one should consider both the survival time and the event type ($k = 1, ..., K$).

Figure 1.4: Cumulative Incidence of Different Types of Transplants



Notes: The plots capture the probability of being removed from the transplant wait list from exchange, direct-living and deceased transplants, respectively.

Chapter 2

The Effect of the National Kidney Registry on the Quality of Donors

2.1 Introduction

A kidney transplant is the preferred method of treatment for end-stage renal disease (ESRD) patients because it can increase the life expectancy of the recipients and it is a most cost-effective option compared to the alternative treatment which is dialysis. However, the prohibition of monetary transactions for human organs under U.S. law generates a shortage of kidneys available for transplant. Creation of distinct kidney-exchange networks that find compatible matches between patients who each have willing but incompatible living kidney donors reduced this shortage. Previous literature has focused on expanding the number of potential transplants by creating a thick pool of incompatible patient-donor pairs in national kidney-exchange networks. However, the effect of such expansions on the quality of patients and donors interested in kidney exchanges is unknown.[1]

[1] Agarwal et al. (2018) provide a mean-comparison of age, BMI, and blood-type of living-donors involved in exchanges between NKR and non-NKR hospitals, and concludes that except for blood-type, there is no observable difference between donors in these hospitals.

The number of exchange transplants grew gradually as hospitals' adoption of the largest national network, National Kidney Registry (NKR), expanded following its introduction in 2007; and as of today, NKR is still the leading network in accommodating across-hospital kidney-exchange transplants. This paper is the first to empirically investigate the causal effect of the adoption of the NKR, by a hospital on the expected quality of donors. Participation in a kidney-exchange network enables patients to swap their incompatible living donors in a bigger pool of incompatible patient-donor pairs. Therefore, it increases the marginal value of donors. However, the effect of these networks on the marginal value of the quality of donors is ambiguous. One might expect to see a decline in the quality of donors after the adoption of a network if patients are willing to trade a relatively lower quality donor for shorter wait-time on the waiting list. Alternatively, kidney-exchange networks can increase the incentive of patients in bringing a high-quality donor that is more desirable for trade, to improve their chance of finding a compatible donor.

I use a difference-in-differences model to estimate the effect of participation in the NKR on the quality of donors in that hospital. To address the non-random assignment of treatment and control groups, I use the Coarsened Exact Matching (CEM) method which allows for a reduction in the imbalance of covariates across control and treatment groups following Iacus et al. (2008), Blackwell et al. (2009), and Nilson (2017). One might worry that even if NKR adoption lowers the average donor's quality immediately, perhaps over the long term it improves the quality of donors. To test this hypothesis, I augment the previous estimates with lead and lag covariates to capture the dynamics of NKR adoption and quality of donors following (1969) and Autor (2003).

My results suggest that although NKR participation increases the probability of receiving a living transplant conditional on wait-time, it decreases the quality of living donors in those hospitals. Specifically, compared to non-NKR affiliated hospitals, NKR participation increases the age of donors by 8 months, increases the body mass indexes of donors by 0.19 points, and decreases the pool of O blood-type donors by 3.8 percent. The

negative effect of NKR on the average donor's quality is not due to hospitals' anticipatory responses before joining NKR, but post-adoption reactions drive it. Finally, I investigate the effect of NKR adoption on one-year and three-year follow-up outcomes of recipients after transplant. I find that patients in NKR hospitals have worse outcomes in one year after transplant follow-up compared to non-NKR hospitals. Recipients of living donors in NKR hospitals are 0.35% more likely to die before the one year after transplant follow-up, and 0.29% more likely to require full assistance for their daily activities.

Finally, I investigate the potential mechanisms by which creating a thick marketplace can affect the pool of available donors for exchange using the moving behavior of patients. I find no evidence that the decline in the quality of donors is due to patients' moving behavior since there is no increase in the distance patients are traveling to NKR member hospitals after their adoption.

2.2 Institutional Background

For an ESRD patient, a kidney transplant is the preferred method of treatment compared to dialysis, due to its higher life expectancy and lower cost. Before 2004, the only option for an end-stage renal disease patient with a willing but incompatible living donor was waiting on the deceased-donor list for a cadaver kidney. The shortage of transplantable kidneys, created from the prohibition against monetary compensation of organ donors by the United States law, pushed researchers to come up with creative solutions to make better use of the incompatible living donors. Introduction of kidney-exchange provided the opportunity of donor swapping for incompatible patient-donor pairs (Roth et al. 2005).

Donors can engage in a transplant when they are blood-type and tissue-type compatible with the recipient of their organ. Blood-type compatibility happens when the donor does not have a blood protein that the patient lacks. There are two types of blood proteins, A and B, and the blood type of each individual is an indicator of proteins found in that person's blood. An O blood-type stands for the absence of any of these proteins.

This makes O blood-type donors very valuable since they are blood-type compatible with a broader range of patients (Danovitch 2009). Tissue-type compatibility happens when the donor lacks a protein that the patient has an immune response against. The Panel Reactive Antibody (PRA) is a measure indicating patients tissue-type sensitivity. It reveals the percentage of the general population with whom the patient is likely tissue incompatible. For example, a patient with a PRA of 20 is incompatible with 20% of the population.

The donor's general health status affects the expected length of the graft survival of a transplant.[2] There is a negative relationship between the donor's age and the graft survival after transplant (Figure 2.1), where about 21% of kidney transplant failures are the result of insufficient renal mass due to the higher age of donors (Terasaki et al. 1997). The donor's weight is another factor that impacts the length of graft survival. Medical studies have shown that transplants from obese donors have a higher percentage of acute rejection episodes, malfunction of the primary allograft, and surgical complications (Espinoza et al. 2006).[3] Finally, the risk of kidney-failure is higher for patients whose donors had a history of hypertension, smoking, or diabetes (Grams et al. 2016).

Initially, kidney-exchanges were managed by single hospitals within the population of incompatible patient-donor pairs in that hospital. The need for a thick marketplace that constitutes of a larger pool of patients and donors emerged across-hospital kidney-exchange programs, starting from small local networks, and expanding to multiple national ones. Today, there are numerous single-center programs, several multi-center ones, and three major national pairing organizations each with a number of transplant center participants in the United States.

The leading national pairing organization in the U.S. is the National Kidney Registry (NKR), primarily due to the merit of being the first major network to organize exchanges nation-wide since 2007 effectively. The other national networks are the Alliance for Paired Donation (APD) and Kidney Paired Donation Pilot Program (KPDPP) of United Network

[2]Graft survival is an estimate of the probability of the transplant functioning at a finite time after transplantation.

[3]An allograft is a tissue graft from a donor of the same species as the recipient but not genetically identical.

for Organ Sharing (UNOS) which started operating in 2007 and 2010, respectively. Despite a large number of participants in these two networks, mainly because these networks are free of charges, the total number of transplants they facilitate together is about one-fifth of the number of transplants in NKR. Therefore, the focus of my analysis is on the NKR for the remainder of this paper.

2.3 Empirical Framework

By exploiting the fact that different hospitals adopt the National Kidney Registry in different years, I assess its causal impact by contrasting changes in the quality of donors in participant and non-participant hospitals. Specifically, I begin by estimating a difference-in-differences model of the form

$$y_{iht} = \beta_0 + \beta_1 NKR_{ht} + \tau_t + \sigma_h + \epsilon_{iht}, \tag{2.1}$$

where the dependent variable, y_{iht}, measures the quality of donor i in hospital h and year t. The variable of interest, NKR_{ht}, is a dummy for the adoption of NKR network in a hospital and year. In addition, the estimation includes a vector of hospital dummies, σ_h, to control for mean differences in quality of donors across hospitals, and year dummies, τ_t, to control for the average donor's quality changes over time common to all hospitals.

One of the assumptions of a difference-in-differences method is that the decision to adopt the NKR by a hospital is random. However, if this decision is not random but it is made at hospitals with a different set of characteristics and trends, the difference-in-differences framework fails to address bias resulting from the non-random assignment of NKR. Therefore, it hinders our understanding of the total contribution of NKR adoption to the changes in the quality of donors and recipients. Table 12 in Appendix B shows some evidence for concerns about such effects in the evaluation of NKR adoption, as NKR hospitals are performing more transplants overall, and they have relatively older recipients.

One empirical approach to improve the estimation of causal effects is to create a control group with distributional characteristics as similar as possible to the treatment group (Nilsson 2017; Robins, Rotnitzky, and Scharfstein 2000). I use the Coarsened Exact Matching (CEM) method, which allows for a reduction in the imbalance of covariates across control and treated groups. The advantage of CEM method, as opposed to the Propensity Score Matching, is that it is a monotonic imbalance-reducing technique, meaning the balance between the treatment and control group is chosen ex-ante rather than an iterative ex-post balance checking process.[4] So, it reduces the degree of model dependence and the average treatment-effect estimation error. Also, the CEM method ensures that modifying the balance on one covariate does not affect the imbalance of other variables (Iacus et al. 2008; Blackwell et al. 2009).

In CEM method, data are coarsened temporarily for the matching process, and then the analysis is performed on the un-coarsened, matched data. For the matching process, I use the average of recipients' age and the population of the state that the hospital is located in for years 2000 to 2007, as variables reflecting the heterogeneity between treatment and control groups.[5] The weighted fixed-effect panel regressions use the weights created in this procedure.

Alongside these shortcomings, the above discrete specification cannot test the dynamics of NKR adoption and quality variables. To explore these dynamics, I use the leads and lags of NKR adoption and expand (2.1) as

$$y_{iht} = \sum_{\tau=0}^{2} \delta_{-t} NKR_{h,t-\tau} + \sum_{\tau=1}^{4} \delta_{+t} NKR_{h,t+\tau} + \tau_t + \sigma_h + \epsilon_{iht}, \tag{2.2}$$

where the summations on the right-hand side allow for two leads or anticipatory effect, and four lags or post-treatment effect (Angrist and Pischke 2008). The following estimation

[4] "The Propensity Score Matching methods require the user to set the size of the matching solution ex-ante and then checks for the balance ex-post. If the balance resulted from this process is not good, the size should be respecified, until the user obtains an acceptable amount of balance."(King et al. 2010)

[5] The period from 2000 to 2007 is the period before the introduction of the NKR. For treatment hospitals that inaugurate after 2008, I use the average age and distance before they joined NKR, and for control hospitals that open after 2008, I use the average value of the variables in the reported years.

allows us to observe the pattern of post-treatment effects to investigate whether the causal impact of NKR adoption grows over time, or fades away.

Further, I investigate the effect of participation in NKR on transplant outcomes to capture the net effect of changes in the quality of donors and the probability of receiving a transplant conditional on wait-time. I perform the same analysis on one-year and three-year follow-up results after transplant, including controls for the recipient's characteristics.

Finally, to capture the cause of selection of patient-donor pairs into NKR hospitals, I investigate the moving behavior of patients. In this process, I focus on the changes in the travel distance of patients to their hospitals differentiating between NKR and non-NKR participant ones after this program was introduced.

2.4 Data Description

I use the individual level data from the Scientific Registry of Transplant Recipients (SRTR) file for the years 1988-2017. These data provide all the records for each kidney waiting list registrations, their status, and the transplants that occurred with or without association to the deceased donor wait-list. In this paper, I restrict my analysis to all kidney transplants from the beginning of 2000 until July 2017. The period before 2000 is omitted due to the poor reporting quality of the variables of interest and the small number of exchange-transplant incidents in that interval.

The data used in this section focus on all the records for kidney transplants that occurred, including transplants from living and deceased donors during the years 2000-2017. For each observation, detailed medical and demographic characteristics of the individual recipients and donors, who end-up donating, is provided. I investigate the effect of NKR adoption on the quality of donors, regarding both their compatibility value and their health status. I use the donor's age, body mass index (BMI), their history of hypertension, diabetes, and smoking in determining the health components of the quality of donor, and their blood type to capture the quality of donors regarding compatibility value. Further,

to investigate if the different type of recipients in these hospitals originates the change in the quality of donors, I exploit the effect of NKR participation on the recipients. I estimate (2.1) using the demographic and medical characteristics of the recipient as the dependent variable, including recipient's age, gender, race, body mass index (BMI), blood type, Panel Reactive Antibody(PRA[6]), and dummies for college-education, and Medicare. Table 2.1 presents the summary statistics of the data used in this analysis.

The data set provides detailed information on the follow-up results of patients who receive a transplant.[7] To capture the difference in the follow-up outcome of patients, I use death, hospitalization for follow-up, acute rejection of organ, therapy, activity, mobility and work status of recipients post-transplant to compare the transplant outcome of recipients in NKR affiliated hospitals with non-affiliated ones. Table 2.2 describes the summary statistics of the variables used in this analysis. I also use the distance patients travel for a hospital to characterize a specific hospital's value for patients. In generating the distance variable, I use the supplemental data that I requested from SRTR on the zip-code of patients, donors, and hospitals.

The data on the network participation of hospitals is acquired from the NKR network. They provide data on the list of hospitals that joined this network, their adoption year, and the number of registrants, matches, and transplants for each hospital in each year.

2.5 Results

Tables 2.3 and 2.4 present the estimates of (2.1), which capture the effect of NKR adoption on the quality of donors and recipients, respectively. Each column shows a regression of proxies for quality on hospital and time dummies, and an indicator variable for NKR adoption, which is equal to one if NKR is present in a given hospital and year and zero otherwise. The OLS and CEM columns present estimation results for (2.1) with and

[6]This measure, which can be a value between 0 and 100, indicates the percentage of the general population with whom the patient is likely incompatible.

[7]The frequency and time of follow-up vary based on recipients needs. For recipients who had more than one follow-up in that period, I only consider their last follow-up results.

without controlling for the non-random assignment of NKR, respectively.

The results in Table 2.3 show the impact of NKR on the quality of donors. Estimates demonstrate that in hospitals that joined NKR the age and body mass indexes of living donors are on average higher than the ones that did not participate by 8 months and 0.192 points, respectively. Also, the O blood-type estimate shows that these hospitals receive 3.796% less of living donors with O blood-type. While the rest of the estimates also move in the direction of lower quality of donors in NKR hospitals (higher hypertension, diabetes, and smoking history), they are not significant at 10% confidence interval.

Checking the result of the same estimations for deceased-kidney donors provides a falsification check for the reported results. As the NKR increases the probability of receiving a transplant from a living donor with no effect on all transplants, we should only observe differences in the donors of living transplants when comparing NKR and non-NKR affiliated hospitals. The results under deceased transplant columns show no statistically significant difference between the donors of deceased transplants. These results confirm that the trade-off between higher probability of receiving a transplant and lower quality of donors is happening amongst the recipients of living-donor transplants, and unobserved differences between NKR and non-NKR hospitals do not drive the difference in the average donor's quality.

On the other hand, separate interpretation of the results of equation (2.1) for the recipients of living and deceased donors creates selection bias. The results from the previous section confirm that there is some degree of substitution between the recipients of living and deceased kidney transplants in NKR affiliated hospitals. This substitution can move the marginal recipient of a living donor to the deceased-kidney waiting list, in the form of trading a living donor for getting priority on the waiting list. The data can not distinguish between the recipient of deceased kidney transplants with and without living donors. Thus, in interpreting the effect of NKR on the quality of recipients, the focus should be on all transplants. The results in Table 2.4 show that there is no statistically significant difference between recipients in NKR and non-NKR participant hospitals. Furthermore,

Table 2.5 captures the effect of NKR participation on the quality of donors controlling for the characteristics of recipients, and the results are consistent with my findings in Table 2.3.

The results explained above do not provide an understanding of the dynamics of NKR adoption and quality of donors over time. It is not clear how quickly the donor's quality changes after NKR is adopted and whether this effect escalates, stabilizes, or reverts. Also, if the low quality of donors in a hospital leads to the adoption of the NKR rather than vice versa, the above estimates would conceal this reverse causality. To investigate these dynamics, I augment Table 2.3 estimates with leads and lags of NKR adoption. Specifically, I include two lead variables capturing one and two years before a hospital joins NKR, and four lags that express years zero to three after participation, and year four onward.[8]

Figure 2.2 provides an environment for testing if the hospitals that have donors with higher age and body mass index, or smaller number of O blood-type donors are the ones who adopt NKR, as opposed to NKR adoption making them prone to get these donors.[9] There is no evidence of an anticipatory reaction within hospitals about to join NKR, as the lead coefficients do not show any specific trends. The lag trends provide evidence for a sudden decline of the quality of donors right after NKR adoption, with a gradual decline in the following years.

Finally, I use the follow-up result of patients who received a transplant to investigate the net effect of the higher probability of receiving a living transplant conditional on wait-time and the decline in the quality of living donors in NKR participant hospitals. Tables 2.6 and 2.7 provide the results for the effect of NKR on one-year and three-year after transplant follow-ups, respectively. These estimates contain a set of patients' characteristics to control for the selection bias of patients' movement from living to deceased donors. Table 2.6 presents some evidence of a worse outcome of recipients in NKR hospitals. According

[8]Limiting the post-treatment effects to four lags is due to data limitation. The NKR was introduced in 2007 and until 2012 about 70% of hospitals that eventually form the treatment group joined the NKR. It means that I can observe the fourth lag only for those observations. The pattern in which hospitals join NKR through years is shown in Table 3.1 in Appendix B.

[9]Table 2.9 in Appendix B shows the results from which these graphs are depicted.

to this table, recipients of transplants, regardless of their type, in NKR affiliated hospitals compared to non-NKR ones are 0.756% more likely to experience acute rejection of organ one year after transplant. Furthermore, recipients of living kidney transplants in these hospitals are 0.345% more likely to die in one year after transplant, and 0.288% more likely to require full assistance for their daily activities. The results show no significant difference in the follow-up outcome of recipients of deceased kidney donors.

Table 2.7 shows the estimated impact of NKR adoption on recipients' follow-up outcome three years after transplant. Results presented in this table do not show a clear pattern of difference between the recipients' three-year follow-up outcome in NKR and non-NKR affiliated hospital.

One explanation for a decline in the quality of donors is that patients with lower quality donors travel to NKR participant hospitals to expand their chances of finding a better donor through an exchange of donors. I use the moving behavior of patients to investigate if the declining quality of donors in NKR participant hospitals is due to this hypothesis. Figure 2.3 captures the distribution of the Euclidean distance from the recipients' zip-code to the hospital's zip-code. Based on Figure 2.3 the majority of the recipients are listed in a hospital within their 50 miles radius.[10] Assuming patients are choosing hospitals based on their distance to these transplant centers and some other quality characteristics of hospitals (Capps, Dranove, and Satterthwaite 2003; Town and Vistnes 2001), adoption of NKR should induce some patients with lower quality donors to travel longer distances to NKR member hospitals to increase the possibility of finding a higher quality donor.

Table 2.8 shows no evidence of an increase in patients' travel distance to NKR participant hospitals after their adoption. Augmenting the above regression with leads and lags of NKR adoption allows us to observe changes in the moving behavior of patients through time. Table 2.10 depict the trend of changes in patients' travel distance to NKR hospitals. The results are consistent with the above specification, showing no evidence for

[10]This graph is consistent with previous literature which indicates 70 percent of patients receive a transplant within the 50 miles radius of their living location(Teltser).

an increase in the travel distance of patients to NKR participant hospitals. These patterns are depicted in Figure 2.4.

2.6 Conclusion

With the rise of kidney-exchange transplants and the introduction of national networks expanding the pool of patient-donor pairs willing to participate in exchanges, a question that arises is if such expansions have an impact on patient-donor pairs' selection into these networks. This paper analyzes the effects of the adoption of the National Kidney Registry (NKR) network by hospitals on donors' quality in those centers using variation in NKR adoption by different hospitals and years.

In the absence of Kidney-exchange networks, transplants happen if only donors are compatible matches for their own patients. Whereas, in the presence of exchange networks, a transplant occurs if the donor is compatible with one of the patients participating in that network, therefore these networks increase the marginal value of donors. However, the effect of kidney-exchange networks on the marginal value of the quality of the donor is ambiguous. The quality of donors decreases if patients are willing to accept a relatively lower quality donor for spending less time on the waiting list. Alternatively, participation in an exchange network could increase the incentive of patients to bring high-quality donors that are more desirable for trade. Thus, these networks can result in an improvement in the quality of donors.

This study uses the unique data set of the Scientific Registry of Transplant Recipients (SRTR) merged with NKR claims on participant hospitals. The data allow me to identify the hospitals' participation status in NKR in each year, and their subsequent patients and donors medical and demographic characteristics. To my knowledge, my study is the first to consider the selection effects of patient-donor pairs into hospitals after the adoption of NKR by that center. The estimates suggest that although NKR participation increases the probability of receiving a living transplant, it has adverse effects on the

quality of living donors. In participant hospitals, the age and body mass indexes of living donors increase more compared to non-participant ones, and the proportion of O blood-type donors decreases. I find that NKR participation impacts on donors are not due to the anticipatory response of hospitals about to join NKR; rather it is a post-treatment reaction after adoption. Finally, the effect of NKR adoption on the follow-up outcomes of patients shows no significant difference between the transplant recipients in NKR and non-NKR hospitals.

I also investigate the mechanisms by which why NKR adoption has negative effects on donors' quality using the moving behavior of patients. In my supplemental sample acquired from SRTR, I can observe recipients' travel distance to their hospitals. I observe no evidence of an increase in the distance they travel to these centers after the hospital's adoption of this network. These results are against what one would expect to see in the presence of the selection of patients with worse quality donors into NKR member hospitals.

Although I find that NKR adoption reduces the quality of donors, I show that this decline in quality is small, and it does not change the follow-up outcome of patients after transplant severely. Furthermore, combining these findings with the previous chapter, the NKR induces an expansion in the use of incompatible living donors through exchanges. A relatively lower quality living donor is preferred to a transplant from a deceased donor, due to their higher graft survival rate.

Table 2.1: Summary Statistics of the Quality of Recipients and Donors by Transplant Type

	All Transplants		Living-Donor Transplants		Deceased-Donor Transplants	
	N	Mean	N	Mean	N	Mean
Recipients'						
Age	291,629	48.459	106,274	45.386	185,355	50.221
Body Mass Index	270,439	28.429	98,430	26.916	172,009	29.295
O Blood-Type×100	291,630	45.072	106,274	44.560	185,356	45.366
Panel Reactive Antibody	289,063	18.146	104,664	10.849	184,399	22.287
Female×100	291,630	39.452	106,274	39.316	185,356	39.530
Black×100	291,630	25.027	106,274	13.854	185,356	31.432
Other Ethnicity×100	291,630	6.996	106,274	5.583	185,356	7.806
College Education×100	291,630	42.689	106,274	49.339	185,356	38.875
Medicare×100	291,630	53.770	106,274	35.249	185,356	64.389
distance from current hospital	219,420	74.450	76,775	84.558	142,645	69.009
Donors'						
Age	291,624	38.778	106,268	41.214	185,356	37.381
Body Mass Index	284,203	26.929	98,892	26.899	185,311	26.945
O Blood-Type×100	291,630	53.926	106,274	64.485	185,356	47.871
Hypertension History×100	262,362	18.396	78,242	2.763	184,120	25.040
Smoking History×100	256,718	25.800	73,567	25.125	183,151	26.070
Diabetes History×100	262,223	4.400	77,716	0.060	184,507	6.228

Notes: The sample for characteristics of donors and recipients include every patient who received a transplant between January 2000 to July 2017.

Table 2.2: Summary Statistics of Recipients' Follow-up by Transplant Type

	All Transplants		Living-Donor Transplants		Deceased-Donor Transplants	
	N	Mean	N	Mean	N	Mean
1 Year Follow-up						
Death×100	261,514	2.522	99,110	1.378	162,410	3.221
Hospitalized for Follow-up×100	250,057	27.700	94,720	23.555	155,329	30.233
Acute Rejection×100	208,407	5.404	76,895	4.901	131,512	5.698
Therapy×100	177,953	31.018	71,679	31.037	106,273	31.010
Normal Activity×100	227,503	88.625	84,455	91.517	143,046	86.916
Activity with Some Assistance×100	227,503	10.245	84,455	7.815	143,046	11.682
Activity with Full Assistance×100	227,503	1.130	84,455	0.668	143,046	1.402
Working×100	31,926	69.104	13,586	75.865	18,326	64.144
Normal Mobility×100	112,327	91.709	43,839	93.497	68,483	90.564
3 Years Follow-up						
Death×100	225,221	4.030	87,796	2.666	137,397	4.904
Hospitalized for Follow-up×100	207,694	21.993	81,477	18.982	126,190	23.935
Acute Rejection×100	195,124	3.990	75,706	3.440	119,398	4.339
Therapy×100	133,538	13.875	55,674	14.705	77,855	13.286
Normal Activity×100	188,552	88.078	72,175	91.041	116,357	86.244
Activity with Some Assistance×100	188,552	10.422	72,175	7.922	116,357	11.968
Activity with Full Assistance×100	188,552	1.500	72,175	1.036	116,357	1.788
Working×100	14,997	75.802	6,605	81.347	8,390	71.466
Normal Mobility×100	95,634	90.457	39,129	92.379	56,503	89.130

Notes: The sample for one-year follow-up consists of the last follow-up of recipients in the period of 1 year after transplant, and the sample for three-year follow-up consists of the last follow-up of recipients in the period between one-year and three-year after transplant between January 2000 to July 2017. For recipients who had more than 1 follow-up in that period, I only consider their last follow-up results. Therapies include therapy for Anti-viral, Polyoma virus, Photopheresis, Plasmapheresis, Lymphoid Irradiation.

Table 2.3: The Estimated Impact of NKR Adoption on the Quality of Donors by Transplant Type

	All Transplants		Living-Donor Transplants		Deceased-Donor Transplants	
	OLS	CEM	OLS	CEM	OLS	CEM
Dependent Variables:						
Age	0.0175	-0.128	0.408**	0.642***	-0.400	-0.331
	(0.256)	(0.261)	(0.193)	(0.244)	(0.375)	(0.371)
Body Mass Index	0.0241	0.0172	0.189**	0.192**	-0.00527	-0.100
	(0.060)	(0.069)	(0.076)	(0.098)	(0.084)	(0.107)
O Blood-Type×100	-0.919**	-0.539	-2.62***	-3.79***	-0.630	0.494
	(0.425)	(0.552)	(0.620)	(0.903)	(0.485)	(1.002)
Hypertension History×100	-1.213*	-1.192	0.0837	0.224	-0.562	0.173
	(0.665)	(0.758)	(0.304)	(0.342)	(0.827)	(1.080)
Smoking History×100	0.0290	0.499	1.643	1.471	-0.826	0.472
	(0.764)	(0.960)	(1.253)	(1.360)	(0.792)	(1.014)
Diabetes History×100	-0.0969	0.0689	0.0356	0.287	0.182	0.337
	(0.255)	(0.296)	(0.028)	(0.249)	(0.362)	(0.406)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each entry is a separate regression. I regress the NKR on each characteristic variable individually. The regressions are weighted using the Coarsened Exact Matching Method. The matching is done on the average recipients' age, the population of the state that the hospital is located in before 2008. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and *, respectively. Standard errors are in parentheses and are clustered at the hospital level.

Table 2.4: The Estimated Impact of NKR Adoption on the Quality of Recipients by Transplant Type

	All Transplants		Living-Donor Transplants		Deceased-Donor Transplants	
	OLS	CEM	OLS	CEM	OLS	CEM
Dependent Variables:						
Age	0.315*	0.207	0.676***	0.976***	0.199	0.190
	(0.178)	(0.175)	(0.234)	(0.313)	(0.232)	(0.237)
Body Mass Index	-2.199	-3.738	0.0183	0.0699	-2.978	-4.035
	(2.196)	(3.782)	(0.092)	(0.114)	(2.997)	(4.151)
O Blood-Type×100	-0.422	-0.156	-0.246	-0.733	-0.336	0.582
	(0.354)	(0.431)	(0.590)	(0.707)	(0.465)	(0.887)
Panel Reactive Antibody	-0.866	-1.981	-0.543	0.296	-0.228	0.815
	(1.125)	(1.347)	(0.998)	(1.104)	(1.320)	(1.549)
Female×100	-0.323	-0.164	-0.108	0.713	-0.138	-0.239
	(0.368)	(0.378)	(0.628)	(0.849)	(0.456)	(0.688)
Black×100	0.217	0.146	0.544	0.310	0.799	1.263
	(0.658)	(0.671)	(0.523)	(0.554)	(0.869)	(0.974)
Other Ethnicity×100	0.275	0.263	0.256	0.545	0.335	0.452
	(0.313)	(0.332)	(0.311)	(0.402)	(0.363)	(0.416)
College Education×100	2.026*	1.797	1.638	1.931	1.677	1.279
	(1.153)	(1.176)	(1.455)	(1.662)	(1.178)	(1.162)
Medicare×100	-0.982	-0.562	-0.831	-1.130	0.0571	1.325
	(1.398)	(1.531)	(1.208)	(1.552)	(1.612)	(2.495)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each entry is a separate regression. I regress the NKR on each characteristic variable individually. The regressions are weighted using the Coarsened Exact Matching Method. The matching is done on the average recipients' age, the population of the state that the hospital is located in before 2008. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and *, respectively. Standard errors are in parentheses and are clustered at the hospital level.

Table 2.5: The Estimated Impact of NKR Adoption on the Quality of Donors by Transplant Type

	All Transplants		Living-Donor Transplants		Deceased-Donor Transplants	
	OLS	CEM	OLS	CEM	OLS	CEM
Dependent Variables:						
Age	-0.102	-0.220	0.303	0.421*	-0.464	-0.449
	(0.250)	(0.247)	(0.184)	(0.226)	(0.360)	(0.343)
Body Mass Index	0.0162	0.0191	0.218***	0.207**	-0.0255	-0.0793
	(0.060)	(0.069)	(0.074)	(0.092)	(0.084)	(0.092)
O Blood Type×100	-0.608*	-0.529	-2.340***	-3.252***	-0.287	0.00390
	(0.324)	(0.392)	(0.557)	(0.818)	(0.179)	(0.339)
Hypertension History×100	-1.265**	-1.262*	0.0796	0.249	-0.755	-0.0493
	(0.640)	(0.713)	(0.317)	(0.358)	(0.791)	(1.063)
Smoking History×100	-0.0300	0.335	1.610	1.384	-0.964	0.106
	(0.781)	(0.957)	(1.311)	(1.443)	(0.815)	(0.926)
Diabetes History×100	-0.139	0.0379	0.0371	0.303	0.105	0.404
	(0.258)	(0.288)	(0.027)	(0.257)	(0.357)	(0.424)
Patient Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each entry is a separate regression. I regress the NKR on each characteristic variable individually. Controls that are not shown include recipients' age, body mass index, PRA, dummies for O blood-type, female, black, other ethnicities, college education, and Medicare. The regressions are weighted using the Coarsened Exact Matching Method. The matching is done on the average recipients' age, the population of the state that the hospital is located in before 2008. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and *, respectively. Standard errors are in parentheses and are clustered at the hospital level.

Table 2.6: The Estimated Impact of NKR Adoption on Recipients' One-Year Follow-up by Transplant Type

	All Transplants		Living-Donor Transplants		Deceased-Donor Transplants	
	OLS	CEM	OLS	CEM	OLS	CEM
Dependent Variables:						
Death×100	0.00618	-0.144	0.321*	0.345*	-0.152	-0.153
	(0.159)	(0.203)	(0.163)	(0.178)	(0.207)	(0.242)
Hospitalized for Follow-up×100	0.351	-0.715	-0.042	-0.505	0.876	-1.036
	(1.466)	(1.564)	(1.432)	(1.740)	(1.572)	(1.505)
Acute Rejection×100	0.333	0.756*	0.246	0.630	0.409	0.652
	(0.431)	(0.452)	(0.507)	(0.599)	(0.460)	(0.452)
Therapy×100	-2.166	-2.669	-4.171	-3.887	-0.829	-2.129
	(2.880)	(3.189)	(3.181)	(3.182)	(2.867)	(2.939)
Normal Activity×100	-0.628	-2.740	-1.651	-2.724	-0.267	-0.995
	(2.263)	(2.336)	(2.546)	(2.865)	(2.229)	(2.334)
Activity with Some Assistance×100	0.335	2.603	1.365	2.436	-0.036	0.827
	(2.249)	(2.325)	(2.525)	(2.848)	(2.213)	(2.320)
Activity with Full Assistance×100	0.292**	0.138	0.287**	0.288**	0.303	0.168
	(0.148)	(0.168)	(0.127)	(0.137)	(0.191)	(0.205)
Working×100	0.0388	-4.321	2.478	-3.232	-0.780	-3.743
	(2.747)	(3.117)	(2.730)	(3.318)	(3.590)	(2.661)
Normal Mobility×100	-1.333	-1.754	-2.086	-2.448	-1.038	-1.549
	(1.802)	(1.892)	(2.564)	(2.737)	(1.410)	(1.544)
Patient Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each entry is a separate regression. I regress the NKR on each follow-up variable individually. Controls that are not shown include recipients' age, body mass index, PRA, dummies for O blood-type, female, black, other ethnicities, college education, and Medicare. The regressions are weighted using the Coarsened Exact Matching Method. The matching is done on the average recipients' age, the population of the state that the hospital is located in before 2008. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and *, respectively. Standard errors are in parentheses and are clustered at the hospital level.

Table 2.7: The Estimated Impact of NKR Adoption on Recipients' Three-Year Follow-up by Transplant Type

	All Transplants		Living-Donor Transplants		Deceased-Donor Transplants	
	OLS	CEM	OLS	CEM	OLS	CEM
Dependent Variables:						
Death×100	-0.227	-0.373*	-0.0780	0.00472	-0.356	-0.313
	(0.178)	(0.218)	(0.216)	(0.242)	(0.257)	(0.329)
Hospitalized for Follow-up×100	0.904	0.350	1.090	0.318	0.991	0.216
	(1.104)	(1.172)	(1.128)	(1.321)	(1.189)	(1.193)
Acute Rejection×100	-0.229	0.0833	-0.277	-0.349	-0.143	0.287
	(0.362)	(0.389)	(0.401)	(0.428)	(0.404)	(0.413)
Therapy×100	-1.309	-1.152	-4.199*	-5.67**	0.717	1.090
	(2.134)	(2.289)	(2.301)	(2.561)	(2.198)	(2.411)
Normal Activity×100	-1.559	-2.104	-2.035	-2.832	-1.547	-2.481
	(1.866)	(2.060)	(2.015)	(2.287)	(1.860)	(1.861)
Activity with Some Assistance×100	1.605	2.137	2.032	2.909	1.636	2.524
	(1.853)	(2.043)	(2.004)	(2.264)	(1.836)	(1.833)
Activity with Full Assistance×100	-0.0463	-0.0331	0.00258	-0.0770	-0.0887	-0.0427
	(0.206)	(0.227)	(0.196)	(0.241)	(0.269)	(0.297)
Working×100	2.501	0.551	6.083**	5.700	0.711	-2.178
	(2.455)	(3.023)	(2.739)	(3.637)	(3.239)	(3.548)
Normal Mobility×100	-1.636	-2.21**	-1.512	-1.604	-2.047*	-2.88**
	(1.137)	(1.095)	(1.430)	(1.513)	(1.148)	(1.161)
Patient Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each entry is a separate regression. I regress the NKR on each follow-up variable individually. Controls that are not shown include recipients' age, body mass index, PRA, dummies for O blood-type, female, black, other ethnicities, college education, and Medicare. The regressions are weighted using the Coarsened Exact Matching Method. The matching is done on the average recipients' age, the population of the state that the hospital is located in before 2008. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and *, respectively. Standard errors are in parentheses and are clustered at the hospital level.

Table 2.8: The Estimated Impact of NKR Adoption on Moving Behaviorof Patients

	All Transplants		Living-Donor Transplants		Deceased-Donor Transplants	
	OLS	CEM	OLS	CEM	OLS	CEM
Dependent Variables:						
Patient's Distance	-3.928	-5.66**	-1.075	-4.607	-5.238**	-4.4954*
	(2.957)	(2.311)	(4.916)	(4.306)	(2.462)	(2.495)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each entry is a separate regression. The dependent variable is the distance from patients' zip-code to hospitals' zip-code. The regressions are weighted using the Coarsened Exact Matching Method. The matching is done on the average recipients' age, the population of the state that the hospital is located in before 2008. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and * respectively. Standard errors are in parentheses. They are clustered at hospital level.

Table 2.9: The Estimated Impact of NKR Adoption on the Quality of Donors, years 2005-2017

	Age	BMI	O-Blood Type	Hypertension History	Smoking History	Diabetes History
NKR_2	0.00165	-0.0120	-1.387	-0.609	-0.372	0.207
	(0.301)	(0.117)	(1.266)	(0.440)	(1.549)	(0.277)
NKR_1	-0.0753	0.0306	-1.494	-0.191	-1.382	0.260
	(0.290)	(0.138)	(1.338)	(0.453)	(1.782)	(0.320)
NKR0	0.250	0.167	-3.762**	-0.0731	-0.545	0.469
	(0.331)	(0.132)	(1.592)	(0.532)	(2.037)	(0.465)
NKR1	0.103	0.0333	-5.675***	0.0748	0.182	0.509
	(0.334)	(0.142)	(1.892)	(0.587)	(2.210)	(0.545)
NKR2	0.319	0.156	-5.845***	-0.185	1.621	0.589
	(0.413)	(0.172)	(2.072)	(0.670)	(2.318)	(0.618)
NKR3	0.252	0.223	-5.028**	-0.0814	0.955	0.684
	(0.425)	(0.184)	(2.185)	(0.776)	(2.545)	(0.680)
NKR4 &$_{forward}$	0.191	0.361	-7.380***	-0.0679	4.413	0.896
	(0.512)	(0.238)	(2.467)	(0.840)	(2.705)	(0.848)
Constant	48.10***	26.23***	2.516	1.135***	-0.677	-0.751
	(0.472)	(0.000)	(2.076)	(0.401)	(2.237)	(0.738)
Observations	54,146	52,687	54,147	53,325	53,678	52,768
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes

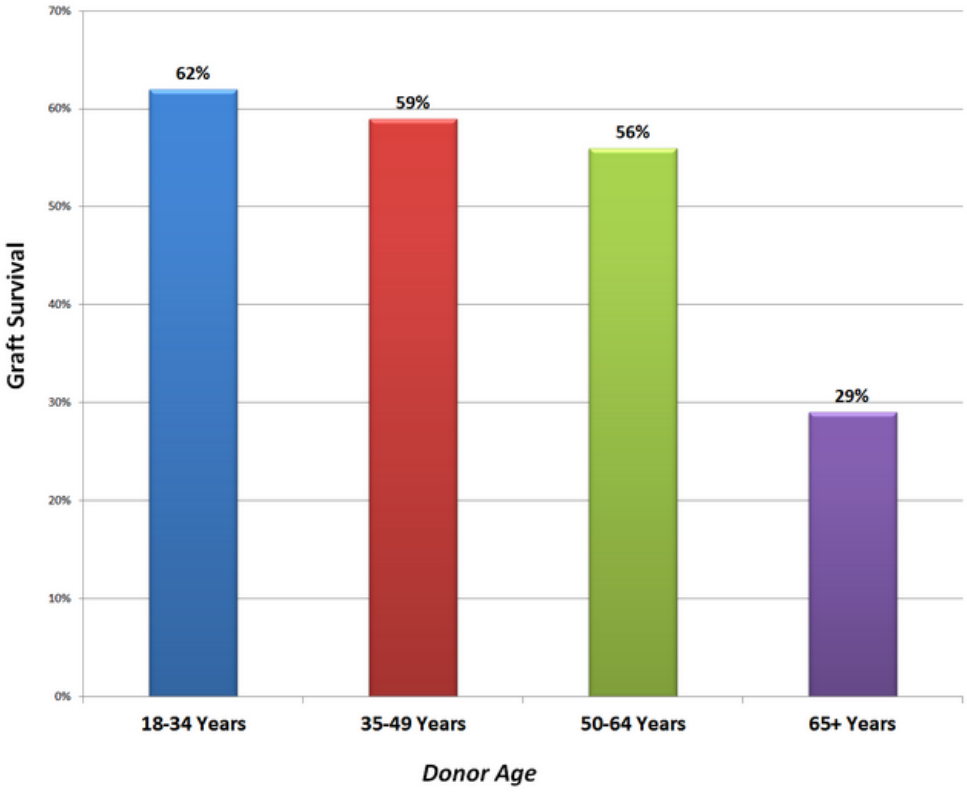
Notes: The dependent variables are the 6 proxies used to measure the quality of donors. The regressions are weighted using the Coarsened Exact Matching Method. NKR dummies -2 to 3 are equal to 1 in only 1 year per adopting hospital. NKR4&$_{forward}$ dummy is equal to 1 in every year beginning with the fourth year of adoption. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and *, respectively. Standard errors are in parentheses and are clustered at the hospital level.

Table 2.10: The Estimated Impact of NKR Adoption on Moving Behavior of Patients, years 2005-2017

	All Transplants	Living Transplants	Deceased Transplants
NKR_2	-7.619**	-11.31**	-0.255
	(3.148)	(5.019)	(3.014)
NKR_1	-6.726**	-5.591	-2.172
	(3.260)	(7.149)	(4.072)
NKR0	-14.83***	-13.31**	-9.045***
	(3.888)	(6.471)	(3.395)
NKR1	-14.86***	-15.85**	-7.200*
	(4.668)	(7.722)	(3.725)
NKR2	-11.76**	-7.042	-8.011**
	(4.966)	(8.501)	(3.686)
NKR3	-17.20***	-16.36*	-8.852**
	(5.102)	(9.676)	(4.412)
NKR4&$_{forward}$	-15.40***	-6.102	-11.10**
	(5.824)	(9.420)	(4.724)
Constant	17.12***	15.61***	17.41***
	(2.387)	(3.888)	(4.003)
Observations	157676	52584	100337
Year FE	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes
Control	Yes	Yes	Yes

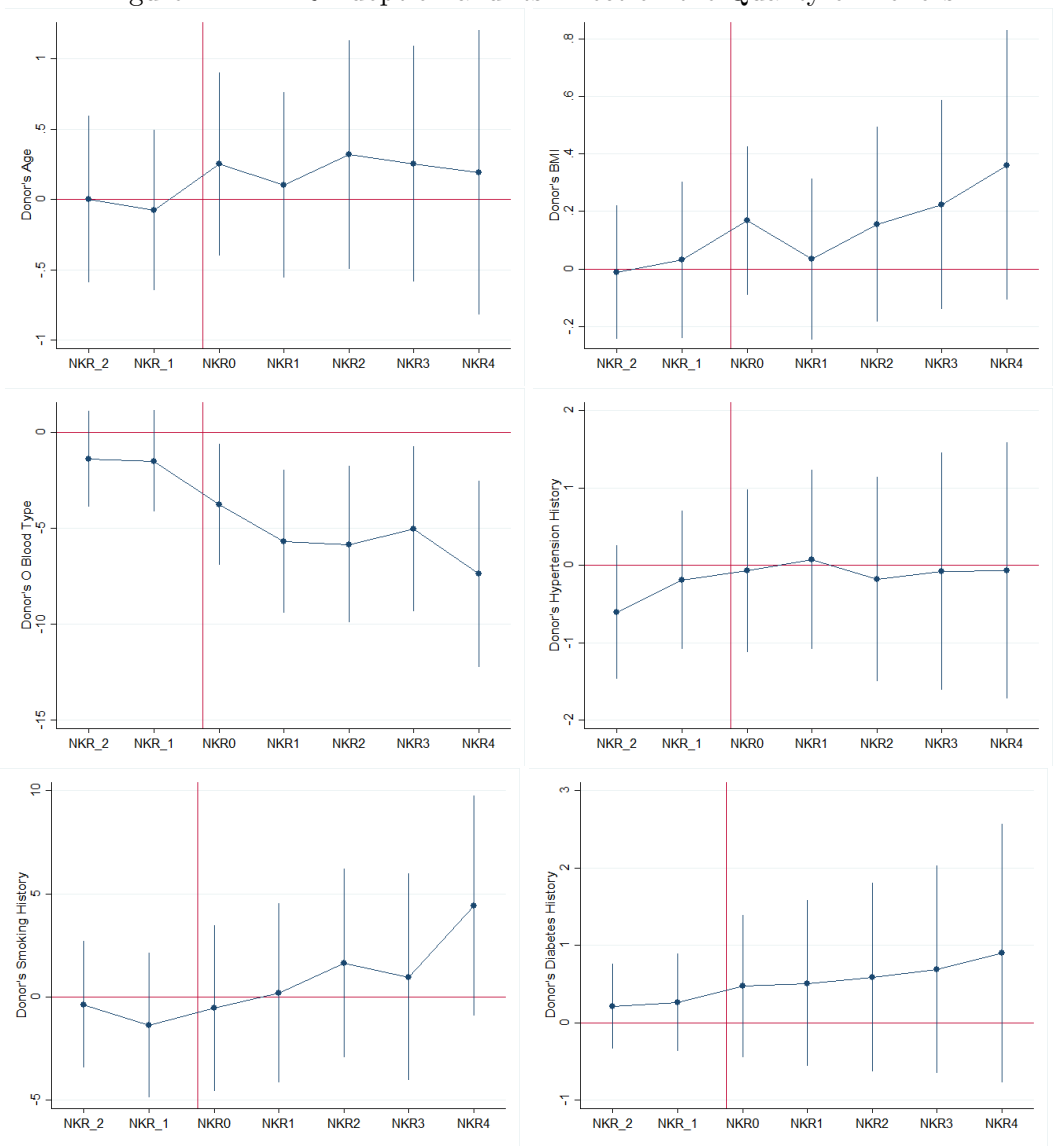
Notes: The dependent variable is the distance from patients' zip-code to hospitals' zip-code. The regressions are weighted using the Coarsened Exact Matching Method. NKR dummies -2 to 3 are equal to 1 in only 1 year per adopting hospital. NKR4&$_{forward}$ dummy is equal to 1 in every year beginning with the fourth year of adoption. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and * respectively. Standard errors are in parentheses. They are clustered at hospital level.

Figure 2.1: Unadjusted Graft Survival of Kidney Transplants at 10 Years



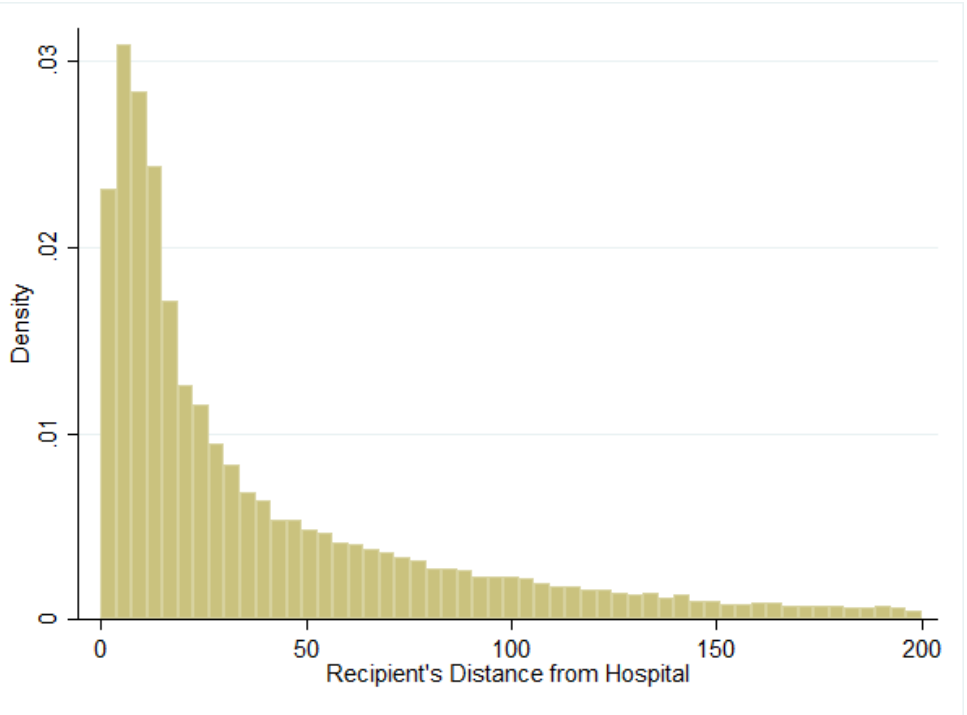
Notes: See https://www.kidneyregistry.org/ (Accessed July, 2018)

Figure 2.2: NKR Adoption and its Effect on the Quality of Donors



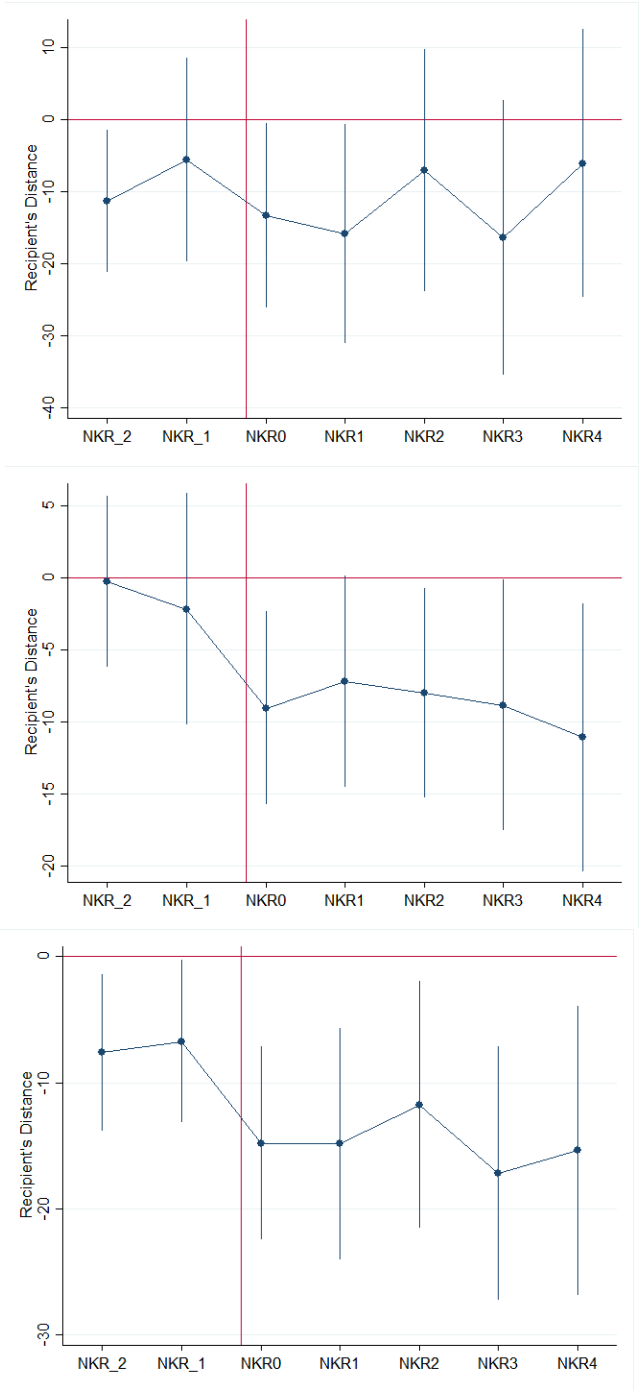
Notes: NKR_1 and NKR_2 capture two lead variables for one and two years before a hospital joins NKR, and NKR1 through NKR4 captures four lags that express years zero to three after participation and year four onward.

Figure 2.3: Distribution of the Distance from Recipient's Location to the Hospital



Notes: The figure capture the distribution of the distance (in miles) recipients travel to their transplant hospital.

Figure 2.4: NKR adoption and patients moving behavior



Notes: The plots capture the distance recipients travel to their transplant hospital. It is divided into recipients of living, deceased, and all transplants combined, respectively.

Chapter 3

The Spillover Effect of Surgeons on Expanding the Use of Kidney-Exchange Networks (with Bobby W. Chung)

3.1 Introduction

National kidney-exchange networks create a large pool of incompatible patient-donor pairs and find compatible matches for them within the pool of registered pairs. The adoption of these networks is at the hospital level. Hospitals are responsible for informing their patients of the available networks, and patient-donor pairs decide whether they want to participate in that network. While one unified pool of patient-donor pairs with many participants creates more potential for finding matches, the current trend shows the adoption decision of hospitals in joining kidney-exchange networks happened in a balkanized fashion. There are three national kidney-exchange networks currently active in the United States, several multi-center programs, and numerous single-center ones with overlapping footprints.

Furthermore, one-in-five hospitals choose not to join any of these national networks.

Previous literature documents two burdens that prevent hospitals from participating in these national networks. The first reason is the conflict in the objective function of hospitals that want to maximize the number of matches within their center, as opposed to national networks that want to maximize the total number of transplants nationally regardless of the hospital (Ashlagi and Roth 2014). The second theory argues the fixed cost of entry prevents hospitals from participation (Agarwal et al. 2018). While these two theories explain part of the behavior observed by some hospitals, a unified explanation for the adoption behavior of all hospitals is missing from this literature.

This study adds to the existing theory by analyzing whether the links between two hospitals, created by mutual surgeons between two hospitals, play a role in the adoption decision of the National Kidney Registry (NKR). The role of opinion leaders in the technology diffusion process of different industries, as well as medicine, has been long documented (Comin, Dmitriev, and Rossi-Hansberg 2012; Escarce 1996; Baicker and Chandra 2010; Rogers 2010). Coleman et al. (1957) argue that technology diffusion in medicine shows the same trend as other industries with a significant role of interpersonal networks. While the empirical evidence of these theories is limited due to identification challenges (Agha and Molitor 2018), the introduction of kidney-exchange networks provides an environment which enables one to overcome those identification issues.

We use data from the Scientific Registry of Transplant Recipients (SRTR) which provides individual-level data on all the transplant recipients in the U.S. from 1988 to 2017. For each transplant, detailed information on the date of transplant, the hospital that the operation happens in it, and the name and the ID of the surgeon who performs the surgery is available. We define two hospitals as connected if one surgeon performs transplant surgery in those two hospitals. Then we look at the effect of the hospital i's total number of connected hospitals who adopted the NKR, which we define as the spillover measure, on the probability of hospital i's participation in that network. Hospitals leave the sample after adoption since we observe no exit, but they are still included in the number

of connected hospitals. Since belonging to the same network might cause the incident of a surgeon performing transplants in multiple centers as opposed to the reverse effect, we restrict our hospitals' connection formation to the period before the introduction of the NKR.[1]

Another identification challenge in the network literature is the reflection problem, which is due to the simultaneity in the behavior of the interacting hospitals. Specifically, when we are studying the effect of the behavior of one hospital on the other one, it is hard to distinguish the direction of this effect. To address this issue, we take two approaches. First, we lag the spillover measure by one year. Second, we focus on the intransitive triad or indirect links for the strict exogeneity requirement following Bramoulle et al. (2009). In this method, to study the effect of hospital j's decision on hospital i, we use hospital k which is connected to j but not i as an instrument for j. This approach corrects for the existence of omitted variable bias as well, conditional on the exogeneity of the instrument. We also examine the non-linearity of the spillover effect by adding different degrees of the polynomial of that effect to our specification. Furthermore, we focus on the strength of link rather than the existence by differentiating between the effect of a surgeon based on the number of surgeries they perform and the number of mutual surgeons between connected hospitals.

Our results confirm the positive effect of surgeon's spillover effect on the NKR network adoption decision by hospitals. Specifically, we show that one more NKR adoption by the connected hospitals increases the probability of the adoption in the original hospital by about four percentage point. Our results hold after we address the reflection problem using indirect connections as the instrumental variables. The IV approach shows a relatively larger magnitude, although the downward bias of OLS is not significantly different. We further find that the increase in the NKR adoption by the connected hospital increases the probability of the focal hospital to participate in this network at a diminishing rate. Finally, we find that superstar surgeons (those who perform more than the median number

[1] All the link formations are limited to the years 1988 to 2006.

of transplants) have a larger influence on the participation decision of the hospital they are active in as opposed to surgeons with a smaller number of transplants. Also, having more than one mutual surgeon between two hospitals increases the spillover effect of surgeons.

3.2 Institutional Background

3.2.1 Creation of Kidney-Exchange Networks

A kidney transplant is the preferred treatment of choice for end-stage renal disease (ESRD) patients, but there is a significant shortage of organs for transplant due to the prohibition of monetary transactions for human organs by law. By 2017 about 110,000 patients were waiting on the long wait-list to receive a kidney transplant from a deceased donor in the United States, while fewer than 12,000 of such operations are performed annually. On the other hand, patients who have a family or friend who is willing to donate one of their kidneys to them can receive a living transplant conditional on medical compatibility requirements. Until 2004 getting a transplant from a living donor was only available for medically compatible patient-donor pairs, and incompatible pairs had to wait for a deceased kidney transplant.

Kidney-exchange transplants started on a small scale, in which transplant specialists would find compatible matches within the pool of their incompatible patient-donor pairs. Introduction of national kidney-exchange networks expanded this practice by creating a platform for hospitals to register all these incompatible patient-donor pairs and find compatible matches for those patients within a larger pool of registered donors.[2] To maximize the number of matches created from a national kidney-exchange program, the need for a large unified pool of patients and donors where all hospitals participate in it actively is necessary. Nonetheless, the evidence on the participation behavior of hospitals shows incomplete or zero participation by some hospitals in national networks.

[2]Alvin Roth is one of the pioneers in this field by focusing on the introduction of a sufficient matching algorithm for kidney paired donation (KPD) programs that can be used nationwide (Roth, Sönmez, and Ünver 2004; Roth et al. 2005).

Previous literature documents various reasons that prevent hospitals from participating in such a unified network. Ashlagi and Roth (2014) argue that hospitals are maximizing the number of transplants within their hospital, and their objective function does not include all the patients in need of a kidney transplant who are not in their center. This creates conflicting incentives between national kidney-exchange networks and hospitals, which results in incomplete participation by a hospital.[3] While this hypothesis supports the deviation in the participation degree of hospitals, it does not provide any understanding of zero participation of them. Another competing theory suggests that hospitals are profit-maximizing like any other firms, and the fixed-cost of participation is preventing them from joining (Agarwal et al. 2018). This theory explains the zero participation by smaller hospitals in some networks, but it does not explain the decision of hospitals in not joining some of these networks that are free of charge.

Furthermore, Ellison (2014) claims that his interviews with transplant coordinators suggest that the contribution decision of hospitals is mainly driven by the perspective of the transplant team about the performance of these networks. In light of this claim, we assume one of the critical players in shaping the view of hospitals towards a new program are surgeons. Therefore, we define a connection between two hospitals if a surgeon belongs to those two hospitals, due to change of hospitals over time or performing surgery at multiple centers at the time. Then we analyze the effect of these connections (defined as the spillover effect) on the decision of hospitals to participate in the NKR network.

3.2.2 National Kidney-Exchange Networks

There are three major national pairing organizations in the United States. The National Kidney Registry, the Alliance for Paired Donation, and the United Network for Organ Sharing Kidney Paired Donation Pilot Program. Each of these networks has some hospitals (with transplant center) participants, and there are about 20% of hospitals that are not participating in any of these networks.

[3]This conflicting incentives is captured in Figure 8 in the Appendix. They argue that hospitals first run an internal matching, and only submit the remaining hard-to-match pairs to the national networks.

The leading pairing organization in the U.S. is the National Kidney Registry (NKR), largely due to the fact that it was the first major player to arrange exchanges nationwide since 2007 effectively, and 96 transplant centers are currently using this program.[4] The pairing in this network is daily and based on medical compatibility and some recipients preferences. The matching algorithm attempts to maximize the number of transplants, except when there is a pair for hard-to-match patients or time is limited. The NKR dictates the timetable and sets forth strict guidelines as to the transportation of kidneys between centers, and charges hospitals a fee to cover operational costs that amount to roughly 5,000 dollars per transplant.

The Alliance for Paired Donation (APD) was founded initially in 2001 when Ohio's nine transplant centers joined together to engage in kidney paired donation with small success. In May 2006, the group reorganized and started their nationwide program since late 2007 and 83 transplant centers are currently using this program. APD is famous for using a sophisticated but more restrictive matching software, which scores recipients based on eight criteria, and performs match runs daily. Hospitals are in charge of coordination after the APD found a match for them. The APD does not charge fees for its services; instead, it relies entirely on philanthropic donations.

Kidney Paired Donation Pilot Program (KPDPP) was initially proposed by United Network for Organ Sharing (UNOS) as early as 2004, UNOS performed its first match in 2010, starting with 77 transplant center participants and reaching 152 centers by the end of 2016. UNOS administers the nations deceased organ transplant system; therefore it enjoys widespread access to hospitals across the country. The pairing process is performed weekly based on medical compatibility, and some recipients and donors preferences which is more restricted than NKR. The UNOS does not charge patients or hospitals beyond the flat fee required to register for the UNOS kidney transplant waiting list, but hospitals are in charge of arrangements after finding a match. Furthermore, it requires hospitals to provide follow-up care for donors but does not reimburse hospitals' fee of this follow-up care.

[4]Figure 3.2 captures all the NKR participant hospitals in the United States.

The NKR network enjoys its first-mover advantage, with a strong reputation in terms of the largest number of matches by allowing for the placement of the least amount of restrictions on their algorithm. Furthermore, the restrictive schedule that they mandate enables them to have the fastest and easiest process after finding the match. Between the increase in the number of matches and the fastest matching procedure, the NKR is known as the most effective national network in the United States. The other national networks together constitute a small part of across hospitals exchange transplants. Therefore, the focus of our analysis is on the NKR for the remainder of this paper.

3.3 Data Description

This study used data from the Scientific Registry of Transplant Recipients (SRTR). The SRTR data system includes data on all donor, wait-listed candidates, and transplant recipients in the US, submitted by the members of the Organ Procurement and Transplantation Network (OPTN). The Health Resources and Services Administration (HRSA), U.S. Department of Health and Human Services provides oversight to the activities of the OPTN and SRTR contractors. For each transplant information on the date of transplant, the hospital that the operation happens in it, and the name and the National Provider Identifier (NPI) of the surgeon who performs the surgery is available.[5]

We drop 66,092 observations that have both missing surgeon's name and surgeon's NPI. Further, we drop 25,647 surgeons who do not have an official 10-digit NPI. This restricts our analysis to 326,088 transplants that have known surgeon name and NPI with 1,280 unique surgeon NPIs. We merge transplants data with the data from the NKR network on the list of hospitals in the network by adoption year. The NKR started its activity in 2007, beginning with one hospital. Table 3.1 shows the number of hospitals that joined the NKR network each year, and by 2017 out of 239 active transplant centers in the United States, 96 of them joined the NKR.

[5]The NPI number is a unique 10-digit identification number issued to covered health care providers by the Centers for Medicare and Medicaid Services.

To study the effect of surgeon's spillover on the NKR adoption by a hospital, we define links between two hospitals whenever surgeons perform transplant surgery in multiple hospitals by the end of the year 2006. Specifically, whenever the same surgeon is observed in hospital A and B, A and B are defined as connected. These links can be formed either because surgeons are performing operations at more than one hospital at a time, or they change hospital over time. We are limiting our link formation to the period before 2007 (before the introduction of NKR) to avoid selection. Specifically, we assume the link between 2 hospitals is formed randomly before 2007, and the NKR network does not affect the relocation decision of surgeons, or their decision to perform surgery in multiple hospitals.

We use the described data to test whether the probability of adopting the NKR network by a hospital increases as more of the connected hospitals by surgeons adopt this network.

3.4 Empirical Framework

We estimate a local aggregate model in which an action by hospital i is determined by the *total* effort made by i's connected nodes (Calvo-Armengol and Zenou 2004).[6]

The adjacency matrix $\mathbf{G}$ is defined with each entry g_{ij} equals 1 if i and j are connected and equals 0 otherwise.[7] The spillover variable then is defined as the total number of connected hospitals having adopted NKR by some point in time.

$$\mathbf{G}NKR_{t,h} = \text{Total number of connected hospitals having adopted NKR by time t,} \quad (3.1)$$

[6]We define a utility maximization problem by hospital i in network r as

$$u_i(y_i, g_{ij,r}) = f(y_i) + \alpha y_i \sum_{j=1} g_{ij,r} y_j,$$

in which $f(y_i)$ captures the benefit and cost of effort y_i, $g_{ij,r}$ equals 1 if i and j are connected in network r, and equals 0 otherwise. The reduced-form regression in Equation 3.2 is then obtained by deriving the best-response function. This exercise also demonstrates the source of the reflection problem.

[7]For now, assume all hospitals belong to the same network.

where

$$Y_{t,h} = \begin{cases} 0, & \text{if} \quad t < \hat{t} \\ 1, & \text{if} \quad t \geq \hat{t} \end{cases}$$

and $\hat{t}$ refers to the year when hospital h adopts NKR, and the hospital leaves the sample after adoption as we observe no exit. The reduced-form representation of the network model is then defined as

$$Y_{t,h} = \beta_0 + \beta_1 \mathbf{G}NKR_{t,h} + \mathbf{X}_{t,h}B + \tau_t + \sigma_h + \epsilon_{t,h}, \tag{3.2}$$

in which $\mathbf{X}_{t,h}$ refers to a vector of time-varying control variables at the hospital level including the sum of living and deceased transplants in a hospital, population of the state that the hospital is located in, percentage of female patients, and percentage of black patients in that hospital. τ_t and σ_h are time and hospital fixed effects respectively. β_1 is the coefficient of interest that measures the change in the probability of NKR adoption at time t when the total number of adoption by connected hospitals changes *by* time t ($\mathbf{G}NKR_{t,h}$).

In Equation 3.2, there are two identification challenge. The first problem is the direction of the effect; i and j are connected, but we do not know whether i affects or being affected by j. This is the renowned 'reflection problem' in the estimation of the spillover effect due to the simultaneity of actions (Manski 1993). To augment Equation 3.2, we replace the spillover measure with a lagged variable $\mathbf{G}NKR_{t-k,h}$, where k is the number of lag chosen. The second issue is the omitted variable bias, and under strict exogeneity, we do require an instrument to identify a causal effect (Bramoulle, Djebbari, and Fortin 2009). We utilize the intransitivity in connections and use the aggregate adoption of indirect links by time $t-1$ ($\mathbf{G^2}NKR_{t-1,h}$) as the instrument. Conditional on exclusion restriction, using the number of indirectly connected hospitals as an IV corrects for the omitted variable bias. Exclusion restrictions arise naturally from the non-overlapping nature of our hospital

network. Our first stage is then defined as

$$\mathbf{G}NKR_{t,h} = \alpha_0 + \alpha_1 \mathbf{G^2} NKR_{t-1,h} + \mathbf{X}_{t,h}\Gamma + \theta_t + \phi_h + u_{t,h}. \tag{3.3}$$

Suppose i is connected with j and j is connected with k, but i and k are not. We can use the behavior of k to instrument for the behavior of j. To ensure the exclusion restriction holds, i.e. $\mathbf{I}, \mathbf{G}$, and $\mathbf{G^2}$ are linearly independent, common connections are eliminated in $\mathbf{G^2}$. Also, the hospital network is assumed to be static after 2007 so that the non-overlapping nature is not affected by the adoption of NKR.

3.5 Results

In Tables 3.3, we show that there is a positive relationship between the probability of the NKR adoption by a hospital and the total number of adoption by its connected hospitals. According to Column (1) of Table 3.3, one more adoption of connected hospitals by period t increases the probability of adoption by the focal hospital in the same period by 3.73 percentage points. Based on Table 3.1 the average adoption rate is about 3.6 percent through the years of 2007 to 2017, which implies that the spillover effect has a substantial magnitude.

To correct for the reflection problem, we also look at the effect of the adoption of NKR by the connected hospital with one year lag. As shown in Column (2) of Table 3.3, the effect of one more adoption of connected hospitals by period $t-1$ increases the probability of adoption in the current period by 3.41 percentage points. Compared to the contemporaneous effect in Column (1), the magnitude decreases by half of the standard deviation. Nonetheless, the effect is still positive and statistically significant. Table 3.3 also captures the effect of an increase in the proportion of connected hospitals that adopted NKR to account for the total number of links hospitals have.[8] Based on the second part

[8]The proportion variable captures the number of connected hospitals that adopted NKR by year t over the total number of connected hospitals. the sample is smaller because we omit hospitals with no connections from this analysis.

of Table 3.3, 10% increase in the proportion of connected hospitals by year t increases the probability of adoption by the focal hospital by 1.74 percentage points.

We further address the reflection problem described in Section 3.4 by instrumenting $\mathbf{G}NKR_t$ using $\mathbf{G^2}NKR_{t-1}$. Because 11 hospitals are dropped when we use the lagged variables, Column (1) of Table 3.4 reports the result of Panel OLS with a comparable sample. In Column (2) of Panel A, the first stage result shows that 5 more total adoptions from the indirectly connected hospitals will bring about 1 more total adoption from the connected hospitals. Column (2) of Panel B in Table 3.4 reports the spillover effect at time t in the second stage. When we compare the result in Column (1), the OLS estimates are understated but the bias is not statistically significant.

In Table 3.5, we further explore the non-linearity of the spillover by adding different orders of a polynomial. We do find a diminishing return to the total adoption as revealed by the negative sign of the second degree in Column (2). The spillover effect becomes insignificant until the 10^{th} adoption (F statistics = 1.30).

3.6 Further Analysis

In the main analysis, a link between two hospitals is defined whenever the same surgeon has ever performed surgery in both hospitals until 2006. In this section, we allow the intensity of a connection to matter. That is, a 'super' surgeon may be more influential in information transmission. This analysis is based on the finding by Agha and Molitor (2018) that superstar physicians, measured by their trial role or citation history, have a broader influence in the adoption of new cancer drugs by a hospital.

More specifically, we define a 'super' surgeon in a hospital by whether the number of surgeries performed by a particular surgeon in the same hospital is above the median of the number of surgeries of all surgeon-hospital pairs in our data. Figure 3.4 shows the distribution of the number of surgeon-by-hospital surgeries and the median number is 35. We then redefine the links between two hospitals into four types. We define a link as

'strong' if the surgeon is a super surgeon in both hospitals; an 'intermediate strong' link is defined if the surgeon is a super surgeon only in Hospital i, whereas an 'intermediate weak' link is defined if the surgeon is a super surgeon only in Hospital j; and a 'weak' link is defined otherwise. This method of categorization indeed gives a good amount of variation as reflected in Table 3.6.

We re-estimate the counterpart of Equation 3.2 separately for the four types and report the results in Column (1) to (4), and jointly in Column (5) of Table 3.7. As reflected in Column (5), the spillover from 'weak' links is small and insignificantly different from zero. Moreover, the spillover from the 'intermediate strong' links is significantly larger than that from 'intermediate weak' links and 'weak' links. The spillover from 'strong' links is also significantly larger than that from 'weak' links. These results are intuitive and consistent with the findings of Agha and Molitor (2018). As the number of transplants surgeons performs in a hospital increases, their influence on the hospital-level decisions in that center will become broader.

Another way to capture the strength of links between two hospitals is to look at the number of mutual surgeons between two connected hospitals as opposed to the existence of mutual surgeons. Figure 3.5 shows the distribution of the number of mutual surgeons between two connected hospitals. This histogram shows that 85% of the connected hospitals are linked through one mutual surgeon. Based on this graph, We define a link between two hospitals as 'weak' if they only have one common surgeon, and 'strong' if they have two or more common surgeons.

We re-estimate the counterpart of Equation 3.2 separately for the two types and report the results in Column (1) to (2), and jointly in Column (3) of Table 3.8. As reflected in Column (3), the spillover from hospitals with 'weak' links is about half of the size of a spillover from hospitals with 'strong' links. These results are again consistent with the information transmission idea, and it confirms that the influence of connected hospitals on each other is more substantial when they have more than one mutual surgeons.

3.7 Conclusion

As the use of national kidney-exchange networks expands the number of transplants for incompatible patient-donor pairs, a question that arises is what makes some hospitals more prone to participate in such networks. Specifically, we are interested in the role of the opinion leaders in the network-adoption decision of a hospital. Our hypothesis is that surgeons play a significant role in the idea transmission and the final decision of participation by hospitals.

This study uses the unique data set of the Scientific Registry of Transplant Recipients (SRTR) merged with NKR data on participant hospitals. The data allow us to identify each transplant, the name and the ID of the surgeon who performed it, the hospital that it took place in, and the subsequent participation status of that hospital in the NKR in each year. We then define a link between two hospitals if those two hospitals had a mutual surgeon who performed transplants in both hospitals. We limit these link formations to the period before the introduction of the NKR network to avoid connections that are made through this network.

Our estimates suggest that hospitals are more likely to adopt the NKR network if surgeons in those hospitals were members of other NKR-participant hospitals. In particular, one more adoption of NKR by connected hospitals increases the probability of adoption by about four percentage points. We address the simultaneity of behavior, known as the reflection problem, by lagging the spillover measure by one year. We further correct for the omitted variable bias by using indirect links, known as intransitive triads, as an instrument for direct links. Our results hold after addressing both of these identification challenges. We also check the non-linearity of the spillover and find a diminishing magnitude in this effect. Additionally, we divide hospitals into four types to investigate the effect of the superstar surgeons by the number of transplants they performed in a hospital. We find that the higher the number of transplants a surgeon performs in a hospital, the broader their influence in the participation decision of that hospital. Finally, we divide hospitals based on the number

of mutual surgeons that two connected hospitals share, and we define hospitals with more than one mutual surgeon as a strong connection. Our result shows that the magnitude of a spillover effect from strong links is twice the effect from weak links.

Our results are consistent with Agha and Molitor (2018) in terms of the direction of the effect. They find prominent physicians play a vital role in the adoption of newly invented cancer drugs by hospitals with a broader influence for the superstar physicians (measured by their trial role or citation history). Nonetheless, the magnitude of the effect is larger in our estimates naturally because the adoption of the NKR network by connected hospitals expands the potential size of the network for all the existing participants as well. In other words, the expansion of the network is beneficiary for the influencer hospital as well as the affected one.

Table 3.1: Participation of Hospitals in NKR Over Years

	Number of Hospitals Joining	Total Number of Hospitals	Percentage of New Participants	Cumulative Percentage of New Participants
Year:				
2007	1	254	0.39	0.39
2008	10	249	4.02	4.41
2009	12	249	4.82	9.23
2010	15	244	6.15	15.38
2011	15	242	6.20	21.58
2012	13	240	5.42	27.00
2013	13	240	5.42	32.42
2014	8	236	3.39	35.81
2015	4	239	1.67	37.48
2016	4	236	1.69	39.17
2017	1	239	0.42	39.59

Notes: This table captures the pattern in which hospitals joined NKR network through years following its introduction in 2007.

Table 3.2: Summary Statistics

Variable	mean	sd	min	max
Own Characteristics (Average Across Time)				
Adoption at time t	0.09	0.15	0.00	1.00
Number of Living Transplants at time t	22.10	27.03	0.00	138.50
Number of Deceased Transplants at time t	41.30	39.12	0.67	234.50
Population of the State the Hospital at time t	12.98	10.55	0.60	39.26
female	0.38	0.09	0.00	0.58
black	0.25	0.20	0.00	0.98
Network Characteristics (Static)				
Direct connection	4.28	3.80	0.00	20.00
Indirect connection	16.34	15.27	0.00	75.00
Network Characteristics (Average Across Time)				
Total adoption of hospital (directly connected) by time t	0.78	1.07	0.00	6.00
proportion of adoption by hospital (directly connected) by time t	0.18	0.19	0.00	0.90
Instruments (Average Across Time)				
Total adoption of hospital (indirectly connected) by time t	3.24	3.88	0.00	16.82

Notes: This table captures the summary statistics of the variables of interest across all years. The numbers are the average of collapsed data at the hospital level. The Number of hospitals observed in the sample is 268.

Table 3.3: Positive Correlation Between the Adoption Decision of Connected Hospitals (Panel OLS)

	(1)	(2)
Total Adoption of Connected Hospitals by		
time t	0.0373***	
	(0.0049)	
time t-1		0.0341***
		(0.0055)
Constant	-0.183*	-0.192
	(0.107)	(0.126)
Observations	2,076	1,800
R-squared	0.043	0.035
N of CTR_ID	268	257
Proportion of Adoption by Connected Hospitals by		
time t	0.1744***	
	(0.0262)	
time t-1		0.1599***
		(0.0289)
Constant	-0.2312*	-0.2490*
	(0.1243)	(0.147)
Observations	1,772	1,543
R-squared	0.043	0.036
N of CTR_ID	221	214

Notes: Dependent variable is an indicator equal to 1 if hospital i joins NKR at time t. The hospital leaves the sample after adoption (we observe no exit). The independent variable is the total number of connected hospitals having joined NKR by different time t ($\mathbf{G}NKR_{t,h}$). Time-varying controls that are not reported include sum of living and deceased transplants in a hospital, population of the state that the hospital is located in, percentage of female patients, percentage of black patients. All regressions include hospital and year fixed effects. Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3.4: The Positive Spillover Remains Robust Under The Instrumental Variable Strategy

	(1) Panel OLS (Comparable Sample)	(2) Panel IV
Panel A: First Stage		
$\mathbf{G^2}NKR_{t-1}$		0.195***
		(0.00455)
F Stat.		1876.73
Panel B: Second Stage		
Total Adoption of Friends at time t	0.0403***	0.0523***
	(0.00589)	(0.00799)
Constant	-0.178	-0.105
	(0.125)	(0.129)
Observations	1,800	1,800
Number of CTR_ID	257	257

Notes 1: Instrument in the first stage includes $\mathbf{G^2}NKR_{t-1}$: the total adoption of indirectly connected hospitals *by* time $t-1$.

Notes 2: Dependent variable in the second stage is an indicator equal to 1 if hospital i joins NKR at time t. The hospital leaves the sample after adoption (we observe no exit). The independent variable is the total number of connected hospitals having joined NKR by time t ($\mathbf{G}NKR_{t,h}$). Time-varying controls that are not reported include sum of living and deceased transplants in a hospital, population of the state that the hospital is located in, percentage of female patients, percentage of black patients. All regressions include hospital and year fixed effects. Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3.5: The Spillover Effect Exhibits A Diminishing Return (Panel OLS)

	(1)	(2)	(3)
Total Adoption of Friends at time t	0.0373***	0.0669***	0.0829***
	(0.00498)	(0.00929)	(0.0160)
(Total Adoption of Friends at time t)^2		-0.00558***	-0.0127**
		(0.00148)	(0.00592)
(Total Adoption of Friends at time t)^3			0.000640
			(0.000519)
Constant	-0.183*	-0.134	-0.128
	(0.107)	(0.107)	(0.108)
Observations	2,076	2,076	2,076
R-squared	0.043	0.050	0.051
Number of CTR_ID	268	268	268

Notes: Dependent variable is an indicator equal to 1 if hospital i joins NKR at time t. The hospital leaves the sample after adoption (we observe no exit). Time-varying controls that are not reported include sum of living and deceased transplants in a hospital, population of the state that the hospital is located in, percentage of female patients, percentage of black patients. All regressions include hospital and year fixed effects. Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3.6: Distribution of the Four Types of Links

Type of Links	Percentage	Frequency
Strong	22.80	414
Intermediate Strong	27.03	491
Intermediate Weak	27.03	491
Weak	23.13	420

Notes: This table shows the distribution of the four types of links. Total number of links are 1,816. A 'strong' link is defined if the surgeon is a super surgeon in both hospitals; an 'intermediate strong' link is defined if the surgeon is a super surgeon only in Hospital i, whereas an 'intermediate weak' link is defined if the surgeon is a super surgeon only in Hospital j; a 'weak' link is defined otherwise.

Table 3.7: Spillover Effects From Strong and Intermediate-Strong Links Are Larger (Panel OLS)

	(1)	(2)	(3)	(4)	(5)
Strong Link	0.0589***				0.0397***
	(0.00963)				(0.0106)
Intermediate Strong Link		0.0809***			0.0511***
		(0.0150)			(0.0161)
Intermediate Weak Link			0.0314***		0.0165**
			(0.00707)		(0.00808)
Weak Link				0.0377***	0.00896
				(0.0129)	(0.0143)
Constant	-0.288***	-0.275***	-0.347***	-0.373***	-0.186*
	(0.105)	(0.107)	(0.105)	(0.105)	(0.107)
Observations	2,076	2,076	2,076	2,076	2,076
R-squared	0.033	0.029	0.024	0.018	0.043
Number of CTR_ID	268	268	268	268	268

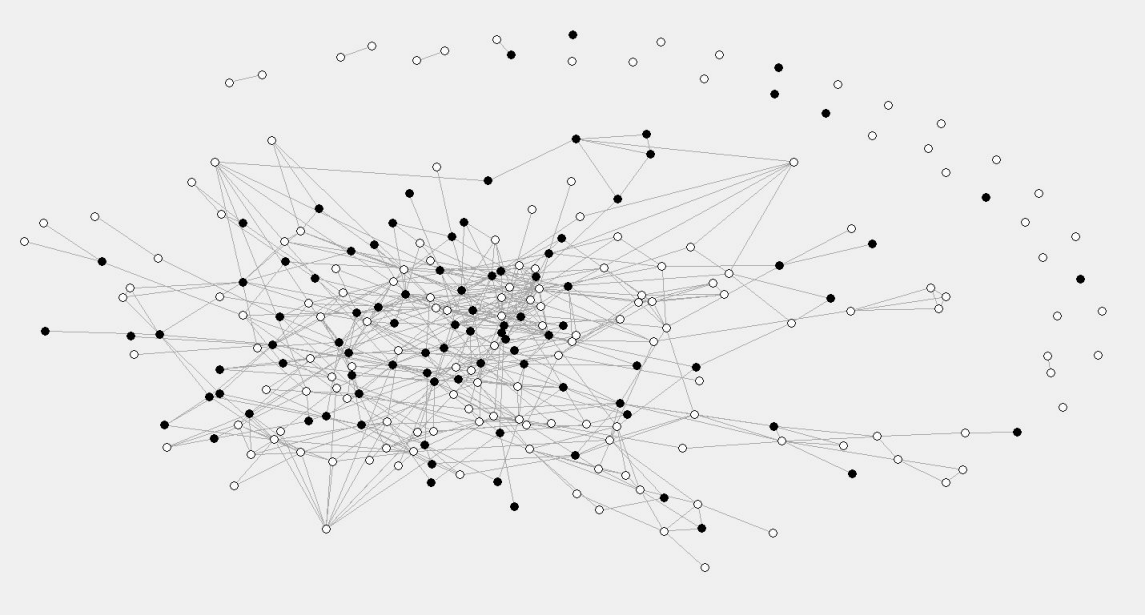
Notes: Dependent variable is an indicator equal to 1 if hospital i joins NKR at time t. The hospital leaves the sample after adoption (we observe no exit). A 'strong' link is defined if the surgeon is a super surgeon in both hospitals; an 'intermediate strong' link is defined if the surgeon is a super surgeon only in Hospital i, whereas an 'intermediate weak' link is defined if the surgeon is a super surgeon only in Hospital j; a 'weak' link is defined otherwise. Time-varying controls that are not reported include sum of living and deceased transplants in a hospital, population of the state that the hospital is located in, percentage of female patients, percentage of black patients. All regressions include hospital and year fixed effects. Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3.8: Strong Links with Stronger Spillover Effect

	(1)	(2)	(3)
Weak Link	0.0370***		0.0329***
	(0.00547)		(0.00556)
Srong Link		0.0926***	0.0701***
		(0.0190)	(0.0192)
Constant	-0.224**	-0.329***	-0.173
	(0.107)	(0.105)	(0.107)
Observations	2,076	2,076	2,076
R-squared	0.037	0.026	0.045
Number of CTR_ID	268	268	268

Notes: Dependent variable is an indicator equal to 1 if hospital i joins NKR at time t. The hospital leaves the sample after adoption (we observe no exit). A 'strong' link is defined if there are more than one mutual surgeon between two hospitals; a 'weak' link is defined if there is only one mutual surgeon between the two hospitals. Time-varying controls that are not reported include sum of living and deceased transplants in a hospital, population of the state that the hospital is located in, percentage of female patients, percentage of black patients. All regressions include hospital and year fixed effects. Standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Figure 3.1: Hospitals' Network Defined by Surgeons' Movement

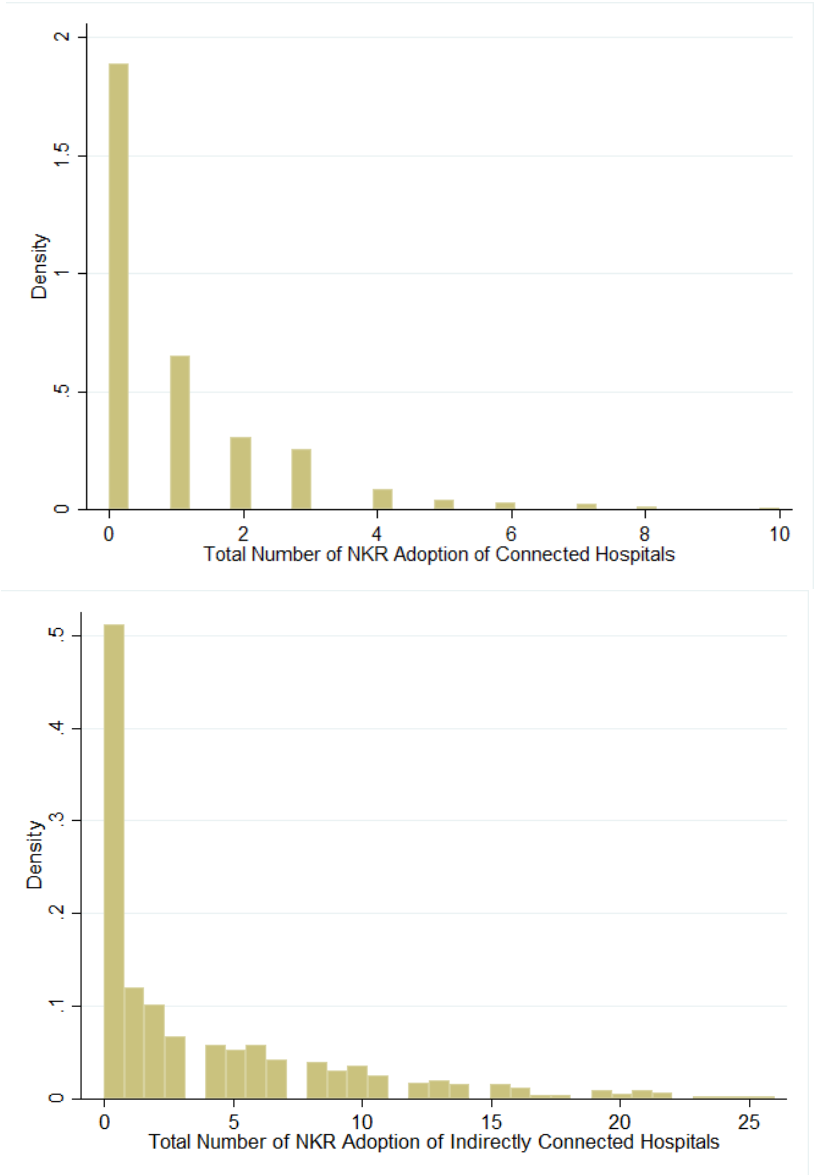


Notes: This graph shows the network of hospitals which is determined by the movement of surgeons between hospitals before 2007. The colored dots indicate the hospital has adopted NKR during the sample period.

Figure 3.2: Map of the NKR Participant Hospitals

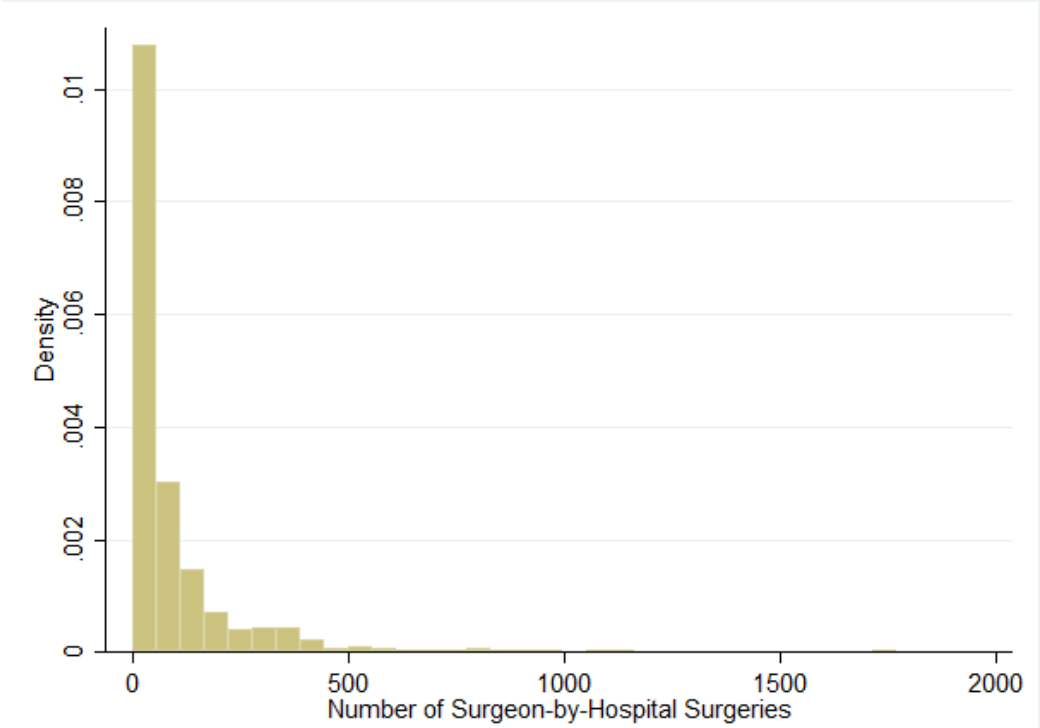
Notes: This graph captures all the NKR participant hospitals in the United States by the end of 2017.

Figure 3.3: NKR Adoption between Directly and Indirectly Connected Hospitals



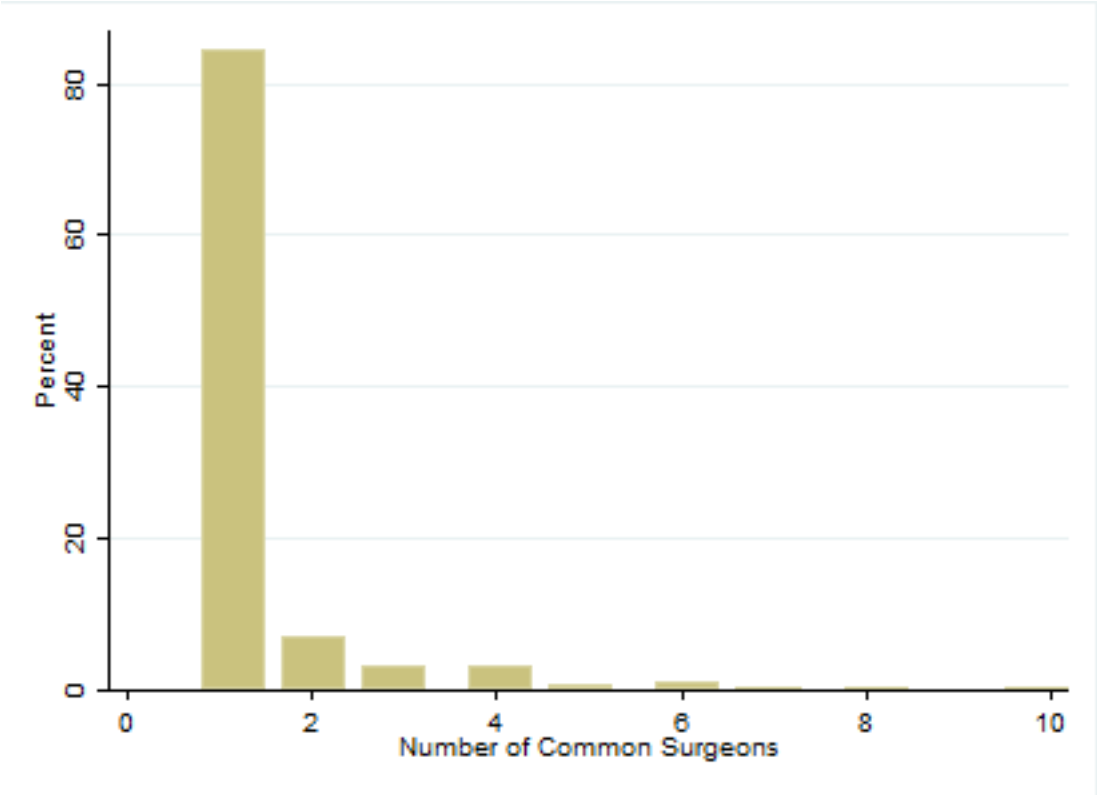
Notes: These histograms show the distribution of the number of connected hospitals and the number of indirectly connected hospitals that adopted NKR during the sample period.

Figure 3.4: Distribution of the Number of Surgeon-by-Hospital Surgeries



Notes: This histogram shows the distribution of the number of surgeon-by-hospital surgeries (1987-2006). We define a 'super' surgeon if the number of surgeries in the same hospital is higher than 35 (median).

Figure 3.5: Distribution of the Number of Mutual Surgeons



Notes: This histogram shows the distribution of the number of mutual surgeons between two connected hospitals. We define a 'weak' link if there is only one common surgeon, and a 'strong' link if there are two or more common surgeons between hospitals. This histogram shows that 85% of the links are defined as 'weak' links.

Appendices

Appendix A The Effect of the National Kidney Registry on the Probability of Receiving a Transplant

Table 9: Testing Different Number of Knots on the Fit of the Model

	Log-Likelihood	DF	AIC	BIC
Number of Knots:				
0	-577,593.1	1	1,155,268	1,155,724
1	-577,589.9	2	1,155,312	1,156,046
2	-576,677.4	3	1,153,465	1,154,076
3	-576,319.9	4	1,152,720	1,153,165
4	-576,269.1	5	1,152,620	1,153,076
5	-576,271.6	6	1,152,633	1,153,134

Note: The model that minimizes the AIC, which is defined as the log likelihood of the model times -2, plus twice the number of model parameters, is the model with 4 knots (5 degrees of freedom), for which AIC is equal to 1,152,620. The knots are placed at the 20^{th}, 40^{th}, 60^{th}, and 80^{th} centiles of the uncensored distribution of log times.(Durrleman and Simon, 1989)

Table 10: Probability of Receiving a Transplant (Different Number of Knots)

	0 Knot	1 Knot	2 Knots	3 Knots	4 Knots	5 Knots
NKR	1.0635	1.0635	1.0651	1.0653	1.0653	1.0653
	(0.044)	(0.044)	(0.045)	(0.045)	(0.045)	(0.045)
Patient's Age	0.9893***	0.9893***	0.9894***	0.9895***	0.9895***	0.9895***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
BMI	0.9781***	0.9781***	0.9780***	0.9780***	0.9780***	0.9780***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
O Blood-Type	0.7134***	0.7132***	0.7116***	0.7115***	0.7115***	0.7116***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
PRA	0.9912***	0.9912***	0.9911***	0.9911***	0.9911***	0.9911***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	1.0905***	1.0906***	1.0907***	1.0906***	1.0905***	1.0905***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Black	0.6899***	0.6896***	0.6884***	0.6883***	0.6883***	0.6883***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Other Eth	0.7159***	0.7157***	0.7151***	0.7152***	0.7153***	0.7153***
	(0.012)	(0.012)	(0.013)	(0.011)	(0.013)	(0.013)
College Educ	1.0741***	1.0741***	1.0746***	1.0745***	1.0745***	1.0745***
	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Medicare	0.9025***	0.9025***	0.9034***	0.9036***	0.9036***	0.9036***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Population	0.9653	0.9653	0.9656	0.9658	0.9658	0.9658
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Observations	498,544	498,544	498,544	498,544	498,544	498,544
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Exponentiated coefficients (hazard ratios) are reported with corresponding standard errors. The hazard ratio is calculated using a single-risk hazard function by fitting a cubic spline function with a different number of knots for the baseline hazard. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and *, respectively. Standard errors are in parentheses and are clustered at the hospital level.

Table 11: Expanding the Data Set

	Wait-Time	Event	Status
ID:			
1	60	Transplant	0
1	60	Death/too Sick	0
1	60	Transferred	0
1	60	Transplant Elsewhere	0
2	25	Transplant	0
2	25	Death/too Sick	1
2	25	Transferred	0
2	25	Transplant Elsewhere	0

Notes: According to this table, each patient is at risk for one of the four events. Patient 1 has been followed for 60 months (5 years) and did not experience any of the events in that period, so he is censored. Patient 2 was at risk of experiencing any of the events for 25 months, but then died and was removed from the waiting list.

Appendix B The Effect of the National Kidney Registry on the Quality of Donors

Table 12: Evidence for the Existence of Imbalance Between Treatment and Control Groups

	(Non-NKR Hospitals)	(NKR Hospitals)	(t_Test)
Transplant Numbers:			
Exchange Transplants	0.48	1.15	-14.09
	(0.62)	(2.36)	
Direct-Living Transplants	16.51	37.02	-24.17
	(23.84)	(32.83)	
Deceased-Donor Transplants	27.70	51.27	-21.42
	(32.08)	(41.10)	
Recipients' Average Age	40.09	45.38	-12.82
	(15.52)	(9.08)	
Hospital's State Population	11,370.11	13,066.71	-5.64
	(9,148.58)	(10,692.42)	

Notes: The reported means are for the period before the introduction of NKR (before 2008). NKR hospitals are all hospitals that eventually join this network. Standard deviations are reported in the parenthesis.

Table 13: The Estimated Impact of the NKR Adoption on Different Typesof Transplants

	exchange share	direct living share	deceased donor share
NKR	1.929***	-0.491	-1.697
	(0.401)	(1.074)	(1.200)
Constant	0.200	41.23***	58.56***
	(0.138)	(0.915)	(0.947)
Observations	4127	4127	4127
Mean (Number)	2.49	33.30	63.98
Adjusted R^2	0.176	0.272	0.153
F	19.58	32.11	13.92
Year FE	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes

Notes: The dependent variables are the division of transplants into exchange, direct living, and deceased donor shares and counts in a hospital/year. These shares are the number of such transplants over the total number of all transplants in a given hospital and year multiplied by 100. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and * respectively. Standard errors are in parentheses. They are clustered at hospital level.

Table 14: The Estimated Impact of the NKR Adoption on Different Types of Transplants (After Matching)

	exchange share	direct living share	deceased donor share
NKR	1.951***	-1.365	-0.909
	(0.410)	(1.083)	(1.211)
Constant	0.286*	40.81***	58.91***
	(0.146)	(0.934)	(0.965)
Observations	3855	3855	3855
Adjusted R^2	0.203	0.280	0.155
F	18.75	29.59	13.34
Year FE	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes

Notes: The dependent variables are the division of transplants into exchange, direct living, and deceased donor shares and counts in a hospital/year. These shares are the number of such transplants over the total number of all transplants in a given hospital and year multiplied by 100. The regressions are weighted using the Coarsened Exact Matching Method. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and * respectively. Standard errors are in parentheses. They are clustered at hospital level.

Table 15: The Estimated Impact of NKR Adoption on Different Types of Transplants, 2005-2017

	exchange share	direct living share	deceased donor share
NKR_2	-0.155	-1.112	1.096
	(0.469)	(1.215)	(1.318)
NKR_1	-0.557	0.608	-0.220
	(0.555)	(1.349)	(1.429)
NKR0	0.573	-0.463	-0.324
	(0.717)	(1.396)	(1.602)
NKR1	1.108	-1.065	-0.457
	(0.678)	(1.503)	(1.557)
NKR2	1.280*	-2.352	0.790
	(0.684)	(1.660)	(1.783)
NKR3	1.623*	-3.346*	1.045
	(0.830)	(1.783)	(1.938)
NKR4&$_{forward}$	2.058**	-2.733	-0.118
	(0.811)	(1.906)	(2.089)
Observations	2332	2332	2332
Year FE	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes

Notes: The dependent variables are the division of transplants into exchange, direct living, and deceased donor shares and counts in a hospital/year. The regressions are weighted using the Coarsened Exact Matching Method. NKR dummies -2 to 3 are equal to 1 in only 1 year per adopting hospital. NKR4&$_{forward}$ dummy is equal to 1 in every year beginning with the fourth year of adoption. Coefficient estimates that are significant at 1%, 5%, and 10% level are denoted with ***, **, and * respectively. Standard errors are in parentheses. They are clustered at hospital level.

Figure 6: NKR adoption and its effect on transplant shares

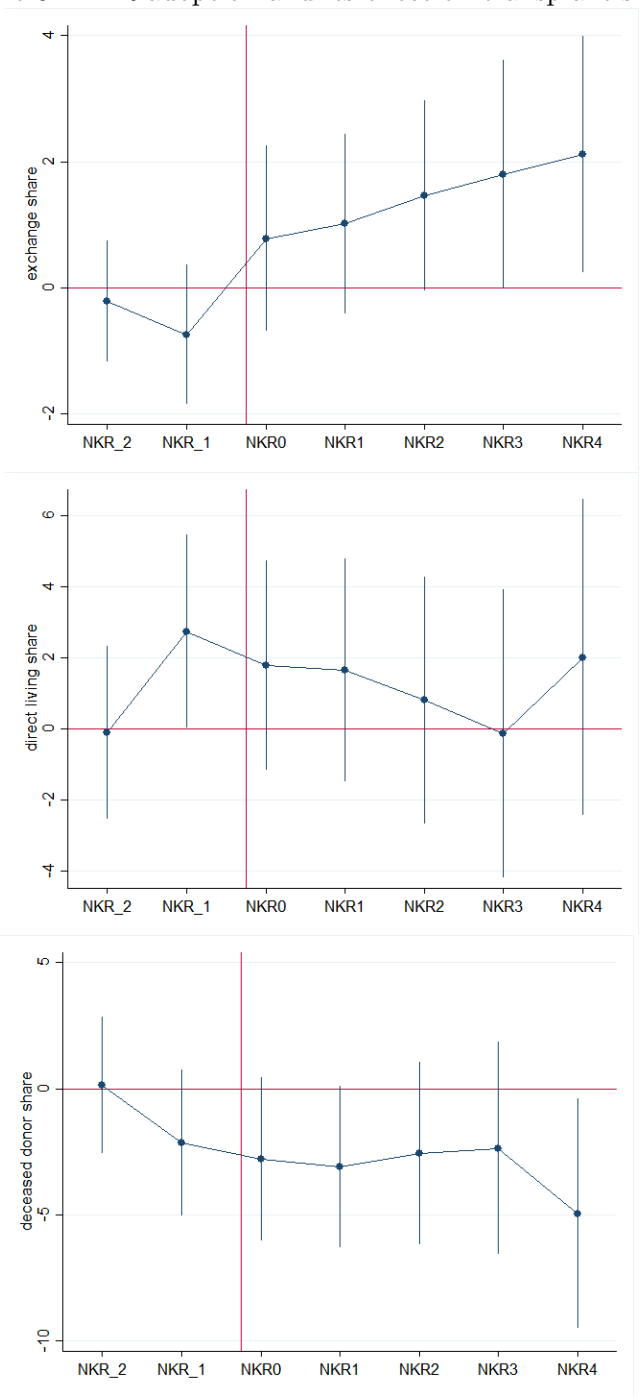
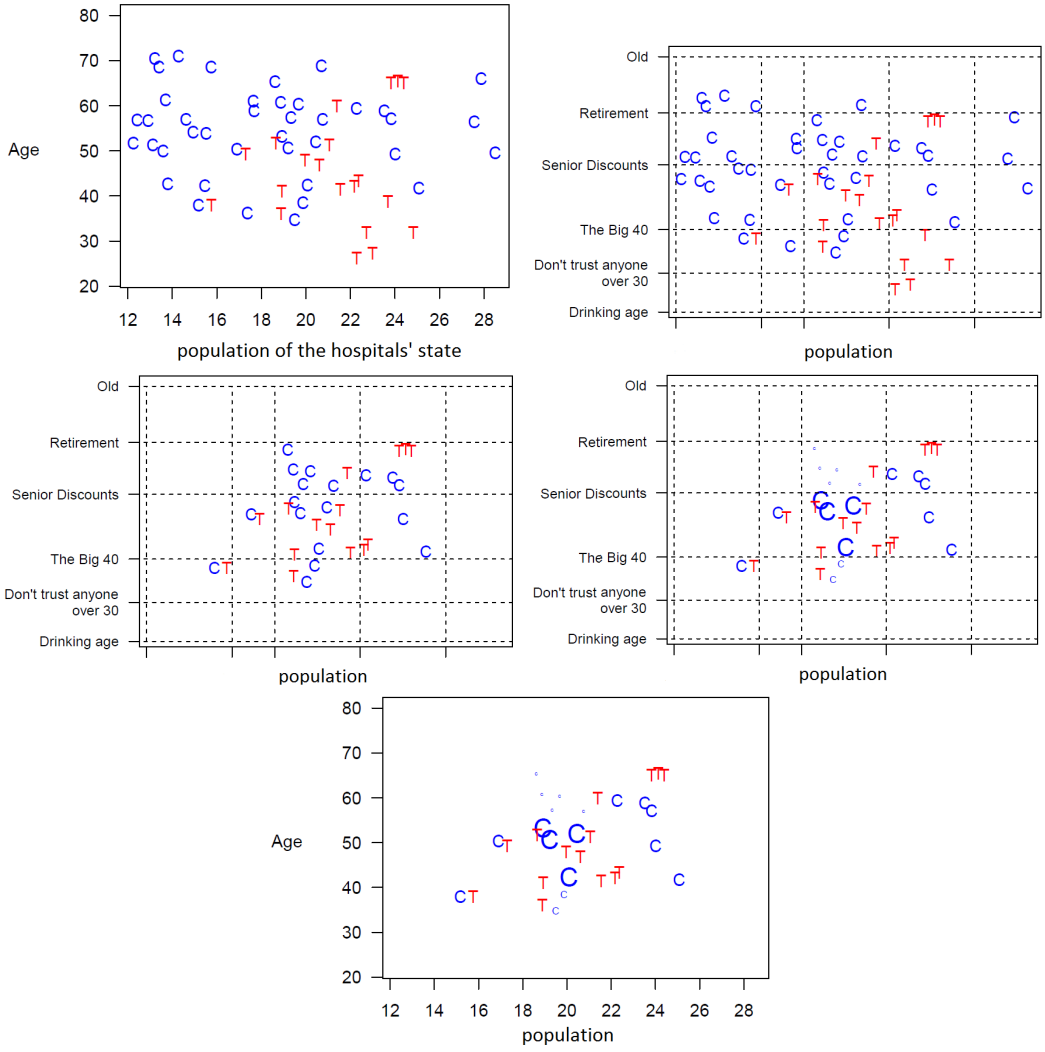
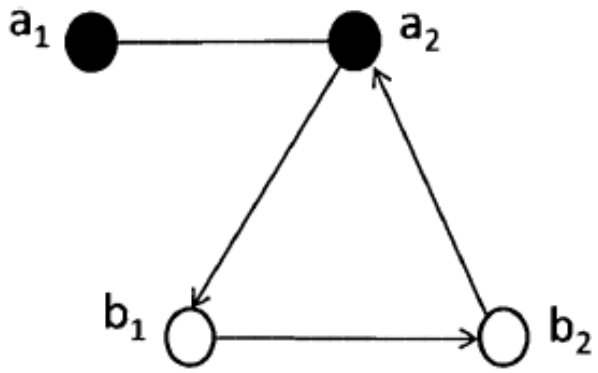


Figure 7: Illustration of Coarsened Exact Matching Method (Source: King 2018)



Appendix C The Spillover Effect of Surgeons on Expanding the Use of Kidney-Exchange Networks

Figure 8: Conflicting Incentives of Hospitals and National Kidney-ExchangeNetworks



Notes: Patient-donor pairs a_1 and a_2 belong to hospital i, and b_1 and b_2 belong to hospital j. Hospital i can arrange an internal match for both pair in its hospital, resulting in two transplants overall. Whereas, by registering these pairs in a national network only one of the pairs in the hospital i gets a transplant, but the total number of transplants increases to three. (source: (Ashlagi and Roth 2014))

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