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Participation Spillover of the National Kidney Registry *

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May 1, 2025

Abstract

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JEL Classification: I11, L14

Keywords: Kidney-exchange networks, National Kidney Registry (NKR), Spillover effect

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1 Introduction

National kidney-exchange networks create a large pool of incompatible patient-donor pairs and enable compatible matches among them, which is a solution proposed by Roth et al. (2004) to address the shortage of transplantable kidneys.[1] Recent research has shown that large-scale kidney exchange networks create more potential matches and benefit patients (Teltser, 2018; Holscher et al., 2018; Ghanbariamin and Chung, 2020).

The participation of hospitals in the exchange networks concerns policymakers because the size of the patient-donor database is vital to promote the efficiency of kidney exchanges (Roth et al., 2005; Flechner et al., 2018). However, the current trend shows hospital participation has been happening in a fragmented fashion (Agarwal et al., 2019). Among various burdens that disincentivize transplant centers from participating, Ashlagi and Roth (2014) suggest that there is a conflict between maximizing the number of matches within their center and in the whole network. There are also substantial costs of participating which particularly discourages small centers (Rees et al., 2012). Medical researchers and practitioners also often discussed the coordination problem among centers, including logistic and billing issues (Gentry et al., 2011; Mast et al., 2011; Ross et al., 2017; Verbesey et al., 2020).[2] The aforementioned concerns all bring about the uncertainty of benefits and costs about joining the networks.

In light of the above problems, this paper documents the existence of participation spillover among transplant centers. Our focus is hospital participation in the National Kidney Registry (NKR), the largest national kidney-exchange network in the US, from 2007 to 2017. We hypothesize that connected hospitals face fewer information frictions. When one of the connections starts participating, knowledge about the program disseminates which then alleviates some of the uncertainty about the benefits and costs. We use surgeons as the source of connection based on the observation that they play a critical role in shaping the

[1] See also Roth et al. (2005) and Ashlagi and Roth (2014) for related discussion.

[2] Nicoló and Rodríguez-Álvarez (2012) also acknowledge the coordination problem of hospitals as a constraint in their model.

participation decision of a hospital (Leeser et al., 2012; Ellison, 2014; American Society of Transplant Surgeons, 2016).

We construct the connections between hospitals using a unique dataset from the Scientific Registry of Transplant Recipients (SRTR), which provides personal identifiers of the surgeons in all organ transplants in the U.S. since 1988. Two hospitals are connected as long as one surgeon performs a transplant surgery in both hospitals by 2007 (the start year of NKR). An important element here is that the hospital connections are static, which avoids a potential issue that NKR participation forms new connections between hospitals. We then look at whether participation by connected hospitals (NKR connection) increases the probability for a hospital to join the NKR. Our preferred specification employs a lagged spillover measure to avoid potential reverse causality concerns (Manski, 1993). In other words, we estimate the effect of the number of connected hospitals who joined NKR in the last year on the current likelihood of NKR participation of the focal hospital.

In our full specification, we control for time-varying area and hospital characteristics to isolate systematic heterogeneity across centers. Our survival analysis reveals that a hospital with one NKR connection in the last period is 1.5 times more likely than its no-NKR counterparts to join the NKR.[3] We further provide evidence on the role of surgeons in explaining the spillover effect. First, the connections based on the presence of superstar surgeons (those who perform more than the median number of transplants in the sample) have a more significant influence on the participation decision of a hospital. Second, having more than one mutual surgeon between two hospitals generates a stronger spillover effect.

One concern is to distinguish the spillover effect from common local shocks.[4] We address this concern by differentiating the connections into within-MSA and across-MSA links, and only across-MSA links generate significant spillover. Common local shocks, if any at the MSA level, do not drive our result. Another concern is the assumption of standard duration models that every observation will eventually experience the event (joining NKR), which

[3]By no-NKR counterparts, we refer them to hospitals without NKR connections in the last period.
[4]This is analogous to the 'correlated effect' discussed by (Manski, 1993).

is not a reasonable assumption in our context. In the robustness section, we estimate a split-population duration model to acknowledge the fact that three-fourths of our sample hospitals indeed did not take up the NKR. This specification gives us a more conservative estimate about the spillover: a hospital with one NKR connection in the last period is 1.2 times more likely than its no-NKR counterparts to join the NKR. Nonetheless, the effect size remains statistically significant.

Overall, we provide the first empirical evidence about the participation spillover of the National Kidney Registry. In fact, there has been research finding technology diffusion in the health care sector (Coleman et al., 1957; Escarce, 1996; Comin et al., 2012; Baicker and Chandra, 2010). For example, in a more recent study, Agha and Molitor (2018) find that the precense of leading physician authors ease information friction and generate spillover of prescribing new cancer drugs in the nearby area. In our earlier project, we have shown that NKR brings about an overall positive impact on patients (Ghanbariamin and Chung, 2020). The next question is how to generalize the benefits to a broader population. From a policy point of view, our finding suggests information friction plays a role in encouraging new participants, which indeed echoes qualitative evidence in the medical sector.

2 Institutional Background

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. [5]

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.[6] 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.

2.2 National Kidney-Exchange Networks

There are three major national pairing organizations in the United States; the National Kidney Registry (NKR), the Alliance for Paired Donation (APD), and the Kidney Paired Donation Pilot Program (KPDPP) proposed by United Network for Organ Sharing (UNOS). 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.[7]

The leading pairing organization in the U.S. is the NKR, largely due to the fact that it was the first major player to arrange exchanges nationwide since 2007 effectively. The NKR network has 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. One notable difference among the three networks is that NKR charges hospitals a fee to cover operational costs that amount to roughly 5,000 dollars per

[5] The alternative proposed solution is providing monetary incentives for donors. See Bilgel and Galle (2015); Lacetera et al. (2014) for related discussions.

[6] 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 et al. (2004); Roth et al. (2005)).

[7] Unfortunately, we do not have information of participant hospitals in APD and KPDPP

transplant, whereas the APD and KPDPP does not charge fees for its services.[8]

Because 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 Data Description

Our primary interest is the timing of NKR participation of all US transplant centers, which is obtained from the NKR network. Among the 261 transplant centers in our sample, 97 of them have joined the NKR network by 2017.[9] As shown in Figure 1, NKR participation has been rising in the first couple of years and peaked in 2011. Since then, new NKR participation faced a stagnated trend.

The crucial part to study the spillover effect is the knowledge of hospital connections. We utilize the unique information on the surgeon of each transplant in the data from the Scientific Registry of Transplant Recipients (SRTR) and construct a network of hospitals based on the presence of common surgeons. For each transplant, information on the date of transplant, the hospital which the transplant takes place, and the name and the National Provider Identifier (NPI) of the surgeon are available.[10] We then define a link between two hospitals as long as there is one surgeon who performs transplants in both hospitals by the end of the year 2006.[11] A link is present either because surgeons are performing operations in more than one hospital at a time, or they switched between hospitals. We assume that the

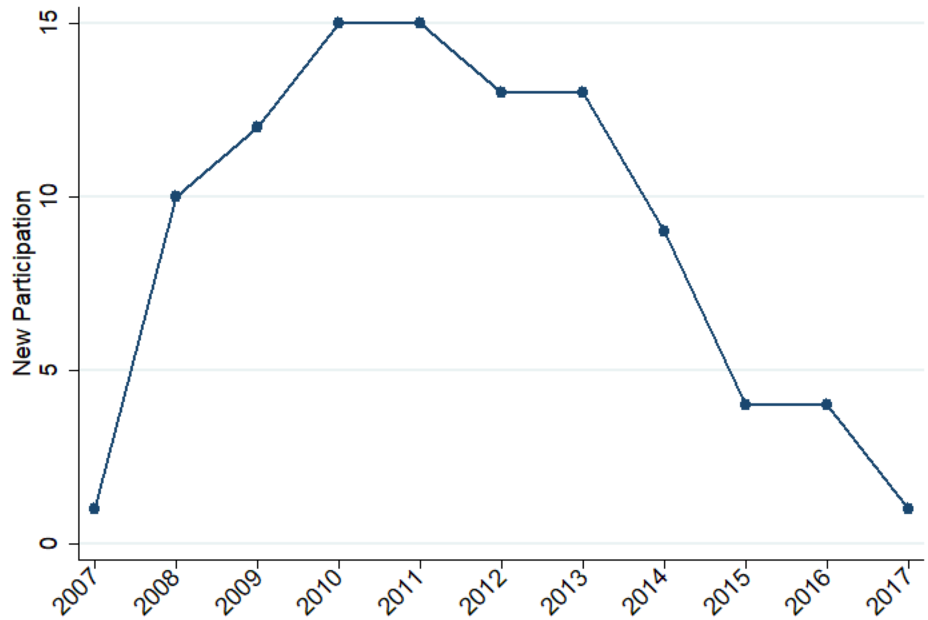
[8]The KPDPP does not charge patients or hospitals beyond the flat fee required to register for the UNOS kidney transplant waiting list, but hospitals are in charge of arrangements after finding a match. Furthermore, it requires hospitals to provide follow-up care for donors but does not reimburse hospitals' fee of this follow-up care.

[9]As of 2018, there are total 98 NKR hospitals.

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

[11]We will explore the heterogeneity by the strength of a connection in Section 6.2.

Figure 1: Stagnated New NKR Participation



Source: The National Kidney Registry

anticipation of NKR participation does not affect the relocation decision of surgeons or their decision to perform surgery in multiple hospitals. Therefore, we restrict the connections to be static to avoid endogenous link formation.

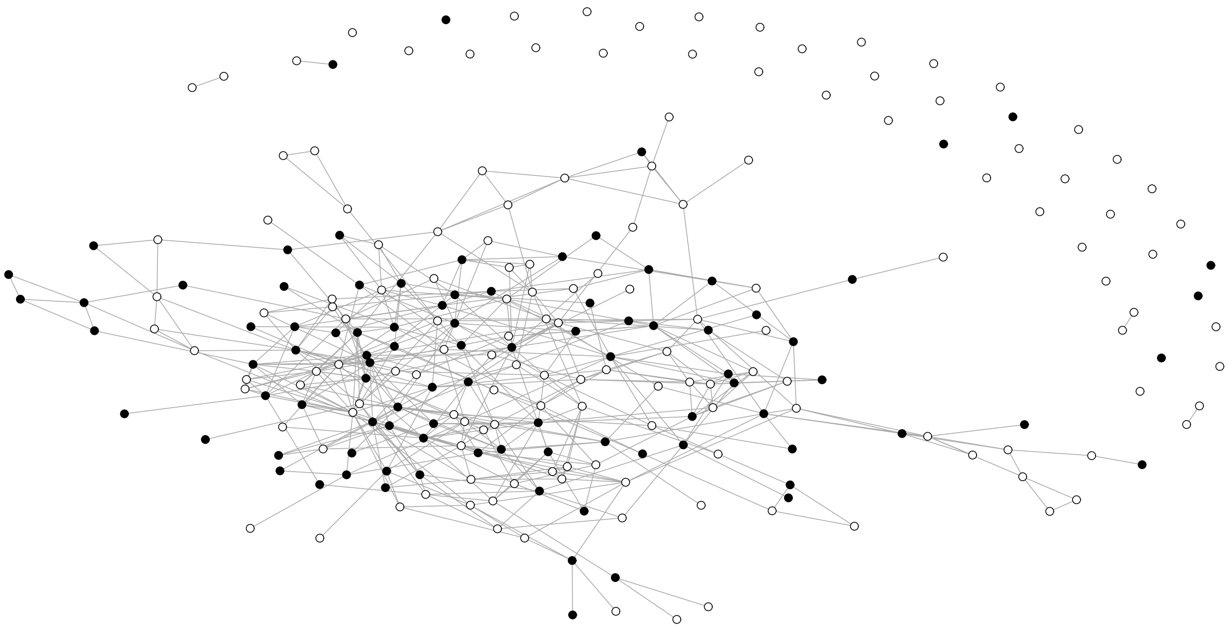
Figure 2 takes a snapshot in 2017 (the end year of the sample period) and shows the distribution of NKR participation among hospitals.[12]

4 Empirical Framework

Our data structure is a censored hospital-by-year panel with a hospital 'leaving' the sample when it joins the NKR. Therefore, the setting can be viewed as a single-risk survival analysis. Formally, define T as the number of sampling years and the event of interest being the participation of NKR. The probability density function of T, $f(t)$, gives the probability that

[12] We notice a typo about the cut-off year in Figure 3 and the related text of our previous paper (Ghanbariamin and Chung, 2020). As in our current analysis, the correct description is 2007 as the cut-off year for the network construction.

Figure 2: Author-Constructed Network Of Hospitals



Note: A static network of hospitals is defined by the presence of common surgeons between hospitals before 2007. The colored dots indicate NKR-participating hospitals in 2017.

a hospital joins NKR by time t. The hazard function, $h_i(t)$, is then defined as

$$h_i(t) = \lim_{dt \to 0} \frac{Pr(t \leq T_i < t + dt | T_i \geq t)}{dt}. \quad (1)$$

which is the conditional probability that a non-participating hospital joins NKR. The hazard rate is modeled as a function of hospital-level covariate vector X, reflecting the corresponding change in risk associated with each of the characteristics. In the estimation, we adopt the proportional hazard model by Cox and Oakes (1984):

$$h_i(t|X_i) = h_0(t) exp(\beta' X_i), \quad (2)$$

where the baseline hazard function $h_0(t)$ describes the risk of the hazard for a hospital with all elements in X_i equal 0. The exponential function captures the relationship between the hazard rate and the covariates. The primary variable of interest is the number of connected hospitals joining NKR in time t ($\mathbf{G}NKR_t$).[13] We also include time-varying control variables obtained from the SRTR data, including the number of transplants from living and deceased donors, percentage of female patients, percentage of black patients, and the state population. We present the summary statistics (average across years) in Table 1. The purpose of these control variables is to address confounding factors related to hospital/population characteristics. For example, bigger hospitals are more likely to participation in national programs.

Table 1: Summary Statistics

Variable	mean	sd	min	max
Own Characteristics (Average Across Time)				
Number of Living Transplants	18.61	23.72	0.00	194.00
Number of Deceased Transplants	38.76	35.44	0.00	243.00
State Population	12.08	10.05	0.59	39.54
Female Patient(%)	0.38	0.13	0.00	1.00
Black Patient(%)	0.25	0.20	0.00	1.00
Network Characteristics (Static)				
Direct connection	4.58	3.75	0.00	20.00
Non-overlapping indirect connection	17.13	14.82	0.00	75.00
Network Characteristics (Average Across Time)				
Total participation of connected hospitals in time t	0.20	0.47	0.00	3.00

Notes: The number of hospitals in the sample is 261.

The main concern of using $\mathbf{G}NKR_t$ to capture the spillover effect is the reverse causality problem: hospital i and j are connected, but we do not know whether i affects or is affected by j. Therefore, our preferred specification is replacing $\mathbf{G}NKR_t$ with a lagged variable $\mathbf{G}NKR_{t-1}$. The lagged effect is also intuitive when taking into account the time needed for administration and decision process.

[13]We borrow the notation from the social network literature. The adjacency matrix $\mathbf{G}$ captures the connections among hospitals. Each entry g_{ij} equals 1 if i and j are connected and equals 0 otherwise. Each link is undirected, and therefore, $\mathbf{G}$ is symmetric.

5 Results

Table 2 present the result of the Cox model. In Column 1, we first assess the significance of contemporaneous spillover. As the hazard ratio tells, an additional NKR connection in time t increases the probability of NKR participation by 65.9%. In Column 2, we further control for hospital and population characteristics. The hazard ratio decreases by about 14% but the magnitude remains statistically significant. For the role of hospital characteristics, the primary determinant for NKR participation is the number of kidney transplants. One more transplant from living and deceased donors increases the chance of NKR participation by 1.3% and 0.7%, respectively. This shows the importance of controlling for the scale of a transplant center.

However, as discussed, there may be a reverse causality problem for using $\mathbf{G}NKR_t$. Column 3, which is our preferred specification, uses a lagged variable to measure spillover effect. The hazard ratio is more or less similar to the model using $\mathbf{G}NKR_t$. As the hazard ratio reveals, an additional NKR connection in time $t-1$ increases the current probability of NKR participation by 50.8%. In other words, a hospital with one NKR connection in the previous year is 1.5 times more likely than its no-NKR counterparts to join the NKR. The spillover fades out in Column 4 and 5 when we look at the NKR connections in previous 2 and 3 years. This diminishing influence gives us credence about the existence of the spillover effect, as oppose to just being a spurious correlation of behaviors among similar hospitals.

In Table 3, we normalize NKR connections by the number of connected hospitals. In other words, our variable of interest is now the proportion of connected hospitals joining the NKR ($\mathbf{W}NKR$) in a year.[14] For example, if a hospital has 10 connections based on the pre-2007 presence of common surgeons and 2 of them joined NKR in year 2012, its $\mathbf{W}NKR_{2012}$ will be 0.2.

Tracking the changes across columns, the spillover measured by $\mathbf{W}NKR$ again exhibits a

[14] $\mathbf{W}$ is called the weighted adjacency matrix. Each entry equals $1/n$ if i and j are connected, where n is the number of links i has.

Table 2: The Existence Of NKR Participation Spillover

	(1)	(2)	(3)	(4)	(5)
Spillover Effect					
$\mathbf{G}NKR_t$	1.659***	1.430**			
	(0.267)	(0.241)			
$\mathbf{G}NKR_{t-1}$			1.508**		
			(0.246)		
$\mathbf{G}NKR_{t-2}$				1.113	
				(0.248)	
$\mathbf{G}NKR_{t-3}$					1.332
					(0.293)
Own Effect					
Number of Living Transplants		1.013***	1.013***	1.013***	1.013***
		(0.00313)	(0.00314)	(0.00308)	(0.00308)
Number of Deceased Transplants		1.007***	1.007***	1.007***	1.007***
		(0.00267)	(0.00270)	(0.00264)	(0.00265)
State Population		1.014	1.013	1.014	1.014
		(0.00983)	(0.00984)	(0.00993)	(0.00988)
Female Patient(%)		1.459	1.330	1.395	1.451
		(1.453)	(1.322)	(1.379)	(1.441)
Black Patient(%)		0.730	0.715	0.728	0.741
		(0.430)	(0.423)	(0.428)	(0.436)
Observations	1,829	1,829	1,829	1,829	1,829

Note: The event of interest is NKR participation in time t. The number of hospitals is 261. The hazard ratio is reported for each variable. $\mathbf{G}NKR_t$ refers to the number of connected hospitals joining NKR in time t. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

diminishing pattern. Contrasting the effect size using $\mathbf{G}NKR$ in Table 2, the hazard ratios here are a lot bigger. Note that a one-unit change in $\mathbf{W}NKR$ indeed represents all connected hospitals joining the NKR (a 100-percent increase) in the same year, which only constitutes less than 1% of the sample. A more appropriate way for interpretation is to look at the effect brought by a proportional change. Because of the difficulty to interpret the hazard ratio in this way, we only use *proportion* as a sensitivity check for the qualitative pattern. Overall, both *total* and *proportion* analyses are qualitatively the same about the existence of participation spillover.

Table 3: Sensitivity Check (Weighted Adjacency Matrix)

	(1)	(2)	(3)
$\mathbf{W}NKR_{t-1}$	4.239**		
	(2.555)		
$\mathbf{W}NKR_{t-2}$		3.824**	
		(2.570)	
$\mathbf{W}NKR_{t-3}$			3.163
			(2.459)
Observations	1,829	1,829	1,829

Note: The event of interest is NKR participation in time t. The number of hospitals is 261. The hazard ratio is reported for each variable. All regressions include the control variables in the main analysis. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

6 Further Analysis

6.1 Robustness

In our analysis, the hospital links are defined by the presence of common surgeons. One threat to the identification is that spillover is just a purely correlation of behaviors being driven by common shocks (Manski, 1993).

In our context, geographic proximity of hospitals is one important factor for the presence of common surgeons. Then, NKR participation among local centers may just reflect underlying demand factors, for example, these connections are formed to accommodate substantial demand for living transplants. If participation spillover is solely driven by common unobserved factors, we should only observe spillover among local connections.

Among the 1,350 unique hospital links, 23% of them belong to the same MSA. We re-estimate the Cox model by separating the adjacency matrix $\mathbf{G}$ into within-MSA and across-MSA links. Column (1) and (2) of Table 4 report the spillover for local and non-local links separately, and Column (3) captures them jointly. This table shows that both types of links generate spillover effect. The hazard ratio for local links is indeed larger than that of non-local links. However, the difference between them is not statistically significant. Moreover, the spillover is only significant among non-local links. This result suggests NKR participation spillover among hospitals is not driven by unobserved local shocks.

Table 4: Robustness - Spillover Not Caused By Local Shock

	(1)	(2)	(3)
Same MSA - $\mathbf{G}NKR_{t-1}$	1.964		1.866
	(0.807)		(0.769)
Different MSAs - $\mathbf{G}NKR_{t-1}$		1.465**	1.442**
		(0.268)	(0.265)
Observations	1,829	1,829	1,829

Note: The event of interest is NKR participation in time t. The number of hospitals is 261. The hazard ratio is reported for each variable. All regressions include the control variables in the main analysis. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Another concern is selection on unobservables. Standard duration models, including the Cox model, assume some form of cumulative distribution function for all observations. In other words, all hospitals in our case will eventually participate in the NKR which is certainly not true. A problem in the estimation is that our main specification will under-predict the proportion of never-participants and overstate the spillover effect. We can in fact view this as a selection issue, for example, the networks (e.g. density and type of connections) between never-participants and participants are inherently different. And therefore, the adjacency matrix G is correlated with the residual term.

To deal with the unobserved heterogeneity, we check the robustness by estimating the split-population duration (SPD) model (Schmidt and Witte, 1989).[15] The essence of this approach is to separate the transplant centers into two sub-groups: the never-participants and participating centers. The model then jointly estimates two sets of parameters: one for the likelihood and one for the timing of NKR participation. Formally, define $G(X_i, \theta)$ as the cumulative function that hospital i will ever participate the NKR, $\bar{t}_i$ as the year of NKR participation, , $f(\bar{t}_i; X_i, \beta)$ as the failure rate at year $\bar{t}_i$, $S(t; X_i, \beta)$ as the survival function at time t, and δ_i as the censoring indicator equals one if the hospital had even participated

[15]The SPD model was first introduced in other fields (Anscombe, 1961; Maltz and McCleary, 1977).

in NKR. Then, the likelihood function of hospital i is then:

$$L_i(\theta, \beta; \bar{t}_i X_i) = \delta_i G(X_i, \theta) f(\bar{t}_i; X_i, \beta) + (1 - \delta_i)[(1 - G(X_i, \theta)) + G(X_i, \theta) S(t; X_i, \beta)] \quad (3)$$

Following the literature, we assume the likelihood of event follows a logistic distribution and the duration part follows a log-logistic distribution (Douglas and Hariharan, 1994; Box-Steffensmeier et al., 2005).[16] By employing the SPD model, we can look at how the spillover affects the propensity and the timing separately.

In Table 5, we report the effect of $\mathbf{G}NKR_{t-k}$ on the timing in the upper panel and the effect on the incidence rate in the lower panel. While $\mathbf{G}NKR_{t-1}$ does not affect the timing of participation, it does increases the incidence rate. In the lower panel, the logit coefficients diminish over time, with only on the effect size of $\mathbf{G}NKR_{t-1}$ being statistically significant at a 5% level. The result from the SPD models suggests that the exposure to NKR connections increases the participation likelihood, but does not make the occurrence quicker.

6.2 Strength of Links

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.

We first test if a 'super' surgeon is more influential in information transmission. This analysis is analogous to the finding by Agha and Molitor (2018), who find that superstar physicians, measured by their trial role or citation history, have a broader influence on the adoption of new cancer drugs by a hospital.

In our context, we use the median number of surgeries a surgeon performs as the cut-off. We define a 'super' surgeon in a hospital by whether the number of surgeries performed by a

[16] We adopt the statistical program in the replication files of Box-Steffensmeier et al. (2005).

Table 5: Robustness - Split-Population Duration Model

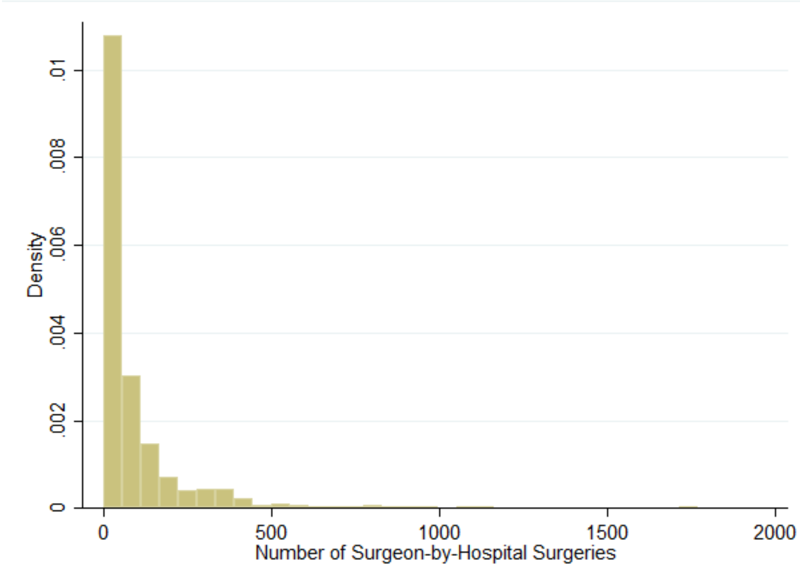
	(1)	(2)	(3)
Duration:			
$\mathbf{G}NKR_{t-1}$	-0.108		
	(0.108)		
$\mathbf{G}NKR_{t-2}$		0.271	
		(0.244)	
$\mathbf{G}NKR_{t-3}$			0.283
			(0.195)
Likelihood of Event:			
$\mathbf{G}NKR_{t-1}$	1.209**		
	(0.614)		
$\mathbf{G}NKR_{t-2}$		0.652	
		(0.975)	
$\mathbf{G}NKR_{t-3}$			0.418
			(0.575)
Observations	1,829	1,829	1,829

Note: The event of interest is NKR participation in time t. The number of hospitals is 261. The coefficient is reported for the lower panel. All regressions include the control variables in the main analysis. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

particular surgeon in the same hospital is above the median. Figure 3 shows the distribution of the number of surgeon-by-hospital surgeries by 2006 and the median is 35. We then redefine the links between two hospitals into four types. A link is 'strong' if the surgeon is a super surgeon in both hospitals; it is 'intermediate strong' if the surgeon is a super surgeon only in Hospital i, whereas it is 'intermediate weak' if the surgeon is a super surgeon only in Hospital j; and a 'weak' link is defined otherwise.

We re-estimate the Cox model separately for the four types of links. As shown in Column 1 to 4 in Table 6, spillover among the 'Strong' links is the strongest. The size of the effect for 'Intermediate Strong' links is also similar to that for 'Strong' links. However, its magnitude is imprecisely estimated. When we estimate the four link types jointly in Column 5, the spillover among 'Strong' links is slightly weaker but remains salient at a 10% level. Regardless of estimating them separately or jointly, we do observe that the spillover diminishes with the strength of links, most apparently for the 'Intermediate Weak' and 'Weak' links.

Figure 3: Distribution of the Number of Surgeon-by-Hospital Surgeries



Note: 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). The min. is 1 and the max. is 1771.

Another way to capture the strength of links between two hospitals is to look at the *number* of common surgeons. Figure 4 shows the distribution of the number of common surgeons between two connected hospitals. The histogram shows that 85% of the connected hospitals are linked through one common surgeon, while the rest is linked through multiple surgeons. 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 again re-estimate the Cox model separately for the two types. As shown in Table 7, although the difference is not statistically significant, the 'Strong' links exhibit notably stronger spillover than the 'Weak' links do. This pattern remains the same regardless of estimating them separately in Column 1 and 2, or jointly in Column 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

Table 6: Stronger Spillover Among Strong Links (Presence of Super Surgeon)

	(1)	(2)	(3)	(4)	(5)
Strong Link- $\mathbf{G}NKR_{t-1}$	1.604**				1.454*
	(0.319)				(0.302)
Intermediate Strong Link - $\mathbf{G}NKR_{t-1}$		1.755			1.474
		(0.616)			(0.531)
Intermediate Weak Link - $\mathbf{G}NKR_{t-1}$			1.276		1.202
			(0.222)		(0.220)
Weak Link- $\mathbf{G}NKR_{t-1}$				1.200	1.034
				(0.538)	(0.500)
Observations	1,829	1,829	1,829	1,829	1,829

Note: The event of interest is NKR participation in time t. The number of hospitals is 261. The hazard ratio is reported for each variable. All regressions include the control variables in the main analysis. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Stronger Spillover Among Strong Links (Number Of Common Surgeons)

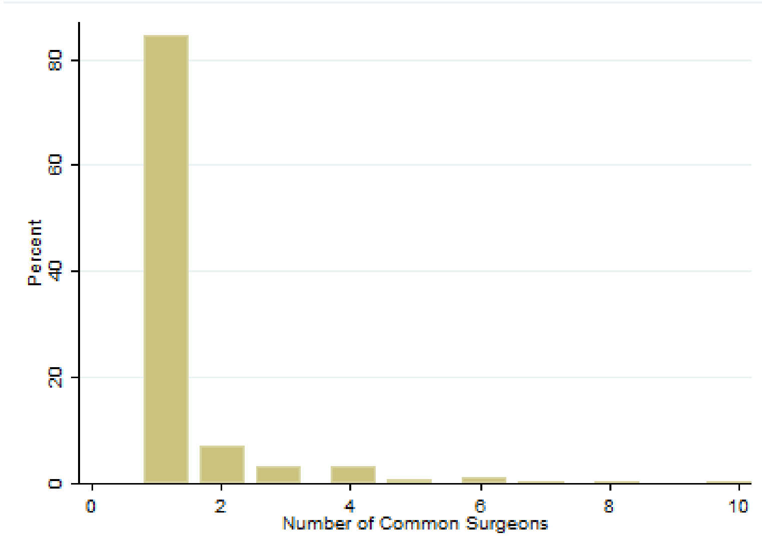
	(1)	(2)	(3)
Weak Link - $\mathbf{G}NKR_{t-1}$	1.379*		1.361*
	(0.255)		(0.253)
Srong Link - $\mathbf{G}NKR_{t-1}$		2.504**	2.446**
		(0.900)	(0.881)
Observations	1,829	1,829	1,829

Note: The event of interest is NKR participation in time t. The number of hospitals is 261. The hazard ratio is reported for each variable. All regressions include the control variables in the main analysis. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

prone to participate in such networks. Specifically, we are interested in the role of the opinion leaders in the participation decision of a hospital. Our hypothesis is that surgeons play a significant role in the idea transmission and affecting the final decision of 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 surgeon movement, which makes the construction of a hospital network feasible. Our results suggest the existence of NKR participation spillover. The spillover is more likely drive by information/idea dissemination, rather than endogeneity concerns. We also make use of the richness of the SRTR data to allow the heterogeneity by the strength of links and find that the spillover concentrates among strong links, which are defined by the presence of 'super surgeons' and the number of common surgeons.

Figure 4: Distribution of the Number of Mutual Surgeons



Note: This histogram shows the distribution of the number of common 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. 85% of the links are defined as 'weak' links.

Overall, we are first attempt to test the existence about participation spillover of a national scale kidney exchange platform. To the extent expanding the donor/patient pool is essential to fully realize the potential of NKR, reducing information friction and enhancing hospital coordination are ways to foster more participation.

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