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Does Transportation Mean Transplantation? Impact of New Airline Routes on Sharing of Cadaveric Kidneys

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Abstract. Every year, nearly 5,000 patients die while waiting for kidney transplants, and yet an estimated 3,500 procured kidneys are discarded. Such a polarized coexistence of dire scarcity and massive wastefulness has been mainly driven by insufficient pooling of cadaveric kidneys across geographic regions. Although numerous policy initiatives are aimed at broadening organ pooling, they rarely account for a key friction—efficient airline transportation, ideally direct flights, is necessary for long-distance sharing, because of the time-sensitive nature of kidney transplantation. Conceivably, transplant centers may be reluctant to accept kidney offers from far-off locations without direct flights. In this paper, we estimate the effect of the introduction of new airline routes on broader kidney sharing. By merging the U.S. airline transportation and kidney transplantation data sets, we create a unique sample tracking (1) the evolution of airline routes connecting all the U.S. airports and (2) kidney transplants between donors and recipients connected by these airports. We estimate the introduction of a new airline route increases the number of shared kidneys by 7.3%. We also find a net increase in the total number of kidney transplants and a decrease in the organ discard rate with the introduction of new routes. Notably, the post-transplant survival rate remains largely unchanged, although average travel distance increases after the introduction of new airline routes. Our results are robust to alternative empirical specifications and have important implications for improving access to the U.S. organ transplantation system.

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> More than smartphones, more than television, more than food, culture, or commerce, more even than Twitter or Facebook, transportation permeates our daily existence. In ways both glaringly obvious and deeply hidden …
>
> —Edward Humes (2016), in *Door to Door: The Magnificent, Maddening, Mysterious World of Transportation*

1. Introduction

Dire scarcity and massive wastefulness are the two poles of the U.S. organ transplantation system, as evidenced by nearly 5,000 people who die every year while waiting for kidney transplants and, perhaps paradoxically, an estimated 3,500 procured kidneys that are discarded (Aubert et al. 2019). Underlying these poles are prevailing U.S. kidney allocation policies that prioritize local matching and hinder organ sharing across regions. Because of insufficient pooling of cadaveric kidneys across regions that differ in their organ supply and demand characteristics, the availability of organs and therefore the waiting time for transplants depend heavily on location.[1] For example, the average waiting time for a kidney transplant is approximately five years in San Antonio, Texas, and six months in Memphis, Tennessee. Pooling resources through broadening organ sharing helps alleviate geographic disparities and improve access to organ transplantation (Ata et al. 2017).

Consistent with the concept of pooling, policymakers have sought to expand organ sharing across regions, mainly through reforming allocation policies. Yet, such efforts rarely account for a key friction in long-distance organ sharing—airline transportation. A lack of direct flights makes transplant centers reluctant to accept kidney offers from far-off locations. For example, in 2019, the United Network for Organ Sharing (UNOS) proposed eliminating donation service areas (DSAs) and regional boundaries used in the current system and allocate kidneys using a 500-nautical-mile (approximately 575-mile) circle surrounding the donor hospital (OPTN 2019a). The proposal drew heavy criticism from a large number of organ procurement organization (OPO) executives and transplant surgeons who expressed concerns in a public forum about the implication of the proposal for increased reliance on air transportation. A case in point, according to Dr. John Friedewald of Northwestern University, is that "Denver falls within the edge of Chicago's 500 nm radius but realistically is much closer than a number of OPOs in between simply because of the variety of daily flights between the two things" (OPTN 2019b).

Without accounting for the friction caused by airline transportation, new kidney allocation policies may not achieve as much pooling as they intend. In particular, the organ transportation capacity provided by the commercial airlines is a crucial link, because they are safer and more affordable than private jets and charter flights. As another comment for the 2019 UNOS proposal states, "the proposal has entirely failed to consider the effect that limited access to direct flights will have on cold ischemic time and the subsequent impact on candidates' access to transplantation" (OPTN 2019b).

Stated differently, the time-sensitive nature of organ harvesting operations means *direct* air flights are often required (Pullen 2019). How does the introduction of new airline routes affect access to organ transportation?[2] This seemingly simple research question has yet to be rigorously examined in the literature and gives rise to this paper.

Addressing this research question is challenging for many reasons. A major challenge is to find an appropriate unit of analysis. On the one hand, an analysis at the level of each donor-recipient pair would have been ideal but is practically infeasible because we do not observe the same donor-recipient pairs across different years. On the other hand, one may be tempted to use the populations served by each pair of donor-recipient OPOs as the unit of analysis. However, the estimation is challenging because an OPO often serves a large geographic area with multiple major airports. Because most pairs of OPOs are well connected throughout our study period, analyzing the effect of the introduction of new airline routes is difficult.

To address this challenge, we use the pairs of *airports* and the populations they serve as the units of analysis, which allows us to estimate the aggregate effect of the introduction of new airline routes in a salient manner and generate implications for policymakers and healthcare executives. We estimate the effect of introducing new airline routes on cross-regional kidney sharing. By merging the U.S. airline transportation and organ transplantation data sets, we create a unique sample tracking both the evolution of airline routes connecting all pairs of airports and kidney transplantation with donors and recipients served by these airports. Thus, our sample can be organized in terms of pairs of airports across different years.

The primary outcome variable we examine is the number of shared kidneys associated with each pair of airports. Using a difference-in-differences design and exploiting the staggered introduction of new airline routes, we find kidney sharing between the populations served by a pair of airports significantly increases with the introduction of an airline route connecting these airports. Specifically, we estimate an introduction of a new airline route increases the volume of kidney sharing by 7.3%. Our result demonstrates the availability of direct flights is an important driver of kidney sharing across geographic regions.

As an illustrative example of our results, consider the Baltimore-Washington International Thurgood Marshall Airport (BWI) and Dallas Love Field Airport (DAL)—both hubs of Southwest Airlines—that were not connected by a direct flight until 2014. Between 2002 and 2013, the average number of kidneys the donors served by DAL shared with the recipients served by BWI was 1.7 per year. In 2014, immediately following the full appeal of the Wright Amendment that had previously restricted Southwest Airlines from flying beyond Texas and its four surrounding states (Tierney 2014), a new route was introduced between BWI and DAL. In the same year, the number of shared kidneys jumped to eight. As another example, in 2011, following the introduction of a new airline route between Charleston International Airport (CHS) and Nashville International Airport (BNA), the number of kidneys the donors served by CHS shared with the recipients served as by BNA increased from 3 in 2011 to 5 in 2012 and then to 12 in 2013.

An important concern about these observed effects is the endogeneity of the introduction of new airline routes. For instance, airports serving expanding economies and growing populations may be more likely to have new routes. Conceivably, such regions may have an increased number of kidney donors and recipients, so kidney sharing may be more likely. In view of such potential local shocks, our estimation does not compare pairs of airport connected by direct flights with those pairs not connected by direct flights. For the same reason, we do not compare the number of kidney shared between the populations served by a pair of airports before and after the introduction of a new airline route. Rather, our estimation identifies pairs of airports without direct-flight options for the entire study period and uses these pairs collectively as a control group; the treatment group consists of airport pairs with new airline routes introduced in various years during the study period.

We conduct further analyses to refine our key finding that the introduction of new airline routes leads to an increase in the volume of kidney sharing. We show route introductions lead to a net increase in the total number of kidney transplants and a decrease in the organ discard rate. In addition, we show the quality of kidney transplantation, as measured by posttransplantation survival, does not decrease even as its quantity increases, meaning expanded kidney sharing does not worsen posttransplantation outcomes.

Our research helps inform organ transplantation policymakers by highlighting logistical issues threatening to hold back the organ transplantation system that are not ready to accommodate new allocation policies and contributing to a better understanding of the flexibility of the U.S. organ transplantation system. Our research provides constructive support for policies reducing the friction because of air transportation of kidneys, including, for example, the establishment of a national transportation system for organs shared across regions, a policy initiative that has gained significant traction recently (Aleccia 2020). Our findings also suggest that, rather than eliminating DSAs and allocating kidneys using a circle of a fixed size, policymakers may consider adjusting DSAs from time to time using airline connectivity as a factor of consideration.

2. Literature

Our paper contributes to a growing, mostly theoretic, operations management (broadly defined) literature on organ transplantation (Su and Zenios 2004, 2006; Kong et al. 2010; Zhang 2010; Akan et al. 2012; Bertsimas et al. 2013; Sandikçi et al. 2013; Gentry et al. 2015; Ata et al. 2017, 2020; Kilambi and Mehrotra 2017; Arikan et al. 2018; Ding et al. 2018; Dai et al. 2020; Wang et al. 2020). This literature focuses on *analytically* modeling the organ transplantation system, with several notable exceptions. Zhang (2010) takes an observational-learning approach and shows allowing patients to observe prior acceptances/rejections of organ offers leads to herd behavior. Arikan et al. (2018) empirically identify the drivers behind the geographic disparities in deceased-donor organ procurement. They show an intent to procure an organ plays an instrumental role in the disparities, and such an intent depends on organ quality, median waiting time, and competition among transplant centers. Ata et al. (2020) structurally estimate the effect of changing organ allocation policy by endogenizing transplant candidates' acceptance behavior. Wang et al. (2020) study the impact of new entry on transplant centers' risk-taking behavior and posttransplantation outcomes. Different from these papers, ours focuses on empirically estimating the impact of transportation, an important yet little-examined driver behind geographic disparities in access to organ transplantation. In doing so, our paper enriches the empirical foundation of geographic disparities and informs related policymaking.

In particular, the empirical estimation in our paper complements the theoretic work by Ata et al. (2017), who propose and analyze OrganJet, a transportation solution that helps organ transplant candidates list in multiple transplant centers. Their analytical and numerical results show such a solution can significantly improve geographic equity. Drawing from air transportation and kidney transplantation data sets, our paper provides a systematic, empirical understanding of the impact of the introduction of new airline routes on cross-regional kidney sharing.

Our paper also contributes to a vibrant literature in economics, finance, and operations management that empirically estimates the impact of transportation, building on the theory that proximity facilitates communication and oversight. Giroud (2013) finds the introduction of new airline routes leads to an increase in plant-level investment from corporate headquarters. Bernstein et al. (2016) show reducing the travel time between venture capitalists and their portfolio companies leads to an increase in innovation, as measured by the number of patents and the number of citations per patent. Bernard et al. (2019) exploit the opening of a high-speed train line in Japan and show transportation connections create buyer-supplier linkages and improve firm performance. Bray et al. (2019) demonstrate supply chain proximity improves product quality and decreases the occurrence of defects. Ahuja et al. (2020) show travel time affects air travelers' service experience and establish it as a useful metric of service quality. Catalini et al. (2020) and Dong et al. (2020) estimate the impact of travel time on cross-regional teamwork. As a key departure from these papers that focus on economic impacts, ours is the first paper to characterize the health impact of transportation by estimating how the introduction of new airline routes influences kidney sharing.

Our paper joins the healthcare operations management literature that features a strength in analytical modeling (Dai and Tayur 2020, Keskinocak and Savva 2020) and has become increasingly empirical in recent years (KC et al. 2020, Terwiesch et al. 2020). Within this literature, our paper speaks to a number of papers related to the concept of pooling. Song et al. (2015) show queue pooling may backfire in an emergency department setting and that a dedicated queue can reduce the length of stay. Song et al. (2020) reveal negative patient-outcome impacts of capacity pooling in a hospital network. Our paper shares the same spirit as theirs by characterizing a key friction in the U.S. organ transplantation system that hinders resource pooling across various regions. Ramdas and Darzi (2017) study shared medical appointments, in which a group of patients visit a physician at the same time. They show such a pooling solution increases healthcare capacity and improves patient satisfaction. Our paper advances this stream of literature by empirically identifying a friction that threatens to weaken the realized benefit of kidney pooling. In doing so, our empirical analysis is also relevant to the work by Kim et al. (2020), who use laboratory experiments to identify frictions in patient admission control due to healthcare providers' behavioral biases. In addition, our paper, by estimating how the efficiency of airline routes—a logistics issue—influences decision making related to organ sharing, relates to the work by Ibanez and Toffel (2019), who show the scheduling of food-safety inspection influences inspectors' stringency.

At a conceptual level, our paper is relevant to the operations management literature on flexibility. In a seminal paper, Jordan and Graves (1995) study a manufacturing environment in which the same facility can manufacture different types of products. They show most of the benefits of full flexibility, under which all facilities can manufacture all types of products, can be reaped through partial flexibility. Other operations management scholars (Van Mieghem and Dada 1999, Graves and Tomlin 2003, Van Mieghem 2007, Hopp et al. 2010, Lu and Lu 2017) have studied flexibility in a broad range of manufacturing and service settings. In the case of organ transplantation, flexibility can be thought of as a measure of the extent to which limited organ resources can be pooled across geographic regions. A more flexible organ transplantation system is more likely to materialize the intended benefit of policy initiatives aimed at expanding the pooling of limited organ resources. Our paper characterizes airline transportation as an important driver of the flexibility of the organ transplantation system, and thereby connecting health and logistics, a key theme in the health and humanitarian systems literature (Keskinocak 2010).

3. Background and Data

In this section, we first provide a brief overview of kidney transplantation and sharing in Section 3.1. Next, in Section 3.2, we describe the data sets used in estimating the effect of the introduction of new airline routes on kidney sharing. Last, in Section 3.3, we describe how we prepare the data for our analysis.

3.1. Kidney Transplantation and Cross-Regional Sharing

The U.S. organ transplantation system is organized as 11 geographic regions and operates as a collection of 58 DSAs, each of which is managed by an OPO that is responsible for evaluating, procuring, and placing deceased organs. Each OPO operates largely as an "unchecked regional monopoly" in terms of organ procurement and allocation (Bridgespan Group 2019, p. 8). Despite multiple changes in organ allocation policy in the past few decades, one fixture of the policy is that it prioritizes proximity from the donor, and the vast majority of deceased kidneys are allocated to local recipients. Of more than 10,000 deceased kidney transplants taking place in the United States each year, only around 1,400 are shipped across geographic regions, mostly by commercial flights as cargo (Aleccia 2020).

Organ transplantation is a time-sensitive operation. As the time between when an organ is procured and transplanted, commonly referred to as cold ischemia time (CIT), increases, the risk of graft failure increases. The maximum allowed CIT for kidney transplantation is 24–36 hours, and an ideal CIT is substantially shorter.[3] For this reason, when a transplant center receives an offer of a procured kidney from a far-off location, CIT becomes a factor of paramount importance. In addition, transplant centers value the quality of kidneys, as measured by the kidney donor profile index (KDPI); a higher KDPI indicates a higher risk of graft failure and hence a low quality. As Locke and Sellers (2019, p. 2971) point out

> [A transplant] center located in an area with limited or no direct flights that receives an organ offer 12 hours after cross clamp for a high KDPI kidney may decline the offer knowing that the next available flight is not for 12 more hours and that on arrival to the center the kidney will already have more than 24 hours of CIT. In contrast, the same high KDPI kidney offered some 12 hours after cross clamp may be accepted by a center located in an area with ready access to direct flights resulting in the kidneys arrival with < 24 hours of CIT.

Because of the absence of a national system for initiating and tracking such shipments and the fact that the risk of transplant failure increases in the time after a kidney has been procured, transplant surgeons and OPO executives are cautious about accepting kidney offers that require air transportation, especially when direct-flight options are unavailable (Locke and Sellers 2019, Aleccia 2020). In October 2019, for example, a donated kidney shipped from Florida to a recipient in North Carolina missed a connection in Atlanta, leading to a near miss that gave surgeons "just 46 minutes to spare" (Aleccia 2020). As another example, a transplant surgeon, Matthew Mulloy, commented in response to the aforementioned 2019 UNOS proposal that his transplant center, despite being "a stone's throw from one of the country's largest airports," had "lost the opportunity to transplant three kidneys that were supposed to be sent to us by commercial airlines" (OPTN 2019b):

> One organ was delayed due to weather and the next available flight wasn't till the next day. Another organ

made it to the airport, but was never placed on the intended flight. The third organ was mistakenly taken to the wrong airport and missed the intended flight.

If each flight connection poses a risk to successful and timely transportation, each additional flight connection will amplify that risk. Sensing an increased number of connections means kidneys are placed "in the hands of entities who are in no way accountable for their welfare" (OPTN 2019b), surgeons in transplant centers may hesitate to accept offers from far-off locations requiring multiple flight connections (Locke and Sellers 2019).

3.2. Data Description

To link airline transportation with kidney transplantation, we draw from the following data sources: (1) the U.S. Bureau of Transportation Statistics' T-100 Domestic Segment Database, which provides monthly air carrier traffic information, and (2) the data set from UNOS, which provides individual-level data for all U.S. kidney transplant candidates, donors, and recipients.

We use the period of 2002 to 2017 for the T-100 Domestic Segment Database. The T-100 data set contains monthly data for each airline and route, which include, for example, the origin and destination airports, flight duration, scheduled departures, performed departures, enplaned passengers, and aircraft type. It offers a complete picture of whether direct-flight options exist between any two airports and, if so, how many flights took place in each given month. A unique feature of the T-100 data set is that it includes all the flights that have taken place between any two airports in the United States, because all the airline companies operating flights in the United States are mandated by law to file Form 41 with the U.S. Department of Transportation and are subject to fines for misreporting.

The kidney transplant data set from UNOS consists of detailed patient-level records about all deceased donor transplants performed in all U.S. hospitals between 2003 and 2017. The data set includes detailed kidney donor features such as demographics, blood type, and cause of death. The data set also includes detailed transplant candidate features such as demographics, blood type, and dialysis status. (A small proportion of candidates in the data set were listed in multiple transplant centers.) These features allow us to control for the quality of donor organs and health conditions of transplant candidates when analyzing the number of shared kidneys. In addition, the data set includes the number of days a transplant candidate survived after receiving a kidney transplant. This posttransplant survival information helps us analyze whether kidney sharing affects medical outcomes. Finally, the data set includes information about the donors' and candidates' hospitals, enabling us to calculate the distance between a hospital and an airport.

3.3. Data Preparation

We focus on airline routes with the service class of scheduled passenger/cargo services; all other service classes are either nonscheduled (e.g., nonscheduled civilian passengers/cargo services, nonscheduled civilian all cargo services) or for cargo only (e.g., scheduled all cargo service). For each pair of airports, we calculate the total number of flights in a year by summing the number of flights performed by different airlines.[4] Because the T-100 data set tracks all the flights operated by all airlines, we let the number of flights be zero if no airline offers a flight between two airports. We use a cut-off frequency (e.g., 180 flights per year) to determine whether two airports are connected by an airline route.

We define the introduction of a new airline route as a change in the number of flights from below to above the cutoff frequency. Likewise, we define the exit of an existing airline route as a change in the number of flights from above to below the cutoff frequency. By definition, an airport pair may have multiple introductions or exits of new airline routes during a given period of time. In this study, we focus on the airport pairs that experienced either (1) the introduction of one new airline route or (2) no introduction or exit of airline routes during the study period. In other words, we exclude the airport pairs with multiple introductions of new airline routes or any exits of existing airline routes. This focus allows us to estimate the effect of the introduction of one new airline route without being confounded with multiple introductions or exits.

We calculate the straight-line distance between two airports based on their longitudes and latitudes. Our calculated distance is close to the actual flight distance recorded in the data set for those airport pairs connected by direct flights.[5] Because driving or using a helicopter might be more convenient than flying a commercial flight when the travel distance is sufficiently short, we focus on the airport pairs with a flying distance of at least 800 miles. As a robustness check, Section 5.3.10 reconstructs the samples by considering alternative cutoff distances (e.g., 700 and 900 miles).

For each kidney donor in the kidney-transplantation data set, we calculate the straight-line distance from the donor's hospital to all airports in the air transportation data set based on their longitudes and latitudes. We designate the nearest airport as the donor's airport in our main analysis because the nearest airport is likely the origin airport where the donated organs will be transported from if a commercial flight is used. Similarly, we calculate the straight-line distance from a transplant candidate's hospital to all airports and designate the nearest airport as the candidate's airport in our main analysis. As a robustness check, in Section 5.3.7, we consider scenarios in which the nearest airports are bypassed and alternative airports are chosen.

Using the UNOS data set, we calculate the total number of kidney transplants involving a donor and a recipient connected by an airport pair in each year. Because our data set records all kidney transplants, we set the number of shared kidneys as zero if the data set shows no kidney shared between the populations served by an airport pair. For each airport pair, we calculate the features of an origin airport using the average features of all donors associated with the origin airport. Similarly, we calculate the features of a destination airport, using the average features of all candidates associated with the destination airport. We exclude those airport pairs that never shared a kidney during our study period or do not have complete information about donor or candidate features.

4. Econometric Model

To estimate the effect of the introduction of new airline routes on the sharing of cadeveric kidneys, we note that whether a new airline route is introduced may be determined endogenously. For example, two airports serving booming metropolitan areas are likely to have a new airline route. At the same time, these airports may be more likely to be used for kidney transportation, because growing economies may be associated with a larger pool of donors and candidates. Therefore, a direct comparison of airport pairs with new airline routes and those without new airline routes may be subject to confounding factors that affect both airline routes and kidney sharing. Another approach is to compare the number of kidneys shared via two airports before and after the introduction of a new airline route. Yet, this approach will lead to a biased estimate of the treatment effect in the presence of time trends of kidney sharing even in the absence of a new airline route.

Taking advantage of the staggered introduction of new airline routes, we isolate these confounding factors and obtain an unbiased estimate of the treatment effect using a difference-in-differences approach with multiple periods (i.e., with staggered treatment adoption), which is prevalent in the literature (see Angrist and Pischke 2008, p. 233–241 for details). The main idea behind the difference-in-differences approach is that if the treatment and control groups have experienced similar time trends (i.e., the parallel-trends assumption), we can compare the pre- and posttreatment outcomes of both the treatment and control groups to estimate the treatment effect. We refer to Ho et al. (2017) and KC (2018) for comprehensive discussions of the difference-in-differences approach; recent applications of this approach in the operations management literature include Gallino and Moreno (2014), Hwang et al. (2021), Li and Netessine (2020), Song et al. (2015), and Wang (2020). In our study, the treatment group consists of the airport pairs that initially did not have a direct flight but were connected by new airline routes introduced between 2002 and 2017; the control group consists of the airport pairs that remain not directly connected between 2002 and 2017.[6] We check the parallel-trends assumption by empirically testing whether the treatment and control groups are statistically significantly different from each other in the pretreatment period.

To describe the difference-in-differences approach, we denote by $SharedVolume_{ijt}$ the total number of kidneys that are harvested from the donors associated with airport i and used by the candidates associated with airport j in year t. We differentiate the origin and destination of an airport pair, because (1) this approach allows us to explicitly control for the features of the origin and destination airports, (2) the volume of shared kidneys and the frequency of flights from airport i to airport j may be different from those from airport j to airport i, and (3) the effect of the introduction of airline routes may be direction dependent for the same pair of airports.

As described in Section 3.3, we calculate $SharedVolume_{ijt}$ by first identifying the set of donors whose nearest airport is i and the set of candidates whose nearest airport is j, and then counting the total number of kidneys shared from donors residing near airport i to recipients residing near airport j in year t. We use the airports that are the nearest to the donors and candidates because they are the most likely to be used to transport kidneys. We acknowledge that the nearest airports are not always used in reality, especially when (1) travel distance is short such that driving is more preferable, or (2) a more distant airport offers a better connectivity (i.e., existence of a direct flight). We consider those scenarios in Section 5.3.7.

Our independent variable of primary interest is the treatment dummy, $DirectFlight_{ijt}$, which is equal to one if airports i and j (1) did not have a direct flight before 2002 and (2) had direct-flight options starting in year t (between 2002 and 2017). Our sample tracks the flight frequency between two airports in a year. In our main analysis, we use 180 per year (i.e., once every two days) as a cutoff frequency to determine whether a pair of airports has a direct-flight option. Section 5.3.10 presents a robustness check with alternative cut-off frequencies for the determination.

We are particularly interested in the relationship between the treatment dummy, $DirectFlight_{ijt}$, and the dependent variable, $SharedVolume_{ijt}$, which measures the average effect of a new airline route on the volume of shared kidneys. A positive relationship would indicate introducing new airline routes increases the number of shared kidneys, and a negative coefficient would indicate otherwise. We establish the causal relationship using the difference-in-differences approach.

To control for the features (denoted by $Features_{ijt}$) of a pair of airports over time, we include a broad range of donor features (e.g., demographics, height/weight, creatinine level, blood type, hypertension, cause of death, and expanded criteria donor) to control for the quality of donor kidneys associated with the origin airport and candidate features (e.g., demographics, height/weight, blood type, diabetes, dialysis status and duration) to control for the health conditions of transplant candidates associated with the destination airport. We calculate $Features_{ijt}$ by first identifying the set of donors whose nearest airport is i and the set of candidates whose nearest airport is j. We then calculate the average features of the donors and candidates associated with the origin and destination airports, respectively. The features of an airport pair may be time variant, because the sets of donors and candidates change over time.

Finally, we use $Airports_{ij}$ to denote a vector of airport-pair fixed effects that control for time-invariant features of origin and destination airports, $Year_t$ to denote a vector of year fixed effects that control for changes in the average number of kidneys shared over the years and ε_{ijt} to denote an idiosyncratic error. The relationship between the dependent and independent variables is

$$\begin{aligned}\ln(SharedVolume_{ijt}) = \alpha_0 + \alpha_1 DirectFlight_{ijt} \\ + \alpha_2 Features_{ijt} + \alpha_3 Airports_{ij} \\ + \alpha_4 Year_t + \varepsilon_{ijt}.\end{aligned}$$

To address one potential concern that some of the features may change because of the treatment, we consider four different models in which $Features_{ijt}$ includes (1) no candidate or donor features, (2) only candidate features (denoted by $CandidateFeatures_{ijt}$), (3) only donor features (denoted by $DonorFeatures_{ijt}$), and (4) both candidate and donor features. For each categorical variable, we first identify all candidates (or donors) served by each airport and then calculate the percentage of candidates belonging to the corresponding category (e.g., blood type or race).

We use the logarithm of the shared kidney volume as the dependent variable because the distribution of the shared volume is right skewed. The coefficient α_1 can thus be interpreted as the percentage increase in the shared volume after the introduction of a direct flight. We do not explicitly include the geographic distance between two airports and whether two airports belong to the same geographic regions as specified by UNOS, because they are captured by the airport-pair fixed effects. We cluster robust standard errors by airport pair because the errors associated with the same pair over different years might correlate with each other.

5. Results and Robustness Checks

In this section, we first describe in Section 5.1 the events used in our main analysis and compare the features of treatment and control groups. Then, in Section 5.2, we present our results from the difference-in-differences model; we also modify the difference-in-differences model by including several pre- and posttreatment dummies to check the parallel-trends assumption and analyze how the effect of the introduction of new airline routes changes over time. Next, in Section 5.3, we perform extensive robustness checks to explore the sensitivity of our results.

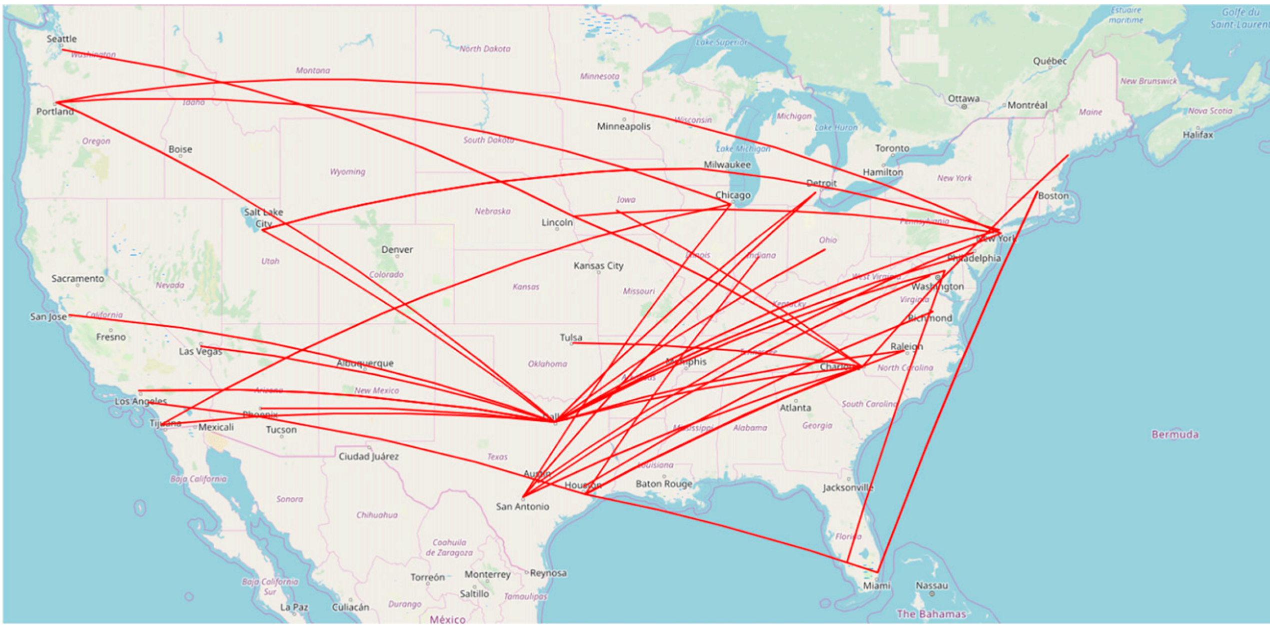
5.1. Summary of Events and Airport-Pair Features

Our main analysis has a treatment group of 61 airport pairs and a control group of 513 airport pairs over a period of 16 years. Figure 1 illustrates the airport pairs in the treatment group. Our treatment group covers a broad range of airports across the United States. Interestingly, a number of airport pairs in the treatment group share the same origin or destination airport. A detailed investigation of the events reveals the overlapping of origin or destination airports is because an airline usually launches multiple new routes from its hub airports. For example, Southwest Airlines launched multiple routes from Dallas Love Field (DAL) to multiple destinations after the repeal of the Wright Amendment in October 2014 (Tierney 2014).

Table A1 in the online appendix provides details (e.g., airport codes and locations and the year and month when a direct flight was introduced) about the treatment group. The year of 2015 witnessed the largest number of introductions of new airline routes (13 airport pairs), followed by 2014, 2012, and 2005, each of which has eight introductions. Because kidney sharing (and therefore an airport pair) is direction specific and we exclude the airport pairs that never shared a kidney during our study period, for the same pair of airports, our treatment group may include a route of one direction (e.g., from DAL to BWI) but not of the other direction (e.g., from BWI to DAL). These unbalanced pairs are unlikely to bias our results, because we apply the same exclusion criteria to both the treatment and control groups. Later, in Section 5.3.6, we use balanced airport pairs that include both directions to reestimate the effect of the introduction of new airline routes.

We summarize in Table 1 the number of shared kidneys and features of candidates and donors associated with the airport pairs in the treatment and control groups. During our study period, the average number of kidneys shared per year is 0.12 for the airport pairs that were never treated and 0.21 for the airport pairs that were. The average number of shared kidneys is relatively small because our data include airport pairs that did not share a kidney in certain

Figure 1. (Color online) New Airline Routes in the Treatment Group



years. The larger magnitude of the number of kidneys shared in the treatment group does not necessarily mean the treatment groups are different prior to the introduction of new airline routes for two reasons. First, these aggregated results are calculated over 16 years, which includes the periods both before and after each introduction. Second, these results do not control for the features of the candidates and donors, which might correlate with the number of shared kidneys.

From Table 1, we observe that the treatment and control groups are similar along many dimensions of candidate and donor features. For example, in both groups, the percentage of male candidates is 40% and the average age of donors is 39. However, some noticeable differences exist between these two groups along some other dimensions. For example, the control group has a higher percentage of white candidates/donors and a lower percentage of Hispanic candidates/donors. These summary statistics seem to indicate the treatment and control groups are not the same. A selection issue may arise if the differences between the treatment and control groups affect both the number of shared kidneys and the introduction of new airline routes. Fortunately, the difference-in-differences approach does not require the treatment and control groups to share the same characteristics along all dimensions of candidate and donor features. It only requires that, in the absence of treatment (i.e., introductions of new airline routes), the treatment and control groups experience parallel trends in the outcome variable (i.e., number of shared kidneys). This assumption cannot be directly verified, because we do not observe the trend of the treatment group if it did not receive the treatment. Next, we examine the trends prior to the event of interest similar to other studies using a difference-in-differences design (Roberts and Whited 2013).

5.2. Results from the Difference-in-Differences Models

We present the results from our difference-in-differences model in Table 2, where columns (1)–(4) correspond to the four econometric models described in the last subsection. Note the number of observations for each model is $(61\ \textit{treatment pairs} + 513\ \textit{control pairs}) \times 16\ \textit{years} = 9{,}184$. The last column summarizes the results from the full model that includes both candidate and donor features. We observe that the coefficient of *DirectFlight* is positive and significant at the 5% significance level. This result indicates the introduction of a new airline route increases the number of shared kidneys. Because we use the logarithm of shared volume as the dependent variable, a coefficient of 0.075 means an estimated 7.5% increase after the introduction of a direct flight. Columns (1)–(3) summarize the results from the models that exclude candidate features, donor features, or both. By comparing these columns with column (4), we see the coefficients of *DirectFlight* share the same significance level and nearly identical magnitudes. These results demonstrate our estimation of the treatment effect is consistent across different model specifications. They also rule out the possibility that introduction of a direct flight changes candidate or donor features.

The results from our main difference-in-differences model rely on the assumption that the treatment and control groups share parallel trends before the treatment. In addition, they do not indicate how the effect

Table 1. Definition and Summary of the Dependent Variable and Features of Candidates and Donors

Variable	Definition	Never treated		Ever treated	
		Mean	Standard deviation	Mean	Standard deviation
Dependent variable					
SharedVolume	Number of kidneys shared in a year	0.12	0.39	0.21	0.60
Candidate features					
CandiAge	Candidate's age in years at listing	49	4	47	5
CandiHeight	Candidate's height in centimeters at listing	169	3	168	5
CandiWeight	Candidate's weight in kilograms at listing	81	5	79	6
CandiMale	Candidate's gender is male	0.40	0.05	0.40	0.04
CandiRaceWhite	Candidate's race is white	0.56	0.22	0.47	0.20
CandiRaceBlack	Candidate's race is black	0.24	0.19	0.24	0.16
CandiRaceHispanic	Candidate's race is Hispanic	0.14	0.19	0.22	0.19
CandiBloodTypeA	Candidate's blood type is A	0.34	0.05	0.33	0.04
CandiBloodTypeB	Candidate's blood type is B	0.14	0.04	0.14	0.03
CandiBloodTypeO	Candidate's blood type is O	0.48	0.06	0.50	0.05
CandiDiabetesYes	Candidate has diabetes	0.45	0.09	0.42	0.10
CandiDiabetesUnknown	Candidate's diabetes status is unknown	0.00	0.02	0.01	0.01
CandiDialysisYes	Candidate is on dialysis	0.72	0.12	0.75	0.08
CandiDialysisYear	Candidate's dialysis duration in years	1.40	0.45	1.49	0.34
Donor features					
DonorAge	Donor's age in years at listing	39	6	39	6
DonorHeight	Donor's height in centimeters at listing	167	6	166	6
DonorWeight	Donor's weight in kilograms at listing	77	7	76	7
DonorCreatine	Donor's serum creatine in milligrams per deciliter	1.33	0.40	1.47	0.44
DonorGenderMale	Donor's gender is male	0.41	0.13	0.39	0.12
DonorRaceWhite	Donor's race is white	0.69	0.21	0.57	0.22
DonorRaceBlack	Donor's race is black	0.12	0.13	0.19	0.14
DonorRaceHispanic	Donor's race is Hispanic	0.15	0.17	0.20	0.16
DonorBloodTypeA	Donor's blood type is A	0.37	0.13	0.35	0.12
DonorBloodTypeB	Donor's blood type is B	0.12	0.09	0.11	0.06
DonorBloodTypeO	Donor's blood type is O	0.48	0.14	0.50	0.12
DonorDiabetesYes	Donor has diabetes	0.09	0.09	0.11	0.09
DonorDiabetesUnknown	Donor's diabetes status is unknown	0.00	0.01	0.01	0.02
DonorHypertensionYes	Donor has hypertension	0.30	0.14	0.33	0.14
DonorHypertensionUnknown	Donor's hypertension status is unknown	0.01	0.02	0.01	0.01
DonorHepatitisCYes	Donor has hepatitis C	0.04	0.06	0.04	0.04
DonorHepatitisCUnknown	Donor's hepatitis C status is unknown	0.00	0.01	0.00	0.01
DonorCodAnoxia	Donor's cause of death is anoxia	0.24	0.16	0.26	0.18
DonorCodCVS	Donor's cause of death is cardiovascular disease or stroke	0.35	0.16	0.36	0.14
DonorCodTrauma	Donor's cause of death is trauma	0.38	0.16	0.35	0.15
DonorECDYes	Expanded criteria donor	0.21	0.13	0.23	0.13
Number of observations		8,208		976	

Notes. We include each feature for all donors from the origin airport area and for all patients in the destination airport area in each year as control variables. The expanded criteria donor (ECD) is defined as a donor who is above 60, or a donor who is above 50 with two of the following: a history of high blood pressure, a creatinine level greater than or equal to 1.5 mg/dL, or whose death is caused by stroke (see https://health.ucdavis.edu/transplant/nonlivingdonors/expanded-criteria-donors.html for details).

of the introduction of new airline routes changes over time. To formally check the parallel-trends assumption and analyze the treatment effect heterogeneity over time, we follow Angrist and Pischke (2008) by using a modified difference-in-differences model:

$$\ln(SharedVolume_{ijt}) = \alpha_0 + \sum_{\tau=0}^{3}\beta_{-\tau}DirectFlight_{ij,t-\tau} + \sum_{\tau=1}^{3}\beta_{+\tau}DirectFlight_{ij,t+\tau} + \alpha_2 Features_{ijt} + \alpha_3 Airports_{ij} + \alpha_4 Year_t + \varepsilon_{ijt},$$

where the sums on the right-hand side allow for three lags (β_{-1}, β_{-2}, and β_{-3}) or posttreatment effects and three leads (β_{+1}, β_{+2}, and β_{+3}) or pretreatment effects. A statistically significant pretreatment effects would indicate the treatment and control groups have different trends before the introduction of a new airline route. Comparing the posttreatment effects enables us to understand how the effect of the introduction of new airline routes might change over time.

The results from the modified difference-in-differences model with pre- and posttreatment dummies are

Table 2. Results from the Difference-in-Differences Model

	(1)		(2)		(3)		(4)	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Direct flight	0.073**	0.030	0.074**	0.003	0.073**	0.030	0.075**	0.030
Candidate features			Included				Included	
Donor features					Included		Included	
Airport-pair fixed effects	Included		Included		Included		Included	
Year fixed effects	Included		Included		Included		Included	
Number of observations	9,184		9,184		9,184		9,184	
Adjusted R^2	0.062		0.063		0.061		0.063	

Note. Robust standard errors clustered by airport pair.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

presented in Table 3 and illustrated in Figure 2. In Table 3, the "3 and more years after" dummy (corresponding to "3+" in the x-axis of Figure 2) captures the accumulative effect (i.e., the average effect three or more years after the treatment), whereas "1 year after" and "2 year after" dummies (corresponding to "1" and "2" in the x-axis of Figure 2) are not accumulative. For example, if the treatment is in year 2010, "3 and more years after" indicates the average effect over 2013–2017, "1 year after" indicates the average effect in 2011, and "2 years after" indicates the average effect in 2012. Several observations can be made. First, the coefficients of all three pretreatment dummies are of small magnitude and are not statistically different from zero in all four models. These results suggest the treatment and control groups are not statistically different from each other after controlling for the airport-pair and year fixed effects. Second, the coefficients of $DirectFlight_{YrTreat}$ are of a large magnitude and are statistically significant at the 10% significance level. These results suggest the introduction of new airline routes has an immediate effect, possibly because airlines run marketing campaigns and promotions, and, as a results, a substantial portion of the populations are aware of such new airline routes on their launching. However, the effect diminishes for a while (as indicated by the coefficients of $DirectFlight_{1YrAft}$ and $DirectFlight_{2YrsAft}$) before it becomes significant again (as indicated by the coefficients of $DirectFlight_{3YrsAft}$). These results indicate the long-term effect is significant, although transplant centers may need time to become aware of and take up the new route for kidney transportation. Finally, the statistical significance of the coefficients of $DirectFlight_{3YrsAft}$ addresses potential concerns that the insignificance of pretreatment dummies is caused by a lack of statistical power.

5.3. Robustness Checks

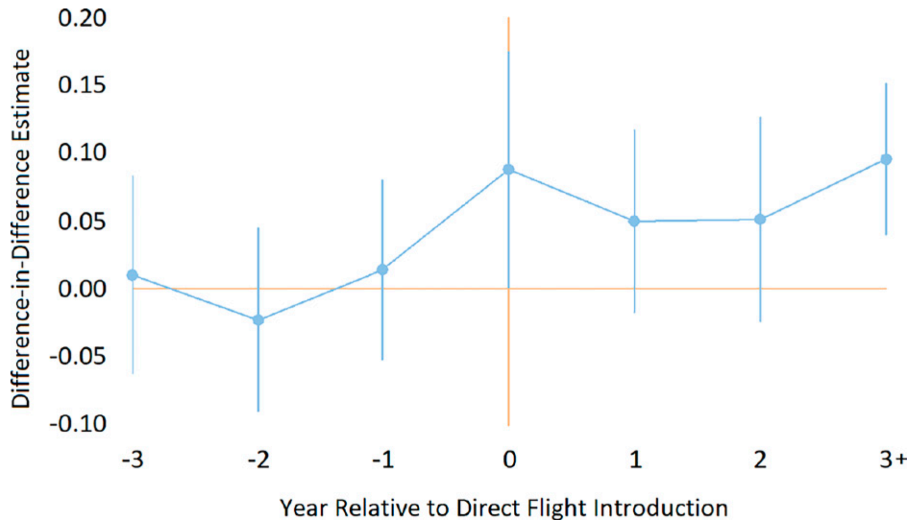
We now perform extensive robustness checks to analyze the sensitivity of our results. In the first two

Table 3. Results from the Difference-in-Differences Model (with Pre- and Posttreatment Dummies)

	(1)		(2)		(3)		(4)	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Direct flight								
3 years before	0.013	0.044	0.011	0.044	0.013	0.044	0.010	0.044
2 years before	−0.021	0.041	−0.022	0.041	−0.022	0.041	−0.023	0.041
1 year before	0.018	0.040	0.015	0.040	0.017	0.041	0.014	0.040
Year of treatment	0.089*	0.053	0.090*	0.053	0.087*	0.053	0.088*	0.053
1 year after	0.050	0.041	0.050	0.041	0.050	0.041	0.050	0.041
2 years after	0.050	0.046	0.050	0.046	0.049	0.046	0.050	0.046
3 and more years after	0.095***	0.035	0.098***	0.034	0.093***	0.035	0.096***	0.034
Candidate features			Included				Included	
Donor features					Included		Included	
Airport-pair fixed effects	Included		Included		Included		Included	
Year fixed effects	Included		Included		Included		Included	
Number of observations	9,184		9,184		9,184		9,184	
Adjusted R^2	0.061		0.063		0.061		0.062	

Note. Robust standard errors clustered by airport pair.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Figure 2. (Color online) Pre- and Posttreatment Effects of Introduction of New Airline Routes



robustness checks, Sections 5.3.1 and 5.3.2 address potential issues of selection based on observable and unobservable time-variant features, respectively. Next, Section 5.3.3 estimates the effect of new airline routes at the individual case level. Section 5.3.4 incorporates different aspects affecting air travel, including airport/air-space congestion, extreme weather, and time of day and day of the week. The next two robustness checks, presented in Sections 5.3.5 and 5.3.6, use balanced panel and balanced airport data, respectively, to address potential concerns that the data used in the main analysis might not be balanced. Then, Sections 5.3.7 and 5.3.8 discuss whether our results might be driven by the nearest airport, one particular airport pair, or a group of airports that share the same origin or destination. Finally, Sections 5.3.9 and 5.3.10 use an alternative dependent variable, cutoff distance, and frequency. The detailed results from all these robustness checks are relegated to Section OA.2 of the online appendix.

5.3.1. Propensity Score Matching. As Section 5.1 states, the treatment and control groups are not the same, giving rise to a potential concern that the differences in candidate or donor features affect our results. We address this concern using a matching method to select from the control group a subset of airport pairs that resemble the airport pairs in the treatment groups in terms of candidate and donor features, as well as the shared volume. In particular, we follow existing studies to use the propensity score matching method to reconstruct the treatment and control groups.

To describe this matching method, we denote by $Features_{ij}$, which is the pretreatment features of airports i and j, and $DirectFlight_{ij}$, which is a dummy that indicates whether airports i and j had a direct route introduced during our study period. The propensity score is calculated as $e(x) = Prob(DirectFlight_{ij} = 1 | Features_{ij} = X)$, where X denotes the underlying features. The intuition behind this matching method is that the treatment and control groups will have similar underlying features if they have similar propensity scores. A major advantage of propensity score matching is that it allows us to match the treatment and control groups based on a single propensity score instead of a large number of features.

To apply the propensity score matching method, we first calculate the average outcome and features between 2000 and 2001 (i.e., pretreatment period) for each airport pair. We then use a probit model to estimate the propensity scores. Finally, we use a caliper of 0.15 to select matched airport pairs in the treatment and control groups. This approach leads to 51 airport pairs in the treatment group and 51 airport pairs in the control group.[7] Table B1 in the online appendix summarizes the average outcome and features of the control (i.e., column Never Treated) and treatment (i.e., column Ever Treated) groups.

We use a t test to check whether the two groups have similar outcomes and features before the treatment. The last column of Table B1 in the online appendix shows all p values are larger than 0.05, meaning the differences between the treatment and control groups are not significant at the 5% significance level. In particular, we observe the difference between these groups in the fraction of White and Hispanic candidates/donors is significant in the unmatched sample but insignificant in the matched sample.

Table B12 in the online appendix summarizes the results based on the matched samples. The total number of observations is $(51\, treatment\ pairs + 51\, control\ pairs) \times 16\, years = 1{,}632$. From Table B12 in the online appendix, we observe the coefficients of $DirectFlight$ are positive and significant across all four models. These coefficients are not statistically significantly different from the results we obtain from the main analysis, mainly because the treatment and control groups are similar along many dimensions of the features.

5.3.2. Potential Selection Issues. A challenge of using observational data for causal inference is that the treatment is not randomly assigned. A selection issue arises if some underlying features affect both the treatment assignment and potential outcomes. The propensity score matching approach addresses potential issues of selection based on observable features, because it makes the treatment and control groups look similar in terms of the observable features. The airport-pair fixed effects in the difference-in-differences model capture all time-invariant unobservable features. Nevertheless, remaining selection issues might arise in the presence of some time-variant features that affect both the treatment assignment and potential outcomes.

To address such potential selection issues, we follow the strategy in the extant literature (Brot-Goldberg et al. 2017, Bapna et al. 2018, Sun et al. 2020) by using the airport pairs with existing direct flights as a new control group. The intuition is that because each pair of airports in both the treatment and control groups were eventually connected by a direct airline route, this approach could potentially capture some of the time-variant features that affect the decisions to introduce a new route. Our newly defined control group consists of 149 airport pairs. The total number of observations in this robustness check is $(61\,\mathit{treatment\ pairs} + 149\ \mathit{control\ pairs}) \times 16\ \mathit{years} = 3{,}360$. Table B3 in the online appendix shows the results from this robustness check. Additionally, we estimate the effect of introducing new airline routes using both controls, including 513 airport pairs without direct airline routes and 149 airport pairs with existing direct flights, and present our results in Table B4 in the online appendix.

In Tables B3 and B4 in the online appendix, we observe that the coefficients of *DirectFlight* are positive and significantly different from zero in all four models. These results are not significantly different from those in our main analysis, suggesting selection issues related to time-variant unobservable features are not a major concern in this study.

5.3.3. Individual-Level Analysis. To understand whether introducing new airline routes increases the likelihood of of accepting an offer from the donor hospital, we perform individual-level analyses by changing the unit of analysis from airport pairs to organ offers. Our new dependent variable is a dummy (denoted by $Accept_{ijt}$) indicating whether candidate i accepts an offer from donor j in year t. Our independent variables are (1) individual characteristics of both the candidate (denoted by $Candidate_{it}$) and donor (denoted by $Donor_j$) at the time of the offer, (2) the number of offers declined (denoted by $Decline_{ij}$) by candidate i prior to receiving an offer from donor j, (3) a treatment dummy (denoted by $DirectFlight_{ijt}$) indicating the introduction of a new airline route that links candidate i and donor j, and (4) fixed effect of airport pairs (denoted by $Airport_{ij}$) and years (denoted by $Year_t$).[8]

To empirically estimate the effect of the introduction of new airline routes on kidney acceptance/rejection, we use a link function (denoted by $F(\cdot)$) to describe the relationship between the dependent and independent variables: $F(Accept_{ijt}) = \alpha_0 + \alpha_1 DirectFlight_{ijt} + \alpha_2 Candidate_{it} + \alpha_3 Donor_j + \alpha_4 Decline_{ij} + \alpha_5 Airports_{ij} + \alpha_6 Year_t + \varepsilon_{ijt}$. Two commonly used link functions are the probit and logit models. In this study, we use the probit model and let $F(\cdot) = \Phi^{-1}(\cdot)$.[9] Table B5 in the online appendix summarizes the results from the probit model estimated based on the organ-offer data set, which records the decision of a candidate upon receiving an offer.[10] We observe that the coefficients of *DirectFlight* are positive and significantly different from zero across all four models. These results suggest introducing new airline routes increases the likelihood of accepting an offer. The magnitudes of the results from this robustness check are different from those in the main analysis because we use different econometric models (i.e., probit versus linear models) and units of analyses (i.e., airport versus donor-candidate pairs).

5.3.4. Practical Considerations Affecting Air Travel. A number of practical considerations, such as airport/air space congestion, weather, and flight timing, play important roles in air transportation. We construct several measures of those factors and conduct relevant robustness checks. First, to measure airport/air space congestion, we follow Arikan et al. (2013) and Deshpande and Arikan (2012) by constructing an aggregate on-time performance measure for each airport in each year using the Department of Transportation (DOT) Airline On-Time Performance data set.[11] For a given airport and year, we calculate the aggregate departure (arrival) delay rate by dividing the total number of delayed flights departing from (arriving at) the airport by the total number of flights departing from (arriving at) the airport in the year. Second, to measure extreme weather conditions, we construct an aggregate extreme weather index for each airport in each year using the U.S. Climate Extremes Index (CEI) data set from the National Oceanic and Atmospheric Administration (NOAA).[12] NOAA has developed a regional CEI, which provides data for all regions of the contiguous United States. For our purpose, we map all airports to those nine regions and calculate a weighted average of seasonal CEI for each airport in each year, where the weight is the fraction of flights in each season. Third, to incorporate the impact of time of day and day of the week, for each airport in each year, we calculate the fraction of flights scheduled to depart or arrive during each hour of the day and on each day of the week using the DOT Airline On-Time Performance data set. Tables B6 to B9 in the online appendix in the online appendix show our results are robust to including those control variables.

5.3.5. Balanced Panel Data. In the main analysis, we include the airport pairs that experienced an introduction of new airline routes in any year between 2002 and 2017. The panel data seem unbalanced in the sense that the airport pairs that experienced route introductions earlier (e.g., 2002) have fewer pretreatment periods, whereas the airport pairs that experienced route introductions later (e.g., 2017) have fewer posttreatment periods in our data. To address this concern, we redefine the treatment group as the airport pairs that experienced new route introductions between 2005 and 2014. The resulting panel data are more balanced, because all airport pairs in the treatment group have at least three pretreatment periods and three posttreatment periods.

Table B10 in the online appendix summarizes the results based on the sample created using the balanced panel data. The number of airport pairs is 34 in the treatment group and 513 in the control group, so the total number of observations is $(34\,\textit{treatment pairs} + 513\,\textit{control pairs}) \times 16\,\textit{years} = 5{,}752$. The number of airport pairs in the treatment group is smaller than in the main analysis, because we exclude pairs that experienced an introduction of new airline routes between 2002 and 2014 and between 2015 and 2017. Table B10 in the online appendix shows the coefficients of *DirectFlight* are positive and significantly different from zero in all four models. These coefficients are not statistically significantly different from the results from the main analysis. Thus, our results are robust to the seemingly unbalanced nature of the data.

5.3.6. Balanced Airport Pairs. As stated in Section 5.2, the airport pairs defined in our study are direction specific, and we exclude the airport pairs that never shared a kidney during our study period. The exclusion criteria might raise a concern that the airport pairs used in this study are unbalanced because we include two airports with flights in one direction but not the other. To address this concern, we reconstruct the control and treatment groups by including two airports with flights in both directions, as long as kidneys were shared between these airports. More specifically, for a pair of airports (i, j), we include both $Airports_{ij}$ and $Airports_{ji}$ if a year t exists such that $\max\{ShareVolume_{ijt}, ShareVolume_{jit}\} \geq 1$. However, we exclude the airport pairs that do not have complete information about the features of donors or candidates.

Table B11 in the online appendix summarizes the results based on the balanced airport-pairs data. The number of airport pairs is 68 in the treatment group and 608 in the control group, so the total number of observations is $(68\,\textit{treatment pairs} + 608\,\textit{control pairs}) \times 16\,\textit{years} = 10{,}816$. The number of observations in this robustness check is different from that in the main analysis, because we (1) include additional airport pairs to make airport pairs balanced and (2) exclude existing airport pairs caused by incomplete information about the features of donors or candidates. From Table B11 in the online appendix, we see the coefficients of *DirectFlight* are positive and significantly different from zero in all four models. These coefficients are not statistically significantly different from the results we obtain from the main analysis. Our results are robust to the unbalanced nature of airport pairs, because we perform an apples-to-apples comparison between the treatment and control groups.

5.3.7. Alternative Nearby Airports. In our main analysis, we assume shared kidneys are transported using the pair of airports that are the nearest to the donors and candidates, respectively. This assumption is consistent with the view of the organ transplantation community (OPTN 2019b). Yet, one might argue that the nearest airport may not always be chosen if an alternative can offer better connectivity. For example, a transplant center that intends to ship a kidney from Lansing, Michigan, to Dallas, Texas, might sometimes bypass the Capital Region International Airport (LAN), which is located 3 miles northwest of downtown Lansing, to use the Detroit Metropolitan Wayne County Airport (DTA), because the latter airport has direct flights to Dallas.

To capture such possibilities, we consider alternative airports by first calculating the distance from a donor or candidate to all airports, and identify the k nearest airports for the donor (designated as donor airport set) and the candidate (designated as candidate airport set), respectively.[13] We then analyze the connectivity (i.e., existence of a direct flight) of each airport in the donor airport set to any airport in the candidate airport set and calculate the extra travel distance should the nearest airports be bypassed. Finally, we identify two airports with the best connectivity and the shortest extra distance for kidney transportation. We do not bypass the nearest airport if the second nearest airport does not offer better connectivity or incurs too much extra distance.

Table B12 in the online appendix summarizes the results based on the scenario in which (1) both the donor and candidate have a set of two airports and (2) the second nearest airport incurs an extra travel distance of no more than 50 miles. The number of airport pairs is 49 in the treatment group and 376 in the control group, so the total number of observations is $(49\ \textit{treatment pairs} + 376\ \textit{control pairs}) \times 16\ \textit{years} = 6{,}800$. The number of observations in this robustness check is smaller than that in the main analysis, because certain airport pairs in both the treatment and control groups are bypassed and therefore excluded from this robustness check. We observe from Table B12 in the online appendix that the coefficients of *DirectFlight* are positive and significant across all four models. These coefficients are of larger magnitude (though the difference is not statistically significant) than those in the main analysis.

5.3.8. Leave-One-Out Analyses. As Section 5.1 describes, our treatment group includes 61 airport pairs with direct flights introduced between 2002 and 2017. One potential concern that our main analysis does not address is the possibility that the introduction of new airline routes has a large effect on certain pairs of airports but a small or no effect on others. If that possibility were true, our results would have been driven by one or a group of airport pairs. To address this concern, we perform three different leave-one-out analyses in which we (1) leave out one airport pair at a time, (2) leave out one origin airport at a time, and (3) leave one destination airport at time. For (2) and (3), we exclude all airport pairs related to the left-out origin or destination airport, respectively.

We present our results from the first leave-one-out analysis in Table B13 in the online appendix, in which all the coefficients are positive and statistically significant. The magnitude of these coefficients ranges from 0.55 to 0.88, which seemingly implies heterogeneity in the treatment effect. Yet, these coefficients are not statistically significantly different from each other and those from the main analysis. Next, we present the results from the second and third analyses in Table B14 in the online appendix in which all the coefficients are positive and statistically significant. Yet, they are not statistically different from each other and those from the main analysis. These comparisons suggest our main analysis is not driven by a particular airport pair, origin airport, or destination airport.

5.3.9. Alternative Dependent Variable. We now perform a robustness check to address a potential concern that the outcome variable defined in our main analysis is sparse because some airport pairs do not share a kidney across many years. To address this concern, we redefine the dependent variable as a binary variable, $SharedKidney_{ijt}$, which equals 1 if airport i shared one or more kidneys with airport j in year t, and 0 otherwise. The control group has 7,321 observations without kidney sharing and 887 observations with kidney sharing, so the probability of kidney sharing is $887/(887 + 7{,}321) = 0.108$ (or 10.8%). As a comparison, the treatment group has 815 observations without kidney sharing and 161 observations with kidney sharing, so the probability of kidney sharing is $161/(161 + 815) = 0.202$ (or 20.2%). This comparison suggests the treatment group is more like to share a kidney. However, it does not control for candidates' or donors' features.

To empirically estimate the effect of the introduction of new airline routes on kidney sharing, we use a link function (denoted by $F(\cdot)$) to describe the relationship between the dependent and independent variables: $F(SharedKidney_{ijt}) = \alpha_0 + \alpha_1 DirectFlight_{ijt} + \alpha_2 Features_{ijt} + \alpha_3 Airports_{ij} + \alpha_4 Year_t + \varepsilon_{ijt}$. In this study, we use the probit model and let $F(\cdot) = \Phi^{-1}(\cdot)$.[14] Table B15 in the online appendix summarizes the results from the probit model. We observe that the coefficients of *DirectFlight* are positive and significantly different from zero across all four models. These results suggest introducing new airline routes increases the likelihood of kidney sharing. Given the features of interest (denoted by X), we can calculate the marginal effect of the introduction of new airline routes using $Pr(SharedKidney_{ijt} = 1 \mid X, DirectFlight_{ijt} = 1) - Pr(SharedKidney_{ijt} = 1 \mid X, DirectFlight_{ijt} = 0)$. For an average airport pair (i.e., one with the average features), we estimate from model 4 that the introduction of new airline routes increases the likelihood of kidney sharing by 6.4%.

5.3.10. Alternative Cutoff Distance or Frequency. In our main analysis, we focus on the pairs of airports that are more than 800 miles away from each other, and use a cut-off frequency of 180 flights per year to determine whether an airport pair has a direct flight. Concerns may exist that our results are driven by these cut-off values. As a robustness check, we have considered alternative cut-off distances and frequencies to analyze the sensitivity of our results.

Table B16 in the online appendix summarizes the results in the case of a cut-off distance of 900 miles. The coefficients of *DirectFlight* are positive and significantly different from zero across all four models. Although these results are not significantly different from those obtained in our main analysis, these coefficients have slightly greater magnitudes, suggesting the effect of the introduction of new airline routes is more salient for the pairs of airports that are farther away.[15]

Table B17 in the online appendix summarizes the results when we use 120 flights per year (or once every three days) as a cut-off frequency to determine whether an airport pair has a direct flight. The coefficients of *DirectFlight* are positive and significantly different from zero in all four models. Interestingly, these results are similar to those obtained in our main analysis, primarily because an airline commonly offers either daily flights (i.e., 360 flights per year) or no flight (i.e., 0 flight per year) between two airports. These results suggest our results are robust to alternative cutoff frequencies.

6. Discussions and Managerial Insights

In this section, we discuss possible mechanisms behind our main findings, complemented by additional analyses helping us draw managerial implications. First, we estimate the impact on the total number of kidney transplants and local transplant volume in Section 6.1. Next, we test potential negative externality of introducing direct flights in Section 6.2. We then investigate the impact on kidney discards and the health outcomes of transplant candidates in Section 6.3. Finally, in Section 6.4, we discuss the heterogeneous effect of flight frequency and timing.

6.1. Impact on the Total Number of Kidney Transplants

In Section 5, we show the introduction of new airline routes between a pair of airports leads to an increase in the number of kidneys shared between the populations served by the pair. This result does not necessarily mean the introduction of new airline routes increases the *total* number of kidney transplants; the latter may remain the same even when the former increase.

To analyze whether the introduction of new airline routes increases the total number of shared kidneys, we define the dependent variable as the total number of kidney transplants at both the origin and destination airports. Table 4 summarizes the results. The coefficient of *DirectFlight* is positive and significantly different from zero at the 10% significance level in all four models. These results suggest introducing new airline routes leads to an increase in the total number of kidney transplants, implying an increased number of kidneys were harvested for transplantation.

Table 4 indicates the impact of new airline routes on the total number of kidney transplants is smaller than that on the number of shared kidneys. The reason is the total transplant volume is far higher than the transplant volume resulting from shared kidneys, so a net increase in the total volume can lead to a smaller percentage increase. To further analyze the effect on local transplant volume, we conduct additional analysis in Table C1 of the online appendix, which shows introducing new airline routes has no significant effect on the volume of local transplants.

6.2. Impact on Airport Pairs with Existing Direct Flights

We investigate whether the increased number of shared kidneys between the newly connected airports may come from those kidneys that would otherwise be shared with other airports. Specifically, we study whether introducing a new direct flight would reduce the number of kidneys shared between existing airport pairs with airline routes that share either the same origin or destination airport with the new airline route. For example, consider three airports A, B, and C. Initially, an airline route existed between A and B, but no airline route existed either between A and C or between B and C. Later, a new airline route between A and C was introduced. We are investigating whether introducing a new airline route between A and C may reduce the number of kidneys shared between A and B.

To do so, we first identify airport pairs with direct flights in all years from 2002 to 2017. We then divide them into three categories depending on whether they share the same origin or destination with the airport pairs that were connected through a new airline route: (1) share the same origin, (2) share the same destination, and (3) do not share the same origin or destination. Finally, we perform two separate analyses using category (3) as the control group and categories (1) and (2) as two treatment groups, respectively. Tables C2 and C3 in the online appendix summarize the results from these two analyses. We see the introduction of new airline routes does not affect the number of kidneys shared via airport pairs with existing direct flights.

Table 4. Effect of New Airline Routes on the Total Number of Kidney Transplants

	(1)		(2)		(3)		(4)	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Direct flight	0.040*	0.022	0.042*	0.023	0.037*	0.022	0.040*	0.022
Candidate features			Included				Included	
Donor features					Included		Included	
Airport-pair fixed effects	Included		Included		Included		Included	
Year fixed effects	Included		Included		Included		Included	
Number of observations	8,784		8,784		8,784		8,096	
Adjusted R^2	0.878		0.879		0.882		0.882	

Note. Robust standard errors clustered by airport pair.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 5. Results from the Difference-in-Differences Model (Discard Rate)

	(1)		(2)		(3)		(4)	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Direct flight	−0.698**	0.280	−0.693**	0.277	−0.602**	0.282	−0.601**	0.279
Candidate features			Included				Included	
Donor features					Included		Included	
Airport-pair fixed effects	Included		Included		Included		Included	
Year fixed effects	Included		Included		Included		Included	
Number of observations	8,784		8,784		8,784		8,784	
Adjusted R^2	0.286		0.294		0.314		0.322	

Notes. Discard rate is defined as the percentage of kidneys that are not recovered for transplantation. For ease of interpretation, we have multiplied all outcomes by 100. Robust standard errors clustered by airport pair.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

6.3. Impact on Discard Rate and Posttransplant Survival

Although we find an increased number of shared kidneys and kidney transplants after the introduction of new airline routes, whether introducing new airline routes improves or worsens the posttransplant outcome remains unclear. On the one hand, the outcomes might improve with the faster traveling option (via direct commercial flights) that allows for better matching between donors and candidates. On the other hand, the outcomes might worsen because of long travel distances and potential usage of low-quality kidneys that would otherwise be discarded.

To answer this question, we first investigate whether the increased number of shared kidneys between the newly connected airports may partly come from kidneys that would otherwise be discarded. Specifically, we study whether introducing a new direct flight would reduce the average discard rate of the two newly connected airports. Our results in Table 5 suggest introducing a new airline route reduces the discard rate of kidneys by facilitating kidney sharing.

Next, we test how introducing new airline routes affects the three-year posttransplant survival rate for shared kidneys. Denote by $RecipientSurvival_{rt}$ a dummy variable that equals one if recipient r survives more than three years after a kidney transplant in year t. For each destination airport j, we identify all the candidates associated with airport j and calculate the average survival rate using $AirportSurvival_{jt} = \frac{1}{N}\sum_{r=1}^{N} RecipientSurvival_{rt}$, where N refers to the total number of candidates associated with airport j. We then calculate the average survival rate of an airport pair using $PairSurvival_{ijt} = (AirportSurvival_{it} + AirportSurvival_{jt})/2$ and use it as a new dependent variable.[16] From Table 6, we observe no statistically significant effect on three-year posttransplant survival rates due to the introduction of new airline routes. To verify the robustness of these results, we present similar results using the five-year posttransplant survival rate as the quality measure in Table C4 of the online appendix.[17]

6.4. Effect of Flight Frequency and Timing

As a robustness check of our our main analysis, in Section 5.3.4, we used different cutoffs of flight frequency to define a dummy variable that indicates whether a new direct flight route is introduced between two airports. To analyze whether the effect of new airline routes depends on flight frequency, we replace the treatment dummy with the number of flights (in

Table 6. Effect of New Airline Routes on Three-Year Posttransplant Survival

	(1)		(2)		(3)		(4)	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Direct flight	0.002	0.003	0.002	0.003	0.003	0.003	0.003	0.003
Candidate features			Included				Included	
Donor features					Included		Included	
Airport-pair fixed effects	Included		Included		Included		Included	
Year fixed effects	Included		Included		Included		Included	
Number of observations	4,862		4,862		4,862		4,862	
Adjusted R^2	0.376		0.383		0.389		0.395	

Note. Robust standard errors clustered by airport pair.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 7. Results from the Difference-in-Differences Model (Continuous Treatment Variable)

	(1)		(2)		(3)		(4)	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Direct flight	0.517***	0.084	0.521***	0.089	0.530***	0.088	0.534***	0.093
Direct flight squared	−0.397***	0.081	−0.395***	0.087	−0.411***	0.085	−0.409***	0.091
Candidate features			Included				Included	
Donor features					Included		Included	
Airport-pair fixed effects	Included		Included		Included		Included	
Year fixed effects	Included		Included		Included		Included	
Number of observations	9,184		9,184		9,184		9,184	
Adjusted R^2	0.062		0.063		0.061		0.063	

Note. Robust standard errors clustered by airport pair.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

hundreds) per year and estimate the following polynomial regression model:

$$\ln(SharedVolume_{ijt}) = \alpha_0 + \alpha_1 DirectFlight_{ijt} + \alpha_2 DirectFlight^2_{ijt} + \alpha_3 Features_{ijt} + \alpha_4 Airports_{ij} + \alpha_5 Year_t + \varepsilon_{ijt}.$$

Our results in Table 7 suggest that, whereas introducing new airline routes facilitates kidney sharing, the marginal benefit of introducing more direct flights is weakening given a higher flight frequency. This nonlinear effect shares the same spirit as the breakpoints in piecewise linear regression models (Muggeo 2003, Ding et al. 2019).

We also investigate whether the benefit of introducing direct flight depends on the operation time of newly introduced airline routes. Specifically, we estimate the heterogeneous effect of new airline routes in terms of (1) time of the day, that is, day (i.e., between 6:00 a.m. and 5:59 p.m.) versus evening (i.e., between 6:00 p.m. and 5:59 a.m. of the following day) and (2) day of the week, that is, weekday (Monday through Friday) versus weekend (Saturday and Sunday). Our results in Table C5 of the online appendix suggest introducing new airline routes facilitates kidney sharing regardless of the time of day. Yet, the effect of introducing a daytime route is of higher magnitude than introducing an evening route. This finding echoes the observation that "organ donation tends to occur in the evening or early morning" (Pullen 2019, p. 1603), meaning daytime flights facilitate long-distance kidney sharing better than evening flights. Likewise, the results in Table C6 of the online appendix suggest introducing new airline routes facilitates kidney sharing regardless of the day of the week, and yet the effect of introducing new airline routes during weekdays is of higher magnitude than introducing them during weekends.

7. Conclusion

A significant number of policy initiatives have been inspired by the U.S. organ transplant system that predominantly favors local matches and hinders organ pooling, leading to approximately 28,000 organs being unrecovered and 3,500 recovered organs being unused every year (Aubert et al. 2019). Although most of these policy initiatives focus on expanding organ sharing, they tend to overlook the airline transportation options that make it possible: sharing organs across a long distance requires convenient flight options, ideally direct flights, because of the time-sensitive nature of organ harvesting operations. In this paper, we echo a view expressed by a large number of OPO officials and surgeons (OPTN 2019b) that, unless policymakers incorporate (or take steps to reduce) a key friction, namely, air transportation needed for cross-regional organ sharing, such proposals are unlikely to lead to intended changes. Our paper estimates the effect of the introduction of new airline routes on the number of shared kidneys, by analyzing a sample tracking both the evolution of flight routes and kidney transplants with donors and recipients living near different pairs of airports. We estimate the introduction of a direct flight between a pair of airports increases the number of kidneys shared between populations served by these airports by 7.3%. The increase in quantity does not come with a decrease in the quality of kidney transplants, as measured by three- and five-year post-transplantation survival rates. We conduct extensive robustness checks and show our findings are robust to alternative empirical specifications.

Our paper represents the first systematic, empirical effort to understand the role of airline logistics infrastructure in organ transplantation. We show the introduction of new airline routes leads to a significant increase in organ sharing, which has a potential to inspire future research into the impact of other treatments in airline routes. To our best knowledge, the United States does not have major national policy initiatives providing incentives for improving the logistics of organ transplantation (Curran 2020). Outside the United States, Italy has issued national guidelines that provide minimum requirements (e.g., packaging, labeling, and traceability) during airline transportation and select organ storage units and shipping agents based on their "efficiency, reliability, and equipment with reference to organ type and ischemia time" (Mantecchini et al. 2016, p. 304); the U.S. policymakers may consider issuing similar national guidelines.

We acknowledge that without financial obligations, commercial airline companies are unlikely to make their routing decisions by accounting for public interest.[18] Our research provides a causal evidence that inefficient airline routing is a significant friction in organ sharing and, on the flip side, better airline logistics infrastructure facilitates broader organ sharing. In light of our empirical finding, U.S. policymakers may consider establishing a national system that initiates and tracks organ shipments through commercial airlines (Aleccia 2020). In recent years, researchers (Gentry et al. 2015, Kilambi and Mehrotra 2017) have proposed a variety of ways to redistribute donation regions to mitigate geographic disparities in organ allocation. In line with these proposals, our results support the idea of adjusting DSAs from time to time by accounting for the network connectivity across various airports, rather than eliminating DSAs and allocating kidneys using a circle of a fixed size.

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Endnotes

[1] As with most operations management literature on kidney transplantation, we focus on the deceased-donor kidney transplantation system and provide an overview of it in Section 3.1. A kidney from a deceased donor is referred to as a cadaveric kidney. Living-donor kidney transplantation is beyond the scope of the paper.

[2] Throughout our paper, consistent with common practice (https://www.anna.aero/all-new-airline-routes/) and the literature (Giroud 2013, Bernstein et al. 2016), an airline route between two airports refers to a *nonstop* route, with the origin being one airport and the destination being the other.

[3] See https://optn.transplant.hrsa.gov/learn/about-transplantation/how-organ-allocation-works/.

[4] Unless specified otherwise, we differentiate the origin from the destination of an airport pair. That is, an airport pair is direction-specific in this study.

[5] We do not use the recorded flight distance because (1) it is unavailable for the airport pairs without a direct flight, and (2) the actual flight distance is affected by weather conditions and flight delays, among other factors.

[6] Because of the staggered nature of the introduction of new airline routes, the airport pairs in the treatment group are treated only after they were connected by new airline routes. Before they are treated, they serve as controls for airport pairs that have been treated in earlier years (Giroud 2013, p. 870–871).

[7] Using a different model (e.g., logit) to estimate the propensity scores or caliper (e.g., 0.1) to select matched samples does not change the main conclusion of this robustness check.

[8] We include the fixed effects of airport instead of donor-candidate pairs because each donor-candidate pair appears only once in our data.

[9] Using logit or other models does not qualitatively change the results of this robustness check.

[10] The data set description is available at https://optn.transplant.hrsa.gov/data/about-data/optn-database/.

[11] Using the DOT definition of on-time performance, we allow a 15-minute buffer beyond the scheduled departure and arrival time of each flight.

[12] According to the National Center for Atmospheric Research (https://climatedataguide.ucar.edu/climate-data/us-climate-extremes-index-cei), the CEI captures extreme weather conditions "in the distribution of much above/below average (top/bottom 10% of occurrence) temperatures, precipitation, drought, and tropical cyclone wind speed across the contiguous U.S." It is measured for each region and for each season. Because long-distance air travel is often affected by extreme weather conditions not only in immediately surrounding areas, but also in broader geographic regions, CEI is a useful metric of extreme weather conditions for the purpose of our estimation.

[13] In this robustness check, we make several assumptions on airport choices for practicality of estimation. An interesting direction for future research entails a full-blown modeling of airport choices, which is beyond our scope.

[14] Using logit or other models does not qualitatively change the results of this robustness check.

[15] As expected, the effect of the introduction of new airline routes is smaller for the pairs of airports that are closer to each other, because healthcare providers may prefer driving to flying when travel distance is not too long.

[16] Using weighted average does not qualitatively change the result of this analysis.

[17] The results are also similar if we use graft survival rate to proxy the posttransplant outcome, which measures whether the transplanted organ still functions.

[18] As a notable exception, the Coronavirus Aid, Relief, and Economic Security (CARES) Act, a $2.2 trillion economic stimulus package in response to the COVID-19 pandemic that was signed into law by President Donald Trump on March 27, 2020, mandates each airline company receiving federal funding to meet minimum required route service levels (Petchenik 2020).

References

Ahuja V, Alan Y, Arikan M (2020) Rethinking service quality in the airline industry: Evidence from the Wright Amendment repeal. Working paper, Southern Methodist University, Dallas.

Akan M, Alagoz O, Ata B, Erenay F, Said A (2012) A broader view of designing the liver allocation system. *Oper. Res.* 60(4): 757–770.

Aleccia J (2020) How lifesaving organs for transplant go missing in transit. *Kaiser Health News*. Accessed December 1, 2020, https://khn.org/news/how-lifesaving-organs-for-transplant-go-missing-in-transit/.

Angrist JD, Pischke JS (2008) *Mostly Harmless Econometrics: An Empiricist's Companion* (Princeton University Press, Princeton, NJ).

Arikan M, Deshpande V, Sohoni M (2013) Building reliable air-travel infrastructure using empirical data and stochastic models of airline networks. *Oper. Res.* 61(1):45–64.

Arikan M, Ata B, Friedewald JJ, Parker RP (2018) Enhancing kidney supply through geographic sharing in the United States. *Production Oper. Management* 27(12):2103–2121.

Ata B, Friedewald JJ, Randa AC (2020) Structural estimation of kidney transplant candidates' quality of life scores: Improving national kidney allocation policy under endogenous patient choice and geographical sharing. Working paper, University of Chicago, Chicago.

Ata B, Skaro A, Tayur S (2017) OrganJet: Overcoming geographical disparities in access to deceased donor kidneys in the United States. *Management Sci.* 63(9):2776–2794.

Aubert O, Reese PP, Audry B, Bouatou Y, Raynaud M, Viglietti D, Legendre C, et al (2019) Disparities in acceptance of deceased donor kidneys between the United States and France and estimated effects of increased US acceptance. *JAMA Internal Medicine* 179(10):1365–1374.

Bapna R, Ramaprasad J, Umyarov A (2018) Monetizing freemium communities: Does paying for premium increase social engagement? *Management Inform. Systems Quart.* 42(3):719–735.

Bernard AB, Moxnes A, Saito YU (2019) Production networks, geography, and firm performance. *J. Political Econom.* 127(2):639–688.

Bernstein S, Giroud X, Townsend RR (2016) The impact of venture capital monitoring. *J. Finance* 71(4):1591–1622.

Bertsimas D, Farias VF, Trichakis N (2013) Fairness, efficiency, and flexibility in organ allocation for kidney transplantation. *Oper. Res.* 61(1):73–87.

Bray RL, Serpa JC, Colak A (2019) Supply chain proximity and product quality. *Management Sci.* 65(9):4079–4099.

Bridgespan Group (2019) Reforming organ donation in America. Accessed December 1, 2020, https://www.bridgespan.org/insights/library/public-health/reforming-organ-donation-in-america.

Brot-Goldberg ZC, Chandra A, Handel BR, Kolstad JT (2017) What does a deductible do? The impact of cost-sharing on healthcare prices, quantities, and spending dynamics. *Quart. J. Econom.* 132(3):1261–1318.

Catalini C, Fons-Rosen C, Gaulé P (2020) How do travel costs shape collaboration? *Management Sci.* 66(8):3340–3360.

Curran A (2020) How human organs are flown for transplants. Simple flying. Accessed December 1, 2020, https://simpleflying.com/human-organ-transplant-flight/.

Dai T, Tayur S (2020) Healthcare operations management: A snapshot of emerging research. *Manufacturing Service Oper. Management* 22(5):869–887.

Dai T, Zheng R, Sycara K (2020) Jumping the line, charitably: Analysis and remedy of donor priority rule. *Management Sci.* 66(2):622–641.

Deshpande V, Arikan M (2012) The impact of airline flight schedules on flight delays. *Manufacturing Service Oper. Management* 14(3):423–440.

Ding Y, Ge D, He S, Ryan CT (2018) A nonasymptotic approach to analyzing kidney exchange graphs. *Oper. Res.* 66(4):918–935.

Ding Y, Park E, Nagarajan M, Grafstein E (2019) Patient prioritization in emergency department triage systems: An empirical study of the Canadian Triage and Acuity Scale (CTAS). *Manufacturing Service Oper. Management* 21(4):723–741.

Dong X, Zheng S, Kahn ME (2020) The role of transportation speed in facilitating high skilled teamwork across cities. *J. Urban Econom.* 115:103212.

Gallino S, Moreno A (2014) Integration of online and offline channels in retail: The impact of sharing reliable inventory availability information. *Management Sci.* 60(6):1434–1451.

Gentry SE, Segev DL, Kasiske BL, Mulligan DC, Hirose R (2015) Robust models support redistricting liver allocation to reduce geographic disparity. *Transplantation* 99(9):e159–e160.

Giroud X (2013) Proximity and investment: Evidence from plant-level data. *Quart. J. Econom.* 128(2):861–915.

Graves SC, Tomlin BT (2003) Process flexibility in supply chains. *Management Sci.* 49(7):907–919.

Ho TH, Lim N, Reza S, Xia X (2017) Causal inference models in operations management. *Manufacturing Service Oper. Management* 19(4):509–525.

Hopp W, Iravani SMR, Xu WL (2010) Vertical flexibility in supply chains. *Management Sci.* 56(3):495–502.

Humes E (2016) *Door to Door: The Magnificent, Maddening, Mysterious World of Transportation* (Harper, New York).

Hwang EH, Nageswaran L, Cho SH (2021) Value of online-offline return partnership to offline retailers. Working paper, University of Washington, Seattle.

Ibanez MR, Toffel MW (2019) How scheduling can bias quality assessment: Evidence from food-safety inspections. *Management Sci.* 66(6):2396–2416.

Jordan WC, Graves SC (1995) Principles on the benefits of manufacturing process flexibility. *Management Sci.* 41(4):577–594.

KC DS (2018) Econometric methods. Dai T, Tayur SR, eds. *Handbook of Healthcare Analytics: Theoretical Minimum for Conducting 21st Century Research on Healthcare Operations* (John Wiley & Sons, Hoboken, NJ), 381–402.

KC DS, Scholtes S, Terwiesch C (2020) Empirical research in healthcare operations: Past research, present understanding, and future opportunities. *Manufacturing Service Oper. Management* 22(1):73–83.

Keskinocak P (2010) Quantitative methods in health and humanitarian systems. Accessed December 1, 2020, https://smartech.gatech.edu/handle/1853/61827.

Keskinocak P, Savva N (2020) A review of the healthcare-management (modeling) literature published in *Manufacturing & Service Operations Management*. *Manufacturing Service Oper. Management* 22(1):59–72.

Kilambi V, Mehrotra S (2017) Improving liver allocation using optimized neighborhoods. *Transplantation* 101(2):350–359.

Kim SH, Tong J, Peden C (2020) Admission control biases in hospital unit capacity management: How occupancy information hurdles and decision noise impact utilization. *Management Sci.* 66(11):5151–5170.

Kong N, Schaefer AJ, Hunsaker B, Roberts MS (2010) Maximizing the efficiency of the U.S. liver allocation system through region design. *Management Sci.* 56(12):2111–2122.

Li J, Netessine S (2020) Higher market thickness reduces matching rate in online platforms: Evidence from a quasi-experiment. *Management Sci.* 66(1):271–289.

Locke JE, Sellers MT (2019) Get on with it!—A novel allocation strategy to reduce kidney discards. *Amer. J. Transplantation* 19(11): 2971–2972.

Lu SF, Lu LX (2017) Do mandatory overtime laws improve quality? Staffing decisions and operational flexibility of nursing homes. *Management Sci.* 63(11):3566–3585.

Mantecchini L, Paganelli F, Morabito V, Ricci A, Peritore D, Trapani S, Montemurro A, et al (2016) Transportation of organs by air: Safety, quality, and sustainability criteria. *Transplantation Proceedings* 48(2):304–308.

Muggeo VMR (2003) Estimating regression models with unknown break-points. *Statist Medicine* 22(19):3055–3071.

Organ Procurement and Transplantation Network (OPTN) (2019a) Public comment proposal: Eliminate the use of DSA and region in kidney allocation policy. Accessed December 1, 2020, https://optn.transplant.hrsa.gov/media/3104/kidney_public comment_201908.pdf.

Organ Procurement and Transplantation Network (OPTN) (2019b) Public comments for "Eliminate the use of DSA and Region in kidney allocation policy." Accessed December 1, 2020, https://optn.transplant.hrsa.gov/governance/public-comment/eliminate-the-use-of-dsa-and-region-in-kidney-allocation-policy/.

Petchenik I (2020) The impact of the CARES Act on US domestic aviation. *Flightradar24* (May 29), https://www.flightradar24.com/blog/the-impact-of-the-cares-act-on-us-domestic-aviation/.

Pullen LC (2019) Tackling the growing problem of transporting organs. *Amer. J. Transplantation* 19(6):1603–1604.

Ramdas K, Darzi A (2017) Adopting innovations in care delivery-the case of shared medical appointments. *New England J. Medicine* 376(12):1105–1107.

Roberts M, Whited T (2013) Endogeneity in empirical corporate finance. Constantinides G, Stulz R, Harris M, eds. *Handbook of the Economics of Finance*, vol. 2A (Elsevier, Amsterdam), 493–572.

Sandikçi BL, Maillart M, Schaefer AJ, Roberts MS (2013) Alleviating the patient's price of privacy through a partially observable waiting list. *Management Sci.* 59(8):1836–1854.

Song H, Tucker AL, Murrell KL (2015) The diseconomies of queue pooling: An empirical investigation of emergency department length of stay. *Management Sci.* 61(12):3032–3053.

Song H, Tucker AL, Graue R, Moravick S, Yang JJ (2020) Capacity pooling in hospitals: The hidden consequences of off-service placement. *Management Sci.* 66(9):3825–3842.

Su X, Zenios SA (2004) Patient choice in kidney allocation: The Role of the queueing discipline. *Manufacturing Service Oper. Management* 6(4):280–301.

Su X, Zenios SA (2006) Recipient choice can address the efficiency-equity trade-off in kidney transplantation: a mechanism design model. *Management Sci.* 52(11):1647–1660.

Sun S, Lu SF, Rui H (2020) Does telemedicine reduce emergency room congestion? Evidence from New York State. *Inform. Systems Res.* 31(3):972–986.

Terwiesch C, Olivares M, Staats BR, Gaur V (2020) A review of empirical operations management over the last two decades. *Manufacturing Service Oper. Management* 22(4):656–668.

Tierney M (2014) Love Field flight limits end, and passengers cheer. *New York Times* (Oct. 21), B8, https://www.nytimes.com/2014/10/21/business/love-field-flight-limits-endand-passengers-cheer.html.

Van Mieghem JA (2007) Risk mitigation in newsvendor networks: Resource diversification, flexibility, sharing, and hedging. *Management Sci.* 53(8):1269–1288.

Van Mieghem JA, Dada M (1999) Price vs. production postponement: Capacity and competition. *Management Sci.* 45(12):1639–1649.

Wang G (2020) The effect of Medicaid expansion on the patient flow in emergency department. Working paper, University of Texas at Dallas, Dallas.

Wang G, Li J, Hopp W (2020) Improving operational efficiency to save lives: An empirical study of new entries in the liver transplant market. Working paper, University of Texas at Dallas, Richardson, Texas.

Zhang J (2010) The sound of silence: Observational learning in the U.S. kidney market. *Marketing Sci.* 29(2):315–335.