Two Essays on the Economics of Organ Transplantation

by

Sarah See Stith

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Doctoral Committee:

Professor Thomas C. Buchmueller, Chair
Assistant Professor Stephen G. Leider
Assistant Professor Mario Macis, Johns Hopkins University
Professor Scott E. Masten
Professor Jeffrey Andrew Smith

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Dedication

To the donors for the lives they save

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Table of Contents

List of Tables

List of Figures

Chapter 1:

Introduction

My dissertation analyzes two important factors in organ transplantation, transplant center performance and organ donation. The two chapters contribute to the economics literature on organizational learning-by-doing and on the effect of legal interventions on pro-social behavior, respectively. Organ transplantation is subject to significant regulation and understanding factors affecting survival outcomes and the constrained supply of organs has potentially life-saving policy implications within organ transplantation and in other areas of healthcare as well.

In the first chapter, I question whether liver transplant centers learn by doing and ask what factors affect the magnitude of organizational learning-by-doing. Organizational learning-by-doing implies that production outcomes improve with increases in cumulative volume produced. Empirical research documents the existence of organizational learning-by-doing, primarily in manufacturing, but provides little insight into why some firms learn while others do not. Using patient-level data on 120 new liver transplant centers, I first establish that organizational learning-by-doing exists, but only shortly after entry. Second, I show that significant variation in organizational learning-by-doing exists across centers. Third, I test whether the timing of entry and pre-entry experience transplanting other organs affect the existence and magnitude of organizational learning-by-doing. I find that organizational learning-by-doing only exists early in the sample period when liver transplantation was a relatively experimental procedure. Pre-entry experience also influences the relationship between survival

outcomes and cumulative volume, with survival benefits from pre-entry experience in lung and pancreas transplantation. My results indicate that current policies discouraging entry into liver transplantation may reduce access without improving outcomes.

The second chapter of my dissertation is co-authored with Nicola Lacetera and Mario Macis and considers whether laws intended to increase organ and bone marrow donation have any effect on increasing donation, which may determine whether a patient receives a potentially life-saving transplant or dies waiting. Many U.S. states passed legislation providing leave to organ and bone marrow donors and/or tax benefits for live and deceased organ and bone marrow donations and to employers of donors. We exploit cross-state variation in the timing and passage of such legislation to analyze its impact on organ donations by living and deceased persons, on measures of the quality of the organs transplanted, and on the number of bone marrow donations. We find that these provisions did not have a statistically significant impact on the quantity of organs donated. The leave legislation, however, did have a positive impact on bone marrow donations. We also find some evidence of a positive impact on post-transplant survival rates. Our results suggest that this legislation works for moderately invasive procedures such as bone marrow donation, but may be too low for organ donation, which is riskier and more burdensome to the donor.

Chapter 2:

Organizational Learning-by-Doing:

Evidence from Liver Transplantation

1. Introduction

Organizational learning-by-doing occurs because the trials and errors inherent in implementing a new production process lead to organizational responses that improve production outcomes. Although individual learning-by-doing can contribute to organizational learning-by-doing, the latter arises independently as well, through improved coordination and management of production and the development of interdependent knowledge among production team members (Bahk and Gort, 1993; Thompson, 2012).[1] The presence of organizational learning-by-doing is well-documented in manufacturing, although in healthcare the literature has found little evidence of any effect of organizational experience on patient outcomes. The literature in general is silent on the existence, magnitude, and sources of heterogeneity in learning-by-doing among firms in the same industry.

I contribute to the literature by using detailed, patient-level data on 120 new liver transplant centers to answer three questions. First, I ask whether liver transplant centers learn by doing and whether any learning-by-doing that does occur is concentrated shortly after entry. Second, I test whether heterogeneity in learning-by-doing exists among centers. Third, I analyze how the timing of entry between 1987 and 2009 and pre-entry experience transplanting other

[1] Hereafter, unless otherwise specified, learning-by-doing refers to organizational learning-by-doing.

types of organs influence the existence and magnitude of learning-by-doing. Both factors are hypothesized to affect learning-by-doing by diminishing the amount of knowledge that must be acquired through learning-by-doing rather than through commonly available knowledge or transferable experience from performing other types of transplants.

Liver transplantation is particularly suited to the study of organizational learning-by-doing. The transplantation process involves a large number of distinct tasks, and at least through the mid-1990's, significant ambiguity existed about the optimal approach for maximizing survival, especially with regard to immunosuppression. In addition, the transplantation process extends from pre-operative care to long-term immunosuppression in a necessarily team-based environment due to the broad range of skills required for a successful transplant. Hospitals also must have or acquire an extensive range of specialized expertise and resources to gain access to the only source of cadaveric organs in the United States, the Organ Procurement and Transplantation Network.[2] (Since 2008, the Organ Procurement and Transplantation Network has restricted live donor transplants to only those hospitals it has approved for live donor organ recovery.[3])

Determining the existence and extent of learning-by-doing in liver transplantation matters for the transplant community, policymakers, and insurers. If learning-by-doing does exist, then the decreased probability of survival for patients at new centers should be weighed against the survival benefits of increased access to transplantation from those entrants. Even as late as 2011,

[2] The requirements to operate a liver transplant program include a primary liver transplant surgeon and a liver transplant physician on staff 365 days a year, 24 hours a day; collaborative involvement with experts from radiology, infectious disease, pathology, immunology, anesthesiology, physical therapy, histocompatiblity, immunogenetics, and hepatology; access to sophisticated microbiology, clinical chemistry, histocompatibility testing, and radiology services; facilities required for monitoring immunosuppressive drugs; extensive blood bank support; a clinical transplant pharmacist; and mental health and social support services (The Organ Procurement and Transplantation Network, 2009.)

[3] The Organ Procurement and Transplantation Network/United Network for Organ Sharing Living Donor Committee, 2008

only 132 liver transplant centers existed in the United States, and 14 states had no center at all. Alternatively, if learning-by-doing does not exist, then public and insurer policies limiting entry into transplantation could lead to unnecessary deaths by limiting access to transplantation. Certificate-of-need laws and preferred provider networks are examples of common consolidation policies that create barriers to entry for new centers.[4]

This paper is also important from a research perspective; little is known about organizational learning-by-doing in healthcare and about heterogeneity among firms in learning-by-doing more generally. Many empirical papers in economics do document the importance of organizational learning-by-doing for reducing unit costs across a wide range of industries, particularly in manufacturing (e.g., Zimmerman, 1982; Irwin and Klenow, 1994; and Benkard, 2000). A recent paper by Levitt, List, and Syverson (2012) finds a learning-by-doing effect on the quality of production (the number of production defects), but the literature in healthcare rarely finds evidence of organizational learning-by-doing on the quality of patient outcomes.

Furthermore, although studies in manufacturing suggest most learning-by-doing occurs shortly after entry, only one study in healthcare analyzes organizational learning-by-doing from entry (Pisano, Bohmer, and Edmondson, 2001.) Other papers studying organizational learning-by-doing in healthcare regress patient outcomes on procedure volume accrued since data collection began or on lagged annual volume measures, rather than on procedure volume accrued since a hospital started offering the studied procedure. Apart from Pisano, Bohmer, and Edmondson (2001), the literature in healthcare does not find evidence of organizational learning-by-doing; only a contemporaneous scale effect appears to exist (e.g., Ho, 2002; Gaynor, Seider,

[4] Twenty-one states have certificate-of-need laws for organ transplantation (National Coalition of State Legislators, 2011.) These laws require state-level approval to open a new transplant center. Most insurers limit coverage to care provided by a specific set of insurer-designated hospitals with inclusion determined in part by minimum volume requirements. Minimum volume criteria, which vary by insurer from 10 per year (Medicare) to 40 per year (Aetna), make it difficult for new or small centers to attract paying patients.

and Vogt, 2005). Pisano, Bohmer and Edmondson (2001) contribute to the literature on organizational learning-by-doing more generally by showing that the magnitude of learning-by-doing differs among the sixteen hospitals in their sample.

Although a large number of papers (outside of healthcare) study learning-by-doing, little has been documented about the mechanisms through which organizational learning-by-doing occurs. Jovanovic and Nyarko (1995) develop and test a theoretical model predicting that the following attributes of the underlying production process determine the existence and magnitude of learning-by-doing: the number of tasks involved, the noisiness of the outcome measure, and the uncertainty about the optimal way to produce a desired outcome. Balasubramanian and Lieberman (2010) support the relationship between these factors and learning-by-doing at the industry level in an analysis of 55,000 new manufacturing plants. If these predictions and empirical results are generalizable, then liver transplantation should be precisely the type of "production" that should exhibit learning-by-doing.

Using data on liver transplants also overcomes two primary data limitations faced by other studies on learning-by-doing in healthcare: a lack of patient-level data since entry into a type of procedure and inadequate risk adjustment variables. With patient-level data for 120 liver transplant centers since entry, volume-based experience can be accurately measured from entry up to the date of a specific patient's transplant. The breadth of variables on donor and match quality and patient health allow me to minimize the possibility of endogeneity arising from missing variables for patient, donor and match characteristics that are correlated with both experience and survival, e.g., more experienced centers might attract sicker patients, who have worse survival outcomes. With 22 years of data, I am able to study the changing role of organizational learning-by-doing as the technology has matured from relatively experimental,

with six-month survival rates below 70% in 1987, to mainstream, with six-month survival rates over 90% in 2009.

My results show that organizational learning-by-doing in liver transplantation does exist, but only when centers are relatively inexperienced. Institutional factors and a rich set of patient, donor and match characteristics ensure that the effect is not due to endogeneity in the relationship between patient survival post-transplant and the cumulative number of liver transplants performed. It also does not arise merely with the passage of time; improvements in survival are linked directly to volume-based experience. However, learning-by-doing does not always occur. Some centers improve from a low initial survival rate, while others start with and maintain high survival rates. I empirically identify two factors influencing heterogeneity in learning-by-doing among centers. First, I show that the negative effect on survival of receiving a transplant at an inexperienced center disappears as liver transplantation becomes a mainstream procedure. Second, pre-entry experience matters; centers performing lung transplants prior to starting their liver programs have better outcomes while they ramp up their liver programs, and prior to 1994, pancreas experience is beneficial for survival outcomes. The fact that the existence and magnitude of learning-by-doing varies widely among centers and over time suggests that policies relying on experience as a predictor of high quality outcomes might unnecessarily restrict access to transplantation.

The next section, Section 2, gives a brief institutional overview of how patients obtain transplants and how organs are allocated, and describes the data. Section 3 answers the question, "Do transplant centers learn by doing?," and confirms that the effect is not driven by the time since a center first started performing liver transplants. Section 4 tests for heterogeneity in the learning-by-doing effect. It then explores the hypotheses that the timing of entry and pre-entry

experience transplanting other organs influence the overall magnitude of learning-by-doing and contribute to explaining the variation in early survival outcomes among centers. Section 5 concludes, highlighting policy implications.

2. Institutional framework and data

With end-stage liver disease, only a liver transplant can save the patient's life. After diagnosis, a patient's doctor refers the patient for transplantation. Usually, patients must choose a transplant center within their insurer's preferred provider network.[5] The decision to waitlist a patient lies with each transplant center. Criteria include the ability to pay for the transplant and long-term immunosuppression, proof that the patient can arrive at the hospital within the limited number of hours in which a liver can be used for transplant, and no physical or psychological contraindications. Once on the waitlist, the patient must undergo frequent testing to maintain his or her priority status. The patient then waits to be matched with a donated organ.[6]

For reference, the data I use in this study indicate that the average transplant recipient is a 47-year-old white male who has spent 221 days on the waitlist before receiving his transplant and is not hospitalized prior to arriving at the hospital for transplantation. The most common diagnosis is cirrhosis, with Hepatitis C and alcohol use the most common causes of cirrhosis in the transplant population. (Hepatitis C- and alcohol-related cirrhosis account for 22% of all primary diagnoses in patients receiving transplants.)

[5] With the University of Michigan's graduate student insurance coverage, I can only obtain a covered liver transplant at the University of Michigan Transplant Center, even though two other hospitals in the area, Henry Ford and William Beaumont, also perform liver transplants.

[6] Although most patients are waitlisted at some point during the transplant process, living donors can direct their donation to an individual patient, allowing that patient to opt out of the cadaveric donor waitlist. About 4% of transplants in the data used live donors, with the first successful live donor liver transplant performed on November 27, 1989. Directed cadaveric donation is possible, but is not tracked in the data and rarely occurs according to conversations with staff at the University of Michigan Transplant Center.

Cadaveric organ donation occurs exclusively through the Organ Procurement and Transplantation Network, created by Congress with the National Organ Transplant Act in 1984 and operated ever since by the United Network for Organ Sharing, a nonprofit contractor. Since 2008, the Organ Procurement and Transplantation Network has had authority over live organ donation as well. The Organ Procurement and Transplantation Network consists of 58 local Organ Procurement Organizations, which each oversee a single exclusive Donation Service Area, containing between one and nine transplant centers. These Donation Service Areas are aggregated into 11 regions. Figure 1 shows a map of the donation service areas outlined in black and the regions differentiated by color.

When a hospitalized patient dies or death is imminent, the hospital must notify the local Organ Procurement Organization, as required by law since 1998. Personnel from the Organ Procurement Organization contact the family of the patient to obtain consent, unless donation already was authorized. If consent is given, then the United Network for Organ Sharing follows the liver allocation algorithm to determine the best matches for the organ, based on medical criteria such as blood type, organ size, and disease severity. Time on the waitlist serves as a tie-breaker. In general, livers are first allocated within a Donation Service Area, before being offered regionally, and then nationally. Sixty-eight percent of organs are allocated within the Donation Service Area, 24% are allocated at the regional level, and 7% are allocated nationally. According to the data used in this study, the average donor is a 36-year-old deceased white male. The most common cause of death is head trauma resulting from a motor vehicle accident.

I obtained the Organ Procurement and Transplantation Network data directly from the United Network for Organ Sharing. The United Network for Organ Sharing has data available on

all liver transplants performed in the United States since October 1, 1987.[7] Data with hospital-level identifiers require a formal proposal and signed confidentiality agreement before the United Network for Organ Sharing will release the data. Pursuant to that agreement, I am not allowed to identify any individual patients or centers. Based on the actual reported transplant dates, the data panel ranges from September 30, 1987, through December 31, 2009, and includes a total of 101,543 liver transplants.

Although the period from September 30, 1987, to December 31, 2009, captures the vast majority of liver transplants, 35 of the 155 centers in the data performed transplants prior to September 30, 1987 (Terasaki, 1986). Based on news archives, only three centers performed liver transplants prior to 1983 in the U.S., so most missing volume information comes from shortly prior to the inception of my panel.[8] Although the first successful liver transplant was performed in 1967, only 15 procedures were performed in 1980. By 1986, the annual number of liver transplants had increased to 924. In total, around 3,000 liver transplants performed between 1980 and 1987 are not included in the 101,543 transplants documented by the Organ Procurement and Transplantation Network between 9/30/1987 and 12/31/2009 (Evans, 1991).

Although the amount and duration of pre-panel data are limited, the theoretical literature on learning-by-doing (dating back to Arrow in 1962), the empirical literature from manufacturing, and the raw data all suggest that most learning-by-doing occurs quite soon after a center enters. Therefore, I include in my analysis only those centers beginning transplantation after September 30, 1987.[9] These 120 centers performed 64,315 transplants or 64% of all

[7] The United Network for Organ Sharing website states October 1, 1987, but the reported transplant dates in the data start on September 30, 1987.

[8] I found documentation of only two transplant teams performing transplants prior to 1983. One team, headed by transplant pioneer Thomas Starzl, performed transplants at the University of Colorado – Denver before the program moved to the University of Pittsburgh. The other team operated out of the University of Minnesota.

[9] To briefly describe the differences between incumbent centers and centers entering during the panel period: the incumbent centers perform more transplants per year on average (115 versus 75), are in larger hospitals (average

transplants between September 30, 1987 and December 31, 2009. Of these, I drop 4,792 patients who were lost during the follow-up period, making it impossible to measure accurately their total survival time.[10] In the regressions controlling for patient, donor, and match characteristics, I lose additional observations due to non-reporting of these variables. (I report the number of observations in all the regression tables and use all 64,315 observations to measure cumulative volume.) Three transplant centers, accounting for 51 of the 4,792 dropped patient observations, are not included in the regression analysis due to non-reporting of covariates.

3. Do liver transplant centers learn by doing?

3.1 Existence of learning-by-doing

Both theory and empirical evidence indicate that learning-by-doing is subject to diminishing returns, and in many cases, those returns diminish quickly to zero, at which point terminal productivity has been reached (e.g., Arrow, 1962; Zimmerman, 1982; Thornton and Thompson, 2001; Levitt, List and Syverson, 2012; Thompson, 2012). This implies that learning-by-doing should be most prevalent shortly after a hospital starts offering liver transplants. Suggestive evidence exists from an early paper in heart transplantation, which compares the mean survival outcomes of the first five transplants at a center with those thereafter and finds

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daily census of 536 versus 494), and are more likely to be government owned (34% versus 28%) and less likely to be privately owned (0% versus 3%). The mean year of entry and average survival rates for incumbents versus entrants are 1983 and 1990 and 85% and 88%, respectively.

[10] I perform a robustness check to verify that the patients lost to follow-up are not biasing my results. The Organ Procurement and Transplantation Network data include dates of death from the Social Security Death Master File. I use the dates of death in the Social Security Death Master File data to impute the survival time for patients lost to follow-up. Including these observations increases the survival penalty from being within transplants 0 to 10 by 0.24 percentage points or 6.8% and decreases the penalty of being within transplants 11 to 20 by 0.82 percentage points or 25.9% (in the full model with center and year fixed effects and patient, donor, and match characteristics). The website for the Social Security Death Master File (www.ssdmf.com) specifically states that "the absence of a particular person is not proof that this person is alive" and the data have been shown to omit individuals, especially those dying at younger ages. I choose not to include these observations because I cannot confirm the validity of the Social Security Death Master File data, which seem to be missing non-randomly. Patients appear to be lost to follow-up essentially at random based on regressions of the probability of being lost to follow-up on patient characteristics. The main non-random element is that follow-up data collection improved over time.

that the first five had worse survival outcomes, using data on centers entering between 1984 and 1986 (Laffel et al., 1992).

Two studies in liver transplantation document what appears to be an early learning effect. Clavien et al. (1994) analyze the first 215 transplants performed at the University of Toronto and find that the last 50 of those transplants had fewer complications than the first 50 transplants. Minor complications drive these differences rather than more serious adverse events such as retransplantation or death. Oltoff et al. (2005) analyze the survival outcomes of 385 adult-to-adult living donor liver transplants in 9 centers and find that the first 15 transplants have worse outcomes than transplants 31 and above, but that transplants 21 to 30 are better than those above 31. These studies suggest early learning-by-doing may exist, but are limited by the small number of centers, restricted types of patients considered, and identification of the effect through a comparison of means across cumulative volume categories.

My first hypothesis is that liver transplant centers learn by doing and that this learning exists only with the initial transplants performed, i.e., that centers quickly reach terminal quality. Figure 2 presents evidence consistent with this hypothesis. The scatter plot graphs the relationship between the mean survival rate across new centers and cumulative volume. Each triangle represents the mean six-month survival rate across the 120 centers for that level of cumulative volume. Given the noisiness even in the averaged raw survival rates, I also graph six-month survival probabilities (predicted using locally weighted regressions) by cumulative volume up to 100 transplants.[11] A clear upward but diminishing trend exists.

[11] I run locally weighted regressions (using Stata's *lowess* command) to estimate the probability of six-month survival post-transplant as a function of cumulative volume up to 100 transplants, using a bandwidth of 0.8, i.e., 80% of the data. I then graph the predicted six-month survival rate by cumulative volume up to 100 transplants, using only the first 100 transplants to focus on the period in which most learning-by-doing occurs. Locally weighted regression estimates provide a smoother regression function estimate, are more precise at the boundaries, and are more robust to outliers than moving average estimates (Cameron and Trivedi, 2005.)

Table 1 presents descriptive statistics for seven different survival time periods; alive at one day post-transplant, alive at one week, alive at one month, alive at three months, alive at six months, alive at one year, and alive at three years. The table reports how survival outcomes change with cumulative volume by relating the survival outcome to cumulative volume for the following groups of patients: 0 to 10, 11 to 20, 21 to 30, and 31 to 40, and also includes a fifth column for transplants 81 to 100 to check whether the raw data indicates that learning-by-doing is isolated in the initial transplants performed by a center. Especially for the survival periods exceeding one day, the numbers in the first two columns are similar, as are the numbers in Columns [3] to [5]. A noticeable jump exists between Columns [2] and [3], however, suggesting that a shift in the importance of learning-by-doing occurs somewhere around the 21st transplant. (This break around the 21st transplant also appears in the regression results that follow.) The last column shows the *p*-value for a one sided *t*-test of the hypothesis that transplants 0 to 20 have an equal or higher survival rate than transplants 81 to 100. In all cases, the *p*-value is equal to zero, indicating that the outcomes of early patients are statistically significantly worse than those of later patients.

Although suggestive, the graph and descriptive statistics do not control for time-invariant center characteristics, factors affecting all centers in a given time period, and patient, donor and match characteristics. Table 2 details patient, donor, and match characteristics included in the regressions and shows that many of the means of these variables differ between the first 21 transplants and the 81st to 100th transplants performed. On the one hand, it appears that early patients might be sicker – they are more likely to have a life expectancy of less than seven days (Status 1), be in an intensive care unit, or be on life support at the time of transplant. On the other hand, their diagnoses are associated with higher survival rates after I control for other patient,

donor, and match characteristics in the regressions that follow. Also associated with improved survival rates, early patients are younger and have shorter wait times, younger donors, fewer African-American donors, and fewer blood type incompatibilities with the donor organs. At the same time, the distance a donor organ must travel to reach the recipient is larger for early transplant recipients and negatively associated with survival.

In the regressions that follow, I focus specifically on early learning, i.e. the within center change in survival outcomes as cumulative volume increases. Given that the only clear and consistent evidence of learning occurs within the first transplants performed, I use the following linear probability model to assess whether improvements in survival come from learning or if early patients are just sicker than patients treated later on:[12]

$$Alive\ at\ six\ months_{iht} = \alpha + CumulativeVolume_{iht}'\theta_{volume} + CaseMix_{iht}'\beta_{casemix} + \gamma_h + \tau_t + \varepsilon_{iht} \quad (1)$$

The dependent variable, *Alive at six months*$_{iht}$, equals one if patient *i* treated at hospital *h* at time *t* survives at least six months and equals zero otherwise. I use six-month survival in order to capture the multiple aspects of the transplant process from surgery through maintenance immunosuppression. For the longer time periods, the effects of learning-by-doing on survival outcomes are less accurately measured due to the influence on survival of other factors exogenous to transplantation and the difficulty in tracking patients as long as three years after surgery. Because the relationship between *CumulativeVolume*$_{iht}$ and survival in the raw data does

[12] Logit results, reported in Table 4, tell the same early learning story, so I use the linear probability model for ease of exposition and to avoid unnecessary complexity in estimation (Angrist and Pischke, 2009). In addition, given that many of the independent variables are dichotomous, the partial effects from these variables are constant and a key benefit of the logit and probit models, allowing the partial effects to vary with the values of the independent variable, does not apply (Wooldridge, 2002).

not follow an obvious functional form and the empirical results in manufacturing suggest that organizational learning-by-doing is a short-lived phenomenon, I tested a variety of categories of cumulative volume to tease out when learning-by-doing occurs. These ranged from individual dummy variables for each transplant below a variety of thresholds to extending the categories up to 500 transplants. $CaseMix_{iht}$ is a vector of controls for patient, donor, and match characteristics that previously have been established by the literature on liver transplantation as important for post-transplant survival (Edwards et al., 1999; Axelrod et al., 2004; Freeman et al., 2008).[13] Also included are center fixed effects, γ_h, to control for time-invariant, center-specific factors and year fixed effects, τ_t, to control for factors affecting all centers in a given year. I cluster standard errors at the center level to control for heteroskedasticity and spatial correlation among patients receiving transplants at a given center.

Equation (1) parallels to some extent the empirical specifications commonly used in the manufacturing literature to study organizational learning-by-doing. In general, those papers use a log-linearized Cobb-Douglas production function as the estimating equation (e.g., Balasubramanian and Lieberman, 2010; Levitt, List, and Syverson, 2013). The specification I use approximates a production function with hospital and industry experience, case mix, and time-invariant hospital-specific factors as inputs in the production of patient survival. Hospital experience I measure using cumulative volume since entry, overall changes in industry experience and technology and regulatory shocks are captured by the year fixed effects, case mix includes donor, patient and match characteristics associated with patient survival, and I include the center fixed effects in order to capture time-invariant hospital characteristics, which might

[13]A subset of the controls I include are the variables used by the Scientific Registry of Transplant Recipients to calculate publicly available risk-adjusted survival rates since 2001. These survival rates are used by the Organ Procurement and Transplantation Network to flag underperforming centers (The Organ Procurement and Transplantation Network, Annual Reports 2004-2012.)

affect survival. Examples of such characteristics include hiring a particularly accomplished liver transplant surgeon to lead the new center, attempting to start up multiple types of transplants centers at the same time, or transplanting other organs prior to beginning liver transplantation, which I discuss in Section 4.2b. Given the dichotomous nature of most of the variables included in the regression, simply using a log-linearized Cobb-Douglas production function is not feasible. Therefore, I use the above-described specification to capture the relationships among the variables. The separate cumulative volume categories also fit the data better than using the natural log of cumulative volume.

Table 3 provides the main regression results exploring the relationship between cumulative volume and survival probabilities. I group transplants below 50 into the cumulative volume categories of 0 to 10, 11 to 20, 21 to 30, 31 to 40, and 41 to 50, with the reported effects relative to being the 51st or above transplant recipient at a center.[14] Column [1] shows clear evidence of a learning curve through all five categories. The importance of the effect generally diminishes with increasing volumes and is consistently negative and significant. Given that I am analyzing learning-by-doing or the within center effect of a change in cumulative volume on survival, I add center fixed effects in Column [2] to account for time-invariant factors specific to a center that might influence survival outcomes. This allows me to compare how survival outcomes change with cumulative experience within an individual transplant center. The evidence for organizational learning-by-doing becomes even stronger with the inclusion of the center fixed effects, although the center fixed effects contribute surprisingly little to explaining

[14] I can group the transplants by as few as three and still identify a learning effect that loses significance around 20 transplants. The coefficients on individual dummies for each transplant within the first 18 are not all statistically significant, but they are jointly statistically different from zero and not statistically different from each other. In order to corroborate that learning-by-doing is isolated shortly after entry, Table 5 reports cumulative volume categories relative to being the 202nd or above recipient in Column [1], the 102nd or above recipient in Column [2] and the 52nd or above recipient in Column [3].

the variation in the outcome variables. The coefficients on the cumulative volume variables imply that an additional four patients die within six months during the first 51 transplants performed by a center relative to 51 transplants performed later in a center's history.

Because important changes in immunosuppression, regulation and insurance coverage occurred in liver transplantation between 1987 and 2009, I include year fixed effects to account for these institutional changes and to capture the overall increase in patient survival that has occurred over time. (Average survival rates increase by 24 percentage points between 1987 and 2009.) Including year fixed effects could lead to conservative estimates of organizational learning because cumulative volume increases over time. However, because the effects of changes in immunosuppression, regulation and insurance coverage affected all centers essentially simultaneously, the inclusion of year fixed effects is appropriate, even at the expense of possibly underestimating the full learning-by-doing effect. Indeed, the inclusion of year fixed effects in Column [3] reduces the size of the coefficients by more than 60% and renders the coefficient on cumulative volume less than or equal to 10 statistically insignificant. The R-squared increases by about 40% with the inclusion of the year fixed effects. The large effect on the coefficients from including the year fixed effects suggests that the importance of organizational learning-by-doing may have changed over time, even though on average only a small amount of learning-by-doing exists. (This possibility will be explored further in Section 4.2a, which analyzes the importance of the timing of entry for learning-by-doing.)

In addition to the effect of secular changes in survival affecting all transplant centers, new centers might face disproportionately lower quality organs, worse matches, and sicker patients than they do later on, which means that what appears to be a learning curve might simply be explained by a less favorable mix of cases treated. In Column [4] I add donor

characteristics, in [5] match characteristics and in [6] recipient characteristics. (The number of observations falls by six with the inclusion of donor characteristics, by 728 with the inclusion of recipient characteristics, and by 6,854 with the inclusion of match characteristics, primarily due to the inclusion of cold ischemia time, the time after an organ is recovered and cooled and before it is transplanted.[15]) It does not appear that patient, donor, and match characteristics are driving the negative coefficients on cumulative volume less than or equal to 10 and cumulative volume between 11 and 20.

The coefficients in Column [6] of Table 3 imply that 0.67 additional patients die in the first six months during a center's first 51 transplants relative to its later transplants. If I compare the coefficients on the experience variables with those on the control variables in Column [6], the only patient characteristics leading to a greater decrease in survival (in percentage points) than being within the first 11 transplants include having had a previous transplant (-10.86), being on life support at the time of transplant (-12.53), and being in the intensive care unit (-7.26) or hospitalized outside of intensive care (-4.85) relative to those patients not hospitalized prior to transplantation. None of the donor or match characteristics have as large an impact on patient survival as being within the first 11 transplants performed at a center.

These results do not hinge on the use of a six-month post-transplant survival period. Relative to the six-month survival results, shorter survival periods have smaller coefficients on the cumulative volume variables, while longer survival periods have larger coefficients. In the full model with center and year fixed effects, and patient, donor, and match characteristics, the

[15] If I include a dummy when cold ischemia time is missing rather than dropping those observations, the results are quite similar, although the coefficients on the cumulative volume variables increase slightly in magnitude and significance. In the specification with center and year fixed effects and patient, donor, and match characteristics, the coefficient on cumulative volume less than or equal to ten increases from -0.0352* to -0.0377** and for cumulative volume between 11 and 20 from -0.0316* to -0.0353**.

coefficient on cumulative volume less than or equal to 10 ranges from -0.0171 ($p < 0.01$) for one-day survival to -0.0397 ($p < 0.05$) for three-year survival.

3.2 Endogeneity

Omitted variables leading to an endogenous relationship between cumulative volume and survival that looks like learning-by-doing would occur if some factor positively influenced both cumulative volume and survival. For example, a center might attract unobservably sicker patients during the first 21 transplants than thereafter. However, the full model used here, including year and center fixed effects and patient, donor, and match characteristics, greatly reduces and essentially eliminates these possibilities.

The inclusion of center fixed effects means that endogeneity between individual survival outcomes and cumulative volume would have to exist within an individual transplant center, which significantly differs in plausibility from a cross-center comparison context. In addition, decreasing the potential that apparent learning-by-doing is actually new centers treating unobservably worse cases, I include a wide range of donor, match, and patient characteristics. The fact that all organizational learning-by-doing is evident only shortly after entry means that the omitted variable issue would apply only to the difference between the first 21 transplants and those thereafter rather than contributing to a longer term relationship. It seems more reasonable that learning-by-doing would be a short-lived phenomenon, as predicted by theory and evidenced in the manufacturing literature, than that omitted variable issues affect the relationship between cumulative volume and survival only shortly after entry.

Apart from the inclusion of center fixed effects and patient, donor, and match characteristics diminishing the probability of endogeneity leading to inconsistent results,

institutional and medical factors make it unlikely that hospitals select or attract sicker patients early on. First of all, hospitals have extensive control over the patients they waitlist and choose to transplant. Systematically selecting unobservably sicker patients could lead to a low survival rate and possible negative impacts to reputation, particularly for a new center without an established track record. Centers also face the possibility of getting flagged by the Organ Procurement and Transplantation Network if the observed survival rate falls too far below the expected survival rate. How expected survival is measured by the Organ Procurement and Transplantation Network has varied over time, but during the period from 1987 to 2009, the most extensive set of risk adjustment variables used in the estimation of expected survival included only age, race, gender, and diagnosis (non-cholestatic cirrhosis versus other). In other words, almost all factors important for survival are not included in the expected survival rates and thus centers have a strong incentive not to select sicker patients for waitlisting along any metric. The possibility that centers systematically select sicker patients shortly after entry is not corroborated by discussions with transplant surgeons. If anything, more experienced hospitals are likely to treat sicker patients than less experienced centers, making my estimates of learning-by-doing more likely to be conservative than overstated. In addition, the coefficients reported in Table 3 suggest that patient, donor, and match characteristics do not have a major impact on the relationship between cumulative volume and patient survival.

Further reducing concerns about reverse causality in particular, neither centers nor patients have much control over the timing of transplant. In other words, it is difficult for a center or a patient to affect whether or not that patient will be within the first 20 transplants. Each center determines which patients to waitlist, but the waitlist itself is aggregated at the Donation Service Area level with organs allocated on the basis of the characteristics of the donor

organ available, how close a patient is to death without a transplant, and prior to 2002, waitlist time. With the scarcity of donor organs and the fact that the liver allocation system prioritizes the sickest patients, it seems unlikely that patients or their doctors would turn down a donor organ in order to wait for the transplant center to become more experienced.

3.3 Learning by doing or by time in operation

An additional issue with studying learning-by-doing is that learning may accrue as a function of the time a center has been performing liver transplants rather than as a function of volume-based experience, but it would still appear that learning was accruing with cumulative volume since cumulative volume is correlated with the age of the transplant center. I explore this possibility by regressing the probability of six-month survival on the age of the transplant center in quarters with the omitted category age greater than one year. Table 6 shows the results with the controls included listed below the table. Once I include year fixed effects, the center age effects become statistically insignificant. Adding in patient, donor, and match characteristics does not materially affect the coefficients, which remain statistically insignificant and small in magnitude. When I include the cumulative volume categories, the coefficients on the cumulative volume variables that were significant in Table 3 (Column [6]) are larger in absolute size and more significant than when I do not control for center age. This is the opposite of what we would expect if learning-by-doing accrues over time rather than with volume. (The coefficients on the time variables become positive but remain insignificant.) These results suggest that center age and cumulative volume do not measure the same phenomenon and that cumulative volume does

not proxy for time in operation.[16] Given the general insignificance of the coefficients on the time in operation variables, it seems reasonable to conclude that most of the learning that occurs is cumulative volume-based rather than that it accrues with existence as a liver transplant center.

4. Heterogeneity in learning-by-doing

4.1 Existence of heterogeneity in learning-by-doing

Although the results in Table 3 show evidence of learning-by-doing on average, the effect could vary across centers. The literature is largely silent about heterogeneity in the existence and magnitude of organizational learning-by-doing across producers in the same industry. Levitt, List, and Syverson (2012) do identify variation across teams in an automobile assembly plant and Balasubramanian and Lieberman (2010) identify differences across manufacturing industries. The only existing paper that econometrically identifies heterogeneity in learning-by-doing across producers within an industry is Pisano, Bohmer, and Edmondson (2001), which finds such heterogeneity using a sample of "high quality" hospitals selected by the manufacturer of a new technology for minimally invasive cardiac surgery. With a sample of sixteen hospitals and using the quality outcome of procedure time, the paper focuses on the fact that learning-by-doing differs across hospitals even when they receive identical training and start using the same technology at approximately the same time.

Given the Pisano, Bohmer and Edmondson (2001) results, I explore the possibility that not all centers learn or learn as much as other centers, or that other omitted variables could be driving what appears to be an early learning effect. To focus on the period during which most learning-by-doing occurs and to simplify the analysis that follows, I reduce the six volume

[16] In Table 7, I run the age regressions using center age up to five years with age greater than five years as the omitted category. Here, again, the inclusion of year fixed effects makes any center age-related early learning effects disappear.

categories (0-10; 11-20; 21-30; 31-40; 41-50; 51+) into one dummy variable for whether a patient received one of the first 21 transplants performed at a center. As shown in Table 8, this does little to affect the explanatory power of the model, and I cannot reject the null that the coefficients on the cumulative volume categories over 20 equal zero.

I use the following specification to explore the existence and magnitude of heterogeneity in learning-by-doing among centers:

$$Alive\ at\ six\ months_{iht} = \theta CumulativeVolume0to20_{iht} + \quad (2)$$
$$CumulativeVolume0to20_{iht} * I_h{}'\delta_{interaction} + CaseMix_{iht}{}'\beta_{casemix} + \gamma_h + \tau_t + \varepsilon_{iht}$$

The key difference between Equation (2) and Equation (1) is the interaction of the dummy variable for cumulative volume between 0 and 20 with the center indicator variables I_h, omitting the constant. Adding the coefficient on the interaction term to the main coefficient for cumulative volume between 0 and 20 gives estimates of the early learning effect by center. I then categorize these centers into those with lower survival rates during their first 21 transplants than thereafter and those with higher initial survival rates that perform worse or the same after completing their first 21 transplants. In other words, I create two groups of centers based on whether the net effect on six-month survival of being within the first 21 transplants is negative or if it is positive or neutral at that center.

Table 9 summarizes the patient-level results from these regressions. Sixty-one centers improve while 49 do worse after their first 21 transplants. (Because seven centers included in these regressions do not reach 21 transplants, I cannot calculate a center-specific learning penalty for those centers.) The average net effect among those that improve after the first 21 transplants

is -12.16 and for those that get worse or stay the same, it is 8.61 percentage points, both with large standard deviations. An *F*-test of the equality of the coefficients can be rejected with a *p*-value of zero. These numbers suggest that heterogeneity does exist across centers.

The last two columns give information on how the learning process occurs. Those centers that improve after performing their first 21 transplants start off with lower initial survival rates than those that get worse or stay the same after performing their first 21 transplants. The gap narrows from a difference of 18 percentage points for transplants 0 to 20 to a difference of 2 percentage points for transplants 21 to 40. The centers that improve gain an average of 15 percentage points, while those that get worse or stay the same only drop by 5 percentage points. In general, one would have expected learning to be positive factor; those that learn do better than those that do not. These results, however, indicate that those centers that learn do so because they start off with low survival rates and improve to the level of centers that enter with and maintain high survival rates. From a policy perspective, this means that the first patients at a center do not necessarily have lower probabilities of survival and that identifying what determines whether centers have higher or lower initial survival rates could save lives. My results also show that poor performance early on does not necessarily lead to future poor performance, in contrast to Levitt, List, and Syverson (2012), who find the opposite across teams in an automobile assembly plant. Specifically, they find that teams with a higher defect rate initially continue to perform worse than those teams with better initial performance. Figure 3 shows a histogram of the net effect of being within the first 21 transplants by center. Although the effect is fairly evenly

distributed around zero, noticeable variation in center-specific learning exists. The left tail has some notable outliers and the distribution is generally left-skewed.[17]

The literature on the economics of education often uses Empirical Bayes' estimation (also referred to as shrinkage estimation) to estimate individual teacher-specific effects on student outcomes (e.g., Kane and Staiger, 2008; Jacob and Lefgren, 2005). In the context of this paper, Empirical Bayes' estimation might be appropriate because the estimates for the center-specific effects could be imprecise due to small sample sizes, and Empirical Bayes' estimation shrinks such estimates toward the average estimated effect of being within the first 21 transplants at a center. When I calculate the center-specific learning penalties using Empirical Bayes' estimation, the standard deviation of the center-specific learning effect shrinks from 0.1466 to 0.0932 and the average center-specific learning effect increases in magnitude from -0.0291 to -0.0498. In Figure 4, I overlay a histogram of the shrunken effects (in gray) on the histogram depicted in Figure 3 (in black). The range of the distribution of effects decreases and also appears even more left-skewed than in Figure 3. Although these new estimates suggest less heterogeneity and more learning-by-doing, a recent paper by Guarino et al. (2012) documents via simulation analysis that Empirical Bayes' estimators diminish the variance in the estimated effects but at the price of bias and inconsistency, especially under non-random assignment of patients to transplant centers, e.g., children's hospitals.

4.2 Sources of heterogeneity

The main results in Section 3 indicate that the inclusion of year fixed effects had a major impact on the size and significance of the coefficients on the cumulative volume variables and

[17] Omitting centers with net effects below the 10th percentile and above the 90th percentile only strengthens the results in the regressions that follow; the coefficient on cumulative volume less than or equal to 20 increases in both size and statistical significance.

the prior section (4.1) established that organizational learning-by-doing varies across centers. Therefore, I now test two hypotheses to further explore those results: centers entering earlier in the sample period and centers with less pre-entry experience transplanting other organs will exhibit more learning-by-doing. To further illustrate how these differences might arise across centers and why these two factors might affect learning-by-doing, I draw on the Bayesian learning model developed by Jovanovic and Nyarko (1995). I discuss it in the liver transplantation context, in order to provide intuition for how the timing of entry and pre-entry experience transplanting other types of organs could affect the learning process.

The learning-by-doing process arises in the Jovanovic and Nyarko (1995) model because the "decisionmaker", i.e., the transplant center, must make decisions based on incomplete information regarding what the optimal decision would be. Decisions could involve staffing, the timing of surgery, or post-transplant dosing of immunosuppressants. After the transplantation process concludes, the transplant center receives a signal regarding how close to optimal its decision (or decisions) was and updates its expectation of the optimal decision for the next transplant based on the new information gained from the signal. The signal received by the decisionmaker does not clearly indicate what the optimal decision would have been due to noise in the signal that arises from transitory disturbances such as having a transplant team member unexpectedly absent on the day of transplantation. With each subsequent transplant, the transplant center continues updating its expectation of the optimal approach and its decisions increasingly approximate the ideal decision. The model predicts that the amount of learning-by-doing that occurs will depend on uncertainty about the optimal approach for a given transplant, the noisiness of the signal received after a transplant has been completed, and the number of decisions involved in each transplant procedure.

The two hypotheses I test in this section can be related back to this model. The timing of entry affects the magnitude of learning-by-doing due to changes in the amount of knowledge available to all centers and thus the associated center-specific uncertainty about the optimal approach. In other words, later in the panel period decisions will more closely approximate the ideal decision because they will be better educated guesses due to common knowledge regarding liver transplantation that will have been disseminated through research publications, conferences, increasingly specialized training programs, and even the expansion in access to the Internet during this time period. These factors along with transplant-specific technology innovations, such as new and better immunosuppressants and organ allocation algorithms, all act to decrease the uncertainty about the optimal approach by standardizing and simplifying liver transplantation.

The second factor I hypothesize affects learning-by-doing is pre-entry experience transplanting other types of organs. Hospital-specific general knowledge of transplantation could improve both initial decisions as well as the amount of knowledge gained from the difference between the post-transplant signal and the decision made. In other words, going through this Bayesian learning process for other types of organs transplanted might lead to an increased understanding of transplantation and its associated learning process in general and thus to better decisions initially and as the learning process proceeds.

4.2a Timing of entry

The first heterogeneity hypothesis I test is whether the amount of learning-by-doing decreases as liver transplantation transitions from experimental to mainstream medicine. In order to analyze this possibility, I split my sample into two periods: pre-1994 and 1994-2009.

Technological innovations and institutional changes occurring in liver transplantation define these two periods. To summarize briefly, the FDA approved two new immunosuppressants, tacrolimus and mycophenolate mofetil, in 1994 and 1995, respectively. Tacrolimus is a more powerful immunosuppressant than its predecessor, cyclosporine, and mycophenolate mofetil has a much better side effect profile than its predecessor, azathioprine (Post et al., 2005). These drugs diffused generally across centers at approximately the same rate until both became the first-line drugs for immunosuppression. By 2009, 88% of patients received tacrolimus versus 7% cyclosporine; for mycophenolate mofetil and azathioprine, the percentages were 74% and 1%.[18] Major changes in organ procurement and allocation include new organ allocation algorithms introduced in 1996 and 2002, and the legal requirement starting in 1998 that hospitals notify their local organ procurement organization of all deaths eligible for donation. Insurers also expanded coverage during this period with Medicare extending transplant coverage from a case-by-case basis to all Medicare eligible individuals with liver failure other than liver failure caused by Hepatitis B or cancer in 1996, to Hepatitis B patients in 1999, and to patients with hepatocellular carcinoma in 2001 (Centers for Medicare and Medicaid Services National Coverage Determination, 2006). Based on discussions with personnel at the University of Michigan's Transplant Center, toward the end of the first period and into the second period, training certification programs for transplant surgeons and physicians became increasingly specialized. This trend continued through the latter part of the second period for other personnel, e.g., transplant administrators, transplant coordinators, and transplant nurses.

Figure 5 replicates the locally weighted regression results depicted graphically in Figure 2 for the two periods. Although both periods have close to the same survival rate by transplant

[18] Conversations with transplantation doctors indicate that tacrolimus is preferred to cyclosporine and that today the latter only would be used in rare cases, such as if a patient cannot tolerate tacrolimus. Unfortunately, the two drugs are in the same class (calcineurin inhibitors) and the inability to tolerate one usually extends to the other as well.

100, how they get to that survival rate varies. Pre-1994, a clear learning curve appears that plateaus around 70 transplants. In the second period between 1994 and 2009, essentially no evidence for learning-by-doing exists.

In Panel A of Table 10, I show the mean and standard deviation by period for three six-month survival measures: overall, during the first 21 transplants, and during transplants 21 to 40. All three survival measures increase between the two periods. The largest increase over time is for transplants 0 to 20 with a 16 percentage point increase from the first to the second period. As in Figure 5, a learning curve is most clearly evidenced in the early period with a 7 percentage point increase between the first 21 transplants and transplants 21 to 40. In the later period, the increase is only 2 percentage points. The standard deviations ($\sqrt{p(1-p)}$) of the survival measures (p) correspondingly decline over time, and in both periods are greater for the first 21 transplants than for transplants 21 to 40.

In Panel B of Table 10, I provide information on the number of centers in the sample for each period. Eighty-six new centers enter between 1987 and 1994 and 34 enter between 1994 and 2009. For the period-level analysis, however, I split the data based on the date of transplant rather than the date of entry. In the last row of Table 15, I show how many centers were completing their first 21 transplants during each period; 86 and 83, respectively. Patient counts are included for each subset of centers.[19]

I replicate Equation (1) by period, and in Table 11, present the results from these regressions. The regressions are run separately by period in order to allow the coefficients on the

[19] Cutting the data by the date of entry or by the date on which 20 or 50 transplants were completed tells the same story; learning-by-doing exists only in the first period and the negative impact of inexperience is concentrated within the first 21 transplants.

other independent variables to change over time as well, which they do.[20] For example, improvements in immunosuppression means an incompatible blood type match between donor and recipient could matter less for survival than it did before the introduction of the new drugs. (For example, an incompatible blood type between patient and donor in the early period is associated with a statistically significant three percentage point reduction in six-month survival, but in the later period the effect is positive and insignificant.) The prevalence of most patient, donor, and match characteristics also changes over time. As shown in Table 13, all the control variables differ statistically from each other between the two periods based on a two-sided *t*-test except for the following three recipient characteristics; diagnosis of biliary atresia, being African-American, and having a blood type O.

Essentially all learning-by-doing occurs before 1994. In the overall sample, 0.67 additional patients die within six months as a center completes its first 51 transplants than would have died during 51 transplants later in that center's history. The cost of inexperience in Period 1 is higher; more than 1.25 additional patients die during the first 51 transplants. In Period 2, however, no significant evidence of learning-by-doing exists. Although this reduces the number of centers completing their first 21 transplants in the last period to only 22, I also split the second period into 1994 to 2002 and 2003 to 2009, and find no evidence of learning-by-doing in either period, as shown in Table 12.

Determining the relationship between how experimental a procedure is and the importance of learning-by-doing is difficult with only one type of procedure. I am, however, able to offer suggestive evidence by reporting the relationship between six-month survival

[20] Using dummy variables for each period and interactions between those dummies and cumulative volume less than or equal to 20, shows a very similar pattern. The coefficients on the period variables are large in size and statistically significant, indicating survival improvements by period. The main difference is that the overall statistical significance of being within the first 21 transplants increases when the coefficients on the control variables are restricted to be constant over time.

probabilities and cumulative volume for the other major types of organs transplanted (kidneys, pancreas, hearts, lungs, and intestines.) The first successful organ transplant was a kidney in 1954. Hearts, livers, and pancreas followed in the late 1960's. Lungs and intestines were not transplanted until 1983 and 1987, respectively. In terms of the total number of transplants between January 1, 1988, and December 31, 2009, kidneys were by far the most common with 300,894 performed. Hearts followed at 48,508. Lungs and pancreases had been transplanted 20,797 and 23,232 times, respectively. Only 1,884 intestinal transplants had been completed by the end of 2009. [21] (Livers were transplanted 101,543 times during this period.)

Figure 6 replicates the locally weighted regression results in Figure 2 for each of the other five organs using patient-level data from the United Network for Organ Sharing for entrants into each type of organ transplant from 1988 through 2009. For hearts, livers, and intestines, I use the six-month patient survival rate. In the case of kidneys and pancreas, I use the six-month graft survival rate because if a kidney or pancreas transplant fails, a patient usually can return to dialysis. Indeed, how mainstream a procedure is generally seems to be correlated with how much of an early learning effect exists. Kidney transplant survival rates do not seem to change much with experience and have an average six-month survival rate above 80%. Pancreas shows perhaps a surprising amount of learning-by-doing, albeit short-lived, given the relatively long history of pancreas transplantation. Most likely this is because pancreas transplantation did not become common as quickly as the transplantation of livers and hearts, which were first successfully transplanted around the same time. Even today, a much wider range of surgical techniques commonly are used in pancreas transplantation relative to the range for other types of transplants (Squifflet, Gruessner, and Sutherland, 2008). Heart transplantation shows minimal

[21] The Organ Procurement and Transplantation Network Organ Datasource: http://optn.transplant.hrsa.gov/latestData/rptData.asp. Accessed 10/30/12.

evidence of learning-by-doing. Lung transplantation does seem to improve with experience, and the most experimental type of transplant, intestines, shows the greatest evidence of learning-by-doing in early transplants. Figure 6 suggests that the liver transplant results are generalizable at least within organ transplantation. Given the predictions in Jovanovic and Nyarko (1995), which were not intended to be specific to any particular industry, and evidence for those predictions across manufacturing industries in Balasubramanian and Lieberman (2010), the reduction in organizational learning-by-doing with decreasing uncertainty about the optimal approach is likely generalizable outside of organ transplantation as well.

4.2b Pre-entry experience

In this section, I test the hypothesis that experience transplanting organs prior to starting liver transplantation will affect the relationship between cumulative volume and survival outcomes. Table 14 reports descriptive statistics for the pre-entry experience variables. For each variable in the table, I include the percent and number of patients receiving transplants with that characteristic during the first 21 transplants, the number of centers in which those patients are transplanted, and the average survival rate among the patients in each category.

The descriptive statistics in Table 14 show that most patients receive transplants at hospitals with kidney transplant programs in operation prior to starting their liver programs. A slight majority receive them at hospitals with heart transplant programs prior to their first liver transplant. A limited number of patients receive transplants at hospitals with pre-entry experience in pancreas and lung transplantation. Note that only one center transplanting lungs pre-entry did not also perform heart transplants pre-entry and no centers performed pancreas transplants pre-entry that did not also perform kidney transplants pre-entry. No liver transplant

centers perform intestinal transplants pre-entry. The six-month survival rates in Column [3] suggest that patients receiving one of the first 21 transplants at centers with experience in lung and pancreas transplantation may have higher survival rates than those receiving them at centers with only heart or kidney transplant experience or no experience transplanting other organs prior to starting their liver transplant program. Other pre-existing transplant programs could be important if learning-by-doing occurs in transplantation in general rather than organ-by-organ. Such benefits might arise from overlap in areas such as radiology, anesthesiology, physical therapy, and mental health services. In addition, some types of organ transplants are more closely related to liver transplants than others.

Within transplantation, a clear divide exists between thoracic transplants (hearts and lungs) and abdominal transplants (kidneys, livers, pancreas, and intestines). In fact, the fellowship training standards for thoracic and abdominal transplants appear to be set by different organizations. The American Board of Internal Medicine provides an advanced heart failure and transplant cardiology certification, while the American Society for Transplant Surgeons has established guidelines for certification in abdominal transplantation. The latter provides a variety of guidelines, including for all four abdominal organs jointly (kidneys, pancreas, livers, and intestines). Conversations with transplant doctors confirm that many perform multiple types of organ transplants. They also stress that a clear divide exists between "above diaphragm" and "below diaphragm" transplants. In terms of interrelated diseases, livers are more frequently transplanted simultaneously with kidneys, intestines, and pancreas than with hearts and lungs. The patient-level data on multi-organ transplants show that livers were transplanted most frequently with kidneys (3,046), followed by intestines (489) and pancreas (384), less frequently with hearts (72), and least frequently with lungs (29).

To explore further how pre-entry experience influences the level of learning-by-doing, I modify Equation (1) by interacting the frequency of transplantation and pre-entry experience variables with cumulative volume less than or equal to 20, which yields the following equation:

$$Alive\ at\ six\ months_{iht} = \alpha + \theta_{iht} CumulativeVolume0to20_{iht} + CaseMix_{iht}'\beta_{casemix} \quad (3)$$
$$+ CumulativeVolume0to20_{iht} * CenterCharacteristic_{ht}'\delta_{center} + \gamma_h + \tau_t + \varepsilon_{iht}$$

Table 15 presents the effects from transplanting other types of organs before starting a liver transplant program on early transplant survival outcomes. Column [1] reports results from regressing six-month survival on a dummy variable for other types of transplants performed before entry into liver transplantation. Operating just any type of other transplant center prior to starting a liver program does not convey a statistically significant advantage or disadvantage during the first 21 liver transplants. Column [2] breaks the pre-entry experience down by type of organ with the omitted category no other types of organs transplanted pre-entry into liver transplantation. The main coefficients for the other types of organ transplants are insignificant, indicating that on average pre-entry experience has no long-term effect on patient survival. Within the first 21 transplants, however, pre-entry lung transplant experience results in a statistically significant improvement in early survival outcomes.

Discussions with transplant surgeons indicated that the benefit of pre-entry lung transplant experience might be related to lung transplant programs' skill in ventilating patients. Liver disease can lead to pulmonary hypertension, and both liver disease and complications associated with surgery and post-operative recovery can lead to acute respiratory distress syndrome. Immunosuppression can increase the probability of infection, including lung

infections such as pneumonia. In Table 16, I test this explanation for the benefit of pre-entry lung transplant experience by interacting two measures associated with a need for ventilation, being on a ventilator or on life support at the time of transplant, with being within the first 21 transplants at a center that performs lung transplants. I focus on transplants early in a center's history because the benefit of pre-entry lung transplant experience appears to apply primarily during the learning period. The reference category for pre-entry lung transplant experience is pre-entry experience transplanting only other types of transplants or no pre-entry experience. The coefficients on the main effects and the interaction terms for the other types of pre-entry experience besides lungs are not jointly significantly different from zero or from each other in the regressions in Table 15, so for ease of presentation, I simplified the regression to focus on the effect of pre-entry lung transplant experience.

The results for the more direct measure, being on a ventilator at the time of transplant, are shown in Column [1]. In Column [2], I present results using the more inclusive measure; whether or not a patient is on life support at the time of transplant. Life support can include ventilation but also can refer to artificial nutrition and hydration and cardiac support. In any event, a person on life support is very sick and thus may be more likely to require mechanical ventilation during or post-surgery regardless of whether they were actually on a ventilator at the time of transplantation. The percent of patients on a ventilator at the time of transplant ranges from a high of 21.2% of patients in 1988 to a low of 5.2% of patients in 2007.[22] Being on a ventilator is highly correlated with being on life support. Just as with being on a ventilator, the percent of patients on life support at the time of transplant peaks in 1988 (21.2%) and drops to a low of 5.7% in 2007.

[22] Given the high correlation between being on life support and being on a ventilator, I omit the variable for life support in the regressions in Column [1] of Table 10.

The three-way interaction terms in Table 16 show that the beneficial effect during the learning period of having pre-entry experience transplanting lungs is particularly beneficial to patients on a ventilator or on life support at the time of transplants, which supports the hypothesis proposed by the transplant doctors; centers with experience performing lung transplants will be more adept at addressing pulmonary complications during and post-liver transplantation. The benefits of receiving a transplant at a center with a pre-existing lung transplant center during the learning period (the interaction between cumulative volume less than or equal to 20 and receiving a transplant at a center with pre-entry lung transplant experience) extends to other patients as well, albeit to a smaller extent. This may be because these regressions do not separately control for patients for whom pulmonary problems only arise due to surgical or post-operative complications. The reported regressions do, however, give a sense of whether patients with pre-existing breathing problems or patients likely to suffer surgical complications benefit disproportionately from receiving a liver transplant at a center with experience performing lung transplants. In addition, the results suggest that the benefits for those on life support extend beyond just those patients receiving one of the first 21 transplants at a liver transplant center.

In all the regressions controlling for pre-entry experience, the main coefficient on cumulative volume less than or equal to twenty increases in magnitude relative to the results in Table 8. This, in combination with the general insignificance of the coefficients on the pre-entry experience variables, suggests that the learning-by-doing effect is not just capturing the importance of pre-entry experience, but exists independently from such experience as well.

4.2c Pre-entry experience over time

So far, the best explanation for differences in early outcomes among transplants centers relates to the decline in the overall uncertainty about the optimal approach to liver transplantation over time, i.e., that on average learning-by-doing exists early in the sample period and does not appear to exist by the end of the sample. These averages by period, however, may mask some underlying heterogeneity among transplant centers even within periods.

In the overall sample, pre-entry experience affected survival outcomes during the learning period (transplants 0 to 20), albeit to a smaller extent than the timing of entry. Both factors are hypothesized to affect survival by their effects on the uncertainty about the optimal approach to liver transplantation. Therefore, the effect of pre-entry experience may disappear over time as knowledge about the optimal approach has become increasingly accessible to new centers. In other words, pre-entry experience may matter more when knowledge of how to perform a transplant originates through organizational learning-by-doing rather than from the generally available knowledge base that arises through industry-level learning and the rapid dissemination of best practices. For pre-entry lung transplant experience, its primary effect is during the first 21 transplants. On average, after Period 1, no statistically significant organizational learning-by-doing exists, and therefore, early survival outcomes may no longer benefit from pre-entry experience in lung transplantation.

Table 17 shows descriptive statistics for pre-entry experience by period. The greatest variation between periods is in the percent of patients affected by lung and pancreas transplant experience and no pre-entry experience. In both periods, the majority of patients receive transplants at centers with pre-entry kidney transplant experience and about half of

patients receive transplants at centers with heart transplant experience prior to entry into liver transplantation.

Table 18 shows the results for pre-entry experience transplanting other organs by period. The coefficient on pre-entry lung transplant experience during the first 21 transplants is 16% larger than in the overall results in Table 15. It is slightly less statistically significant, but still has a *p*-value of less than 0.05. Although the coefficient is still fairly large in Period 2, it is no longer significant, indicating that, as expected, the benefits of lung transplant experience prior to beginning liver transplantation are confined to the period when statistically significant organizational learning-by-doing existed.

Experience transplanting pancreas prior to beginning liver transplantation has a positive effect in the pre-1994 period. The pancreas is closely related to the liver and works with the liver to perform digestive functions. All centers performing pancreas transplants also perform kidney transplants prior to starting their liver transplant programs, so it may be that centers that perform pancreas transplants in addition to kidney transplants are more technically sophisticated and some of this additional expertise translates to liver transplants. Unfortunately, the data do not include variables identifying patients with pancreatic complications. In addition, this effect is not specific to the first 21 transplants.

Again, as in the overall sample, controlling for pre-entry experience increases the size of the coefficients on cumulative volume. Although insignificant, the coefficient on cumulative volume less than or equal to 20 is almost three times larger in the first period. The results by period indicate that pre-entry experience performing other types of transplants does influence the magnitude of learning-by-doing during the period in which learning-by-doing exists. Given that pre-entry experience is hypothesized to diminish the uncertainty about the optimal approach, it is

perhaps not surprising that its influence is less in the second period when there was less uncertainty overall about how to successfully perform a liver transplant.

5. Conclusion

Liver transplant centers learn by doing, but only shortly after entry. The importance of learning-by-doing varies among centers with some centers starting at a low survival rate and improving, while others enter with high survival rates, and in some cases, exhibit decreasing survival rates with experience. The effect of learning-by-doing is primarily evident prior to major innovations in immunosuppression and organ allocation and the increasingly specialized training of transplant personnel. The importance of how experimental a procedure is for learning-by-doing appears to be generalizable to other types of organ transplants and may be indicative of how learning-by-doing operates in healthcare more generally. The effect of receiving a transplant at an inexperienced center is influenced by pre-entry experience performing other types of transplants. Experience in lung transplantation is important for liver transplant survival outcomes at inexperienced liver transplant centers, especially for patients on a ventilator or on life support more generally at the time of transplantation. Prior to 1994, pre-entry experience with transplantation of a type of organ closely related to the liver, the pancreas, conveys positive benefits for liver transplant outcomes during the time period in which learning was most prevalent. The benefits of lung transplant experience for early survival outcomes are also larger and more significant prior to 1994.

These results highlight the importance of focusing on learning-by-doing shortly after entry rather than seeking to identify a constant return to experience, regardless of how experienced an organization is when it first appears in the data. The pattern of early learning-by-

doing I identify follows what has been found in many studies in manufacturing, suggesting that organizational learning-by-doing is not a phenomenon unique to reducing unit costs or production defects. The heterogeneity across centers supports the limited evidence in the literature that the importance of learning-by-doing can vary substantially across firms. The fact that early learning-by-doing dissipates over time suggests that technology and policy shocks and general industry-level learning may diminish the importance of individual centers' learning-by-doing.

The transience and heterogeneity of the learning-by-doing effect makes formulating policy recommendations difficult. In fact, less experienced centers sometimes may have better outcomes. However, on average by the period 1994 to 2009, little support exists for consolidating care in a limited number of centers in order to improve patient outcomes. In fact, restricting entry may negatively affect those suffering from liver disease if entry restrictions limit their access to liver transplantation.

For experimental types of complex healthcare procedures, such as intestinal transplants, the results in this paper may have policy-relevant implications. With intestinal transplantation, in which real uncertainty about the optimal approach still exists, policies consolidating care with large existing healthcare providers might limit the number of patients on whom "learning" occurs and might avoid the opportunity cost of new centers using these organs less effectively. Even with a learning penalty, the probability of extending life would be higher with an intestinal transplant than without one based on a six-month post-transplant survival rate above 80% for intestinal transplant recipients. Figure 8 shows a map of the locations of intestinal transplant centers in 2009. With only 13 centers in 12 states, policies deterring entry into intestinal transplantation may be causing potential transplant recipients to die unnecessarily.

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Table 1: Descriptive statistics for survival outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Transplant #	0-10	11-20	21-30	31-40	81-100	0 to 20 > 81 to 100 *p*-value
Alive at 1 day	96%	97%	98%	98%	98%	0.00
Alive at 1 week	92%	92%	96%	95%	96%	0.00
Alive at 1 month	86%	88%	91%	89%	92%	0.00
Alive at 3 months	80%	82%	86%	85%	88%	0.00
Alive at 6 months	77%	78%	83%	82%	85%	0.00
Alive at 1 year	73%	74%	80%	79%	81%	0.00
Alive at 3 years	63%	66%	74%	71%	75%	0.00

Notes: The *p*-value is for a *t*-test with the alternative hypothesis that the mean of 0 to 20 is less than the mean of 81 to 100.

Table 2: Descriptive statistics for patient, donor, and match characteristics

Transplant #:	0-20	81-100	*p*-value
Patient characteristics			
Status 1 (a week or less to live)	18%	15%	0.04
In ICU at transplantation	28%	23%	0.00
Hospitalized at transplantation (not in ICU)	19%	19%	0.43
Not hospitalized at transplantation	53%	59%	0.00
On life support at transplantation	16%	12%	0.00
Serum creatinine	1.3	1.3	0.15
Age	38	41	0.00
Diagnosis: AHN	7%	7%	0.83
Diagnosis: Biliary atresia	10%	7%	0.00
Diagnosis: Cirrhosis	47%	50%	0.07
Diagnosis: Cholestatic liver disease	13%	11%	0.06
Diagnosis: Metabolic disorder	6%	4%	0.02
Diagnosis: Neoplasm	5%	5%	0.63
Multi-organ transplant	2%	3%	0.15
Previous transplant recipient	8%	9%	0.27
Days on waitlist	97	154	0.00
Male recipient	59%	58%	0.44
African-American recipient	11%	10%	0.31
Whole liver (rather than segment)	95%	95%	0.32
Blood type A	40%	41%	0.34
Blood type AB	4%	3%	0.10
Blood type B	11%	13%	0.07
Blood type O	45%	42%	0.14
Donor and match characteristics			
Live donor	3%	4%	0.46
Donor age	29	31	0.00
Cold ischemia time (hours)	10	9	0.44
Distance from donor hospital to transplant hospital (miles)	214	174	0.00
Incompatible blood types	16%	22%	0.00
Compatible blood types	84%	78%	0.00
Male donor	60%	60%	0.56
African-American donor	12%	14%	0.01

Notes: *p*-values are for two-sided *t*-tests with the null hypothesis that the means for 0 to 20 and 81 to 100 are equal.

Table 3: Main results for early learning-by-doing

Outcome = alive at six months

	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative volume						
0-10	-0.1149***	-0.1185***	-0.0311	-0.0314	-0.0325*	-0.0352*
	(0.0184)	(0.0191)	(0.0190)	(0.0191)	(0.0191)	(0.0185)
11-20	-0.1041***	-0.1133***	-0.0403**	-0.0407**	-0.0332*	-0.0316*
	(0.0186)	(0.0188)	(0.0180)	(0.0180)	(0.0171)	(0.0166)
21-30	-0.0501***	-0.0589***	0.0069	0.0066	0.0030	-0.0096
	(0.0141)	(0.0150)	(0.0140)	(0.0140)	(0.0144)	(0.0132)
31-40	-0.0598***	-0.0654***	-0.0067	-0.0067	-0.0058	-0.0049
	(0.0166)	(0.0176)	(0.0160)	(0.0161)	(0.0170)	(0.0161)
41-50	-0.0333**	-0.0376***	0.0167	0.0162	0.0059	0.0057
	(0.0136)	(0.0130)	(0.0130)	(0.0130)	(0.0138)	(0.0129)
Observations	56,212	56,212	56,212	56,206	49,349	48,620
R-squared	0.0045	0.0187	0.0266	0.0286	0.0312	0.0890
Center fixed effects		Yes	Yes	Yes	Yes	Yes
Year fixed effects			Yes	Yes	Yes	Yes
Donor characteristics				Yes	Yes	Yes
Match characteristics					Yes	Yes
Recipient characteristics						Yes

Notes: The omitted cumulative volume category is cumulative volume > 50. Standard errors are clustered at the center-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Logit results

Outcome = alive at six months						
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative volume						
0-10	-0.0880***	-0.0922***	-0.0392***	-0.0162	-0.0201	
	(0.0112)	(0.0118)	(0.0125)	(0.0126)	(0.0132)	
11-20	-0.0814***	-0.0890***	-0.0398***	-0.0234**	-0.0196*	
	(0.0118)	(0.0118)	(0.0119)	(0.0119)	(0.0115)	
21-30	-0.0444***	-0.0513***	-0.0048	0.0086	-0.0056	
	(0.0109)	(0.0117)	(0.0111)	(0.0111)	(0.0103)	
31-40	-0.0517***	-0.0566***	-0.0137	-0.0022	-0.0005	
	(0.0123)	(0.0131)	(0.0117)	(0.0122)	(0.0127)	
41-50	-0.0310***	-0.0346***	0.0055	0.0162	0.0073	
	(0.0114)	(0.0111)	(0.0119)	(0.0110)	(0.0105)	
Cumulative volume<=20						-0.0193**
						(0.0095)
Observations	56,212	56,178	56,212	56,178	48,580	48,580
Center fixed effects		Yes		Yes	Yes	Yes
Year fixed effects			Yes	Yes	Yes	Yes
Patient, donor, and match characteristics					Yes	Yes

Notes: The omitted cumulative volume category is cumulative volume>=50. Standard errors are clustered at the center-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Additional cumulative volume categories through 200

Outcome = alive at six months			
	(1)	(2)	(3)
Cumulative volume			
0-21	-0.0297*	-0.0327**	-0.0324**
	(0.0159)	(0.0159)	(0.0146)
21-50	-0.0004	-0.0030	-0.0028
	(0.0106)	(0.0109)	(0.0099)
51-100	0.0017	-0.0006	
	(0.0089)	(0.0077)	
101-200	0.0039		
	(0.0075)		
Observations	48,620	48,620	48,620
R-squared	0.0890	0.0890	0.0890

Notes: The omitted volume category in Columns [1] is cumulative volume>200; in Column [2], cumulative volume>100; and in Column [3] cumulative volume>50. Forty-five centers never reach 200 transplants during the sample period and 30 never reach 100 transplants. All regressions include donor, match and recipient characteristics and center and year fixed effects. Standard errors are clustered at the center-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Effect of time in operation by quarter

Outcome = alive at six months

	(1)	(2)	(3)	(4)	(5)
Quarter					
0	-0.151***	-0.150***	-0.0411	-0.0238	0.0198
	(0.0359)	(0.0344)	(0.0366)	(0.0352)	(0.0417)
1	-0.101***	-0.0997***	-0.0166	0.00179	0.0460
	(0.0338)	(0.0308)	(0.0294)	(0.0302)	(0.0340)
2	-0.0899***	-0.0813***	0.00354	-0.00507	0.0330
	(0.0282)	(0.0286)	(0.0288)	(0.0278)	(0.0297)
3	-0.0619***	-0.0619***	0.0247	0.0144	0.0346
	(0.0202)	(0.0196)	(0.0199)	(0.0201)	(0.0219)
Cumulative volume					
0-10					-0.0523**
					(0.0237)
11-20					-0.0396**
					(0.0174)
21-30					-0.0121
					(0.0134)
31-40					-0.0070
					(0.0164)
41-50					0.0045
					(0.0131)
Observations	56,212	56,212	56,212	48,620	48,620
R-squared	0.002	0.016	0.026	0.089	0.089
Center fixed effects		Yes	Yes	Yes	Yes
Year fixed effects			Yes	Yes	Yes
Patient, donor, and match characteristics				Yes	Yes

Notes: Omitted age category = center age > one year. The omitted cumulative volume category is cumulative volume>=50. Standard errors are clustered at the center-level; *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 7: Effect of time in operation in years

Outcome = alive at six months					
	(1)	(2)	(3)	(4)	(5)
Center age (years)					
0	-0.112***	-0.133***	-0.0164	-0.0150	0.0353
	(0.0235)	(0.0211)	(0.0252)	(0.0252)	(0.0328)
1	-0.0680***	-0.0867***	0.0133	-0.000963	0.0258
	(0.0122)	(0.0119)	(0.0160)	(0.0155)	(0.0213)
2	-0.0659***	-0.0894***	-0.00393	-0.0102	-0.0016
	(0.0121)	(0.0107)	(0.0131)	(0.0127)	(0.0157)
3	-0.0533***	-0.0701***	-0.00187	-0.00676	-0.0055
	(0.0119)	(0.0123)	(0.0121)	(0.0113)	(0.0119)
4	-0.0408***	-0.0547***	-0.000882	-0.00697	-0.0071
	(0.00954)	(0.00933)	(0.0106)	(0.00967)	(0.0100)
5	-0.0402***	-0.0488***	-0.00107	-0.00532	-0.0061
	(0.0109)	(0.0101)	(0.00936)	(0.00972)	(0.0097)
Cumulative volume					
0-10					-0.0582**
					(0.0248)
11-20					-0.0457**
					(0.0192)
21-30					-0.0168
					(0.0161)
31-40					-0.0084
					(0.0178)
41-50					0.0043
					(0.0138)
Observations	56,212	56,212	56,212	48,620	48,620
R-squared	0.005	0.021	0.026	0.089	0.089
Center fixed effects		Yes	Yes	Yes	Yes
Year fixed effects			Yes	Yes	Yes
Patient, donor, and match characteristics				Yes	Yes

Notes: Omitted age category = center age > five years. The omitted cumulative volume category is cumulative volume>=50. Standard errors are clustered at the center-level; *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 8: Reducing volume categories to above or below 21 transplants

Outcome = alive at six months

	(1)	(2)	(3)	(4)	(5)
Cumulative volume					
0-10	-0.0352*	-0.0359*	-0.0351**	-0.0335*	
	(0.0185)	(0.0182)	(0.0175)	(0.0175)	
11-20	-0.0316*	-0.0323**	-0.0316*	-0.0302*	
	(0.0166)	(0.0163)	(0.0161)	(0.0161)	
21-30	-0.0096	-0.0102	-0.0096		
	(0.0132)	(0.0129)	(0.0126)		
31-40	-0.0049	-0.0055			
	(0.0161)	(0.0158)			
41-50	0.0057				
	(0.0129)				
0-20					-0.0314**
					(0.0136)
Observations	48,620	48,620	48,620	48,620	48,620
R-squared	0.0890	0.0890	0.0890	0.0890	0.0890

Notes: In Column [1], the omitted cumulative volume category is cumulative volume>50; for Column [2], cumulative volume>40; for Column [3], cumulative volume>30, and for Columns [3] to [6], cumulative volume>20. All regressions include patient, donor, and match characteristics, and center and year fixed effects. Standard errors are clustered at the center-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9: Heterogeneity in learning-by-doing

Better/same or worse during first 21 transplants	# of centers	# of patients	Average net effect	Standard deviation	Six-month survival: 0-20	Six-month survival: 21-40
Worse	61	34,392	-0.1216	0.1236	69%	84%
Better/same	49	29,643	0.0861	0.0727	87%	82%
Total	110	64,035	-0.0291	0.1466	77%	83%

Notes: Those that are worse initially and those that are better or the same initially are identified by interacting the variable *cumulative volume<=20* with the center fixed effects. (Outcome = alive at six months.) The coefficient on the interaction is then added to the main effect of *cumulative volume<=20* to create the net effect of being within the first 21 transplants for each center separately. "Worse" centers have negative net effects; "Better/same" centers have positive or zero net effects. The underlying regressions include patient, donor and match characteristics, and center and year fixed effects with the constant term suppressed. Standard errors are clustered at the center-level.

Table 10: Descriptive statistics by period

	1987-1993		1994-2009	
Panel A				
	Mean	Standard deviation	Mean	Standard deviation
Six-month survival	79%	41%	89%	32%
Six-month survival 0 to 20	69%	46%	85%	35%
Six-month survival 21 to 40	76%	43%	87%	33%
Panel B				
	# of centers	# of patients	# of centers	# of patients
Entrants	86	6,459	34	57,856
Centers with cumulative volume<=20	86	1,215	67	1,199

*Only includes centers entering after 1987, since data on all organs is only available after October 1987.

Table 11: Main results by period

Outcome = alive at six months		
	(1)	(2)
	1987-1993	1994-2009
Cumulative volume		
0-10	-0.0738**	-0.0021
	(0.0298)	(0.0186)
11-20	-0.0520**	-0.0214
	(0.0259)	(0.0205)
21-30	-0.0310	-0.0018
	(0.0236)	(0.0132)
31-40	-0.0429	0.0118
	(0.0273)	(0.0191)
41-50	-0.0159	0.0050
	(0.0257)	(0.0145)
Observations	4,496	44,124
R-squared	0.1742	0.0768

Notes: The omitted cumulative volume category is cumulative volume > 50. All regressions include center and state fixed effects and patient, donor and match characteristics. Standard errors are clustered at the center-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 12: Results for three time periods

Outcome = alive at six months

	(1) 1987-1993	(2) 1994-2002	(3) 2003-2009
Cumulative volume			
0-10	-0.0738**	-0.0186	0.0379*
	(0.0298)	(0.0309)	(0.0219)
11-20	-0.0520**	-0.0187	-0.0160
	(0.0259)	(0.0312)	(0.0221)
21-30	-0.0310	0.0049	-0.0068
	(0.0236)	(0.0185)	(0.0195)
31-40	-0.0429	0.0138	0.0202
	(0.0273)	(0.0302)	(0.0214)
41-50	-0.0159	0.0087	0.0175
	(0.0257)	(0.0196)	(0.0210)
Observations	4,496	17,255	26,869
R-squared	0.1742	0.1046	0.0562

Notes: The omitted cumulative volume category is cumulative volume > 50. All regressions include center and year fixed effects and patient, donor, and match characteristics. Standard errors are clustered at the center-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 13: Patient, donor, and match characteristics by period

	1987-1993	1994-2009	*p*-value: P1 to P2
Patient characteristics			
Status 1 (a week or less to live)	18%	11%	0.00
In ICU at transplantation	23%	18%	0.00
Hospitalized at transplantation (not in ICU)	19%	18%	0.00
Not hospitalized at transplantation	58%	65%	0.00
On life support at transplantation	16%	9%	0.00
Serum creatinine	1.3	1.4	0.00
Age	40	47	0.00
Diagnosis: AHN	7%	6%	0.12
Diagnosis: Biliary atresia	9%	4%	0.00
Diagnosis: Cirrhosis	49%	51%	0.00
Diagnosis: Cholestatic liver disease	18%	10%	0.00
Diagnosis: Metabolic disorder	5%	3%	0.00
Diagnosis: Neoplasm	3%	10%	0.00
Multi-organ transplant	2%	5%	0.00
Previous transplant recipient	9%	8%	0.07
Days on waitlist	82	234	0.00
Male recipient	55%	64%	0.00
African-American recipient	10%	10%	0.89
Whole liver (rather than segment)	100%	93%	0.00
Blood type A	40%	38%	0.00
Blood type AB	4%	5%	0.01
Blood type B	12%	13%	0.02
Blood type O	43%	44%	0.42
Donor and match characteristics			
Live donor	0%	5%	0.00
Donor age	27	37	0.00
Male donor	63%	59%	0.00
African-American donor	11%	14%	0.00
Cold ischemia time (hours)	11	8	0.00
Distance from donor hospital to transplant hospital (miles)	265	155	0.00
Compatible blood types	89%	78%	0.00
Incompatible blood types	11%	22%	0.00

Notes: *p*-values are for two-sided *t*-tests with the null hypothesis that the means for the two periods are equal.

Table 14: Descriptive statistics for pre-entry experience

	(1)	(2)	(3)	(4)
	% of patients within the first 21 transplants	# of patients within the first 21 transplants	Six-month survival rate for patients within the first 21 transplants	# of centers
Pre-liver heart transplants*	52%	1206	79%	61
Pre-liver lung transplants*†	20%	453	83%	23
Pre-liver kidney transplants*	85%	1960	77%	100
Pre-liver pancreas transplants *†	19%	445	82%	22
Pre-liver intestines transplants*	n/a	0	n/a	0
No pre-liver transplants*	13%	297	75%	16

*Only includes centers entering after 1987, since data on all organs is only available after October 1987.
†Only one transplant center performs lung transplants that does not perform heart transplants prior to starting liver transplantation. No centers perform pancreas transplants that do not perform kidney transplants prior to starting liver transplantation.

Table 15: Pre-entry experience

Outcome = alive at six months

	(1)	(2)
Cumulative volume<=20	-0.0700*	-0.0634*
	(0.0387)	(0.0353)
Other organs transplanted pre-liver	-0.0087	
	(0.0095)	
Cumulative volume<=20*pre-liver other center	0.0292	
	(0.0404)	
Pre-liver heart transplant center		0.0003
		(0.0089)
Pre-liver lung transplant center		0.0038
		(0.0083)
Pre-liver kidney transplant center		-0.0074
		(0.0110)
Pre-liver pancreas transplant center		-0.0050
		(0.0078)
Cumulative volume<=20*heart center		-0.0160
		(0.0309)
Cumulative volume<=20*lung center		0.0838***
		(0.0275)
Cumulative volume<=20*kidney center		0.0027
		(0.0402)
Cumulative volume<=20*pancreas center		0.0250
		(0.0295)
Observations	48,620	48,620
R-squared	0.0771	0.0774

Notes: The omitted category for pre-entry experience is no other types of transplants pre-liver. Observations for centers entering before 1988 are not included, since I cannot measure pre-liver activity prior to 1988. All regressions include case mix and year fixed effects. Standard errors are clustered at the center-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 16: Targeted benefit of lung transplant experience

Outcome = alive at six months

	(1)	(2)
Cumulative volume<=20	-0.0615***	-0.0609***
	(0.0180)	(0.0176)
Pre-entry lung transplant experience	-0.0004	-0.0042
	(0.0078)	(0.0069)
On a ventilator at transplant	-0.1343***	
	(0.0115)	
Cumulative volume<=20*lung center	0.0599**	0.0543**
	(0.0247)	(0.0253)
Cumulative volume<=20*ventilator	-0.0102	
	(0.0369)	
Lung center*ventilator	0.0246	
	(0.0286)	
Cumulative volume<=20*lung center*ventilator	0.1104*	
	(0.0586)	
On life support at transplant		-0.1429***
		(0.0106)
Cumulative volume<=20*life support		-0.0150
		(0.0375)
Lung center*life support		0.0640***
		(0.0191)
Cumulative volume<=20*lung center*life support		0.1211**
		(0.0607)
Observations	48,656	48,620
R-squared	0.0771	0.0780

Notes: Pre-entry lung transplant experience is relative to other or no other organ transplant experience prior to beginning liver transplants. Given the high correlation between a patient being on a ventilator at the time of transplant and being on life support at the time of transplants, I only include one of the variables in each of the regressions. All regressions include patient, donor, and match controls and year fixed effects. Standard errors are clustered at the center-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 17: Descriptive statistics for pre-entry experience by period

	1987-1993		1994-2009	
Pre-liver heart transplants*	50%	37	54%	36
Pre-liver lung transplants*†	15%	12	24%	16
Pre-liver kidney transplants*	82%	60	88%	60
Pre-liver pancreas transplants*†	12%	8	26%	17
No pre-liver transplants*	18%	18	9%	5

*Only includes centers entering after 1987, since data on all organs is only available after October 1987.
†No centers perform pancreas transplants but not kidney transplants prior to starting liver transplants. Only one center performed lung transplants that did not perform heart transplants prior to starting liver transplants.

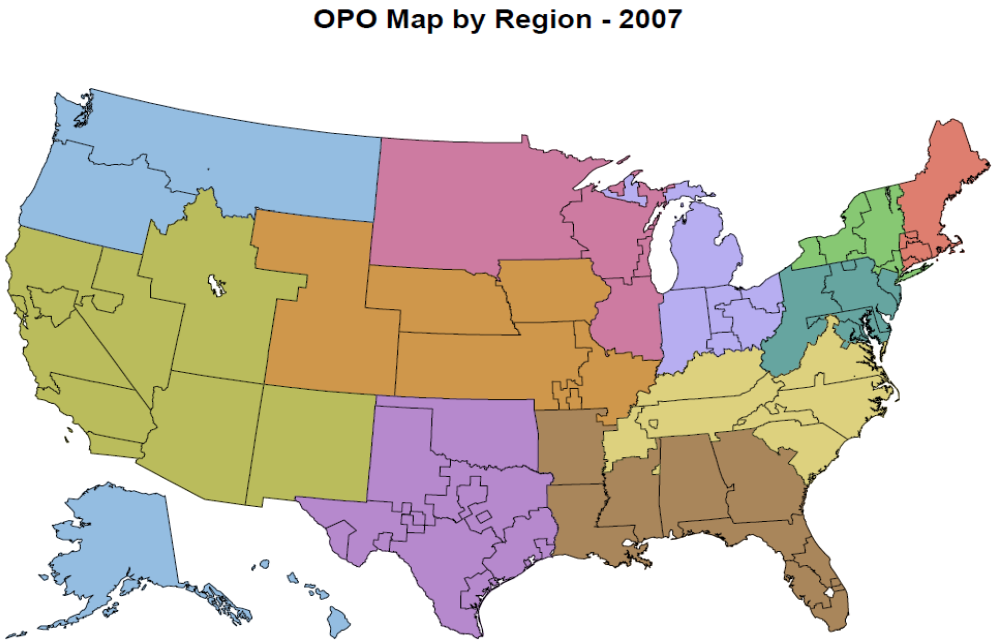
Table 18: Pre-liver experience by period

Outcome = alive at six months

	(1)	(2)	(3)	(4)
	1987-1993	1994-2009	1987-1993	1994-2009
Cumulative volume<=20	-0.0763	-0.0488	-0.0831	-0.0295
	(0.0528)	(0.0313)	(0.0530)	(0.0298)
Other organs transplanted pre-liver	0.0081	-0.0108		
	(0.0222)	(0.0090)		
Cumulative volume<=20*other organs	-0.0092	0.0374		
	(0.0543)	(0.0354)		
Pre-liver heart transplant center			0.0137	-0.0003
			(0.0242)	(0.0082)
Pre-liver lung transplant center			0.0127	0.0037
			(0.0220)	(0.0081)
Pre-liver kidney transplant center			-0.0018	-0.0088
			(0.0270)	(0.0103)
Pre-liver pancreas transplant center			0.0592**	-0.0066
			(0.0236)	(0.0082)
Cumulative volume<=20*heart center			-0.0305	-0.0195
			(0.0455)	(0.0396)
Cumulative volume<=20*lung center			0.0972**	0.0624
			(0.0457)	(0.0385)
Cumulative volume<=20*kidney center			-0.0059	0.0029
			(0.0652)	(0.0362)
Cumulative volume<=20*pancreas center			-0.0531	0.0220
			(0.0429)	(0.0349)
Observations	4,496	44,124	4,496	44,124
R-squared	0.1209	0.0657	0.1233	0.0658

Notes: The omitted category for pre-entry experience is no other types of transplants pre-liver. In Columns [3] and [4], the omitted category for the time variables is time greater than three months since the prior transplant. Observations for centers entering before 1988 are not included, since I cannot measure pre-liver activity prior to 1988. All regressions include patient, donor, and match characteristics and year fixed effects. Standard errors are clustered at the center-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 1: Organ allocation



Source: Association of Organ Procurement Organizations

Figure 2: Six-month survival versus cumulative volume

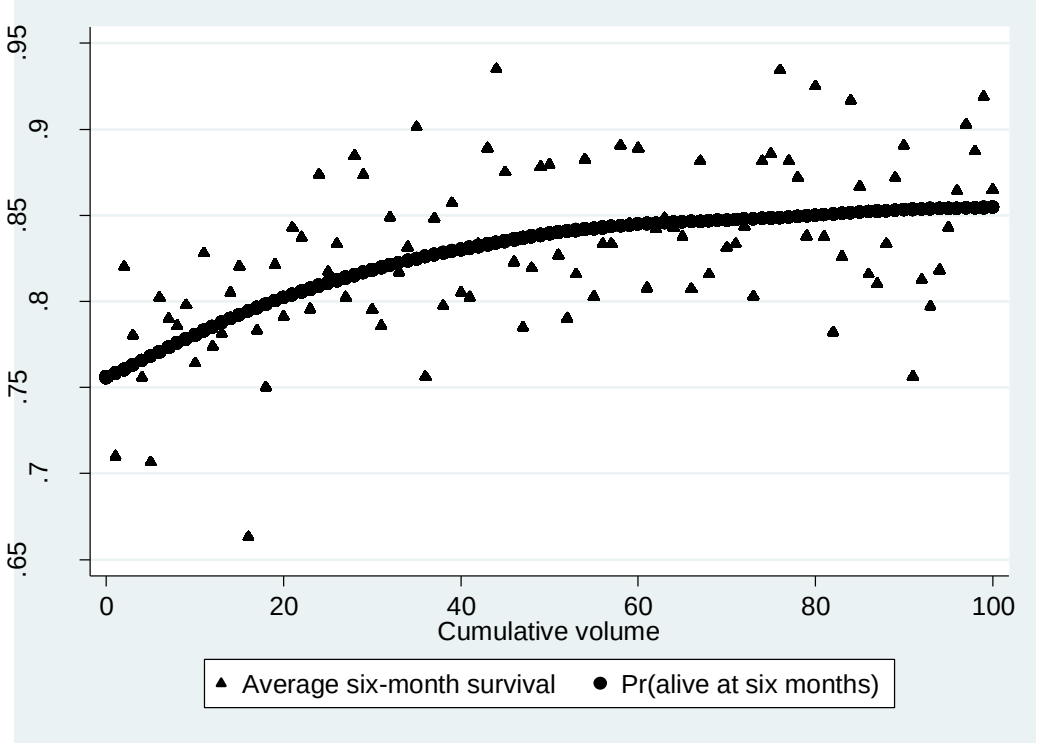


Figure 3: Center-specific learning effects

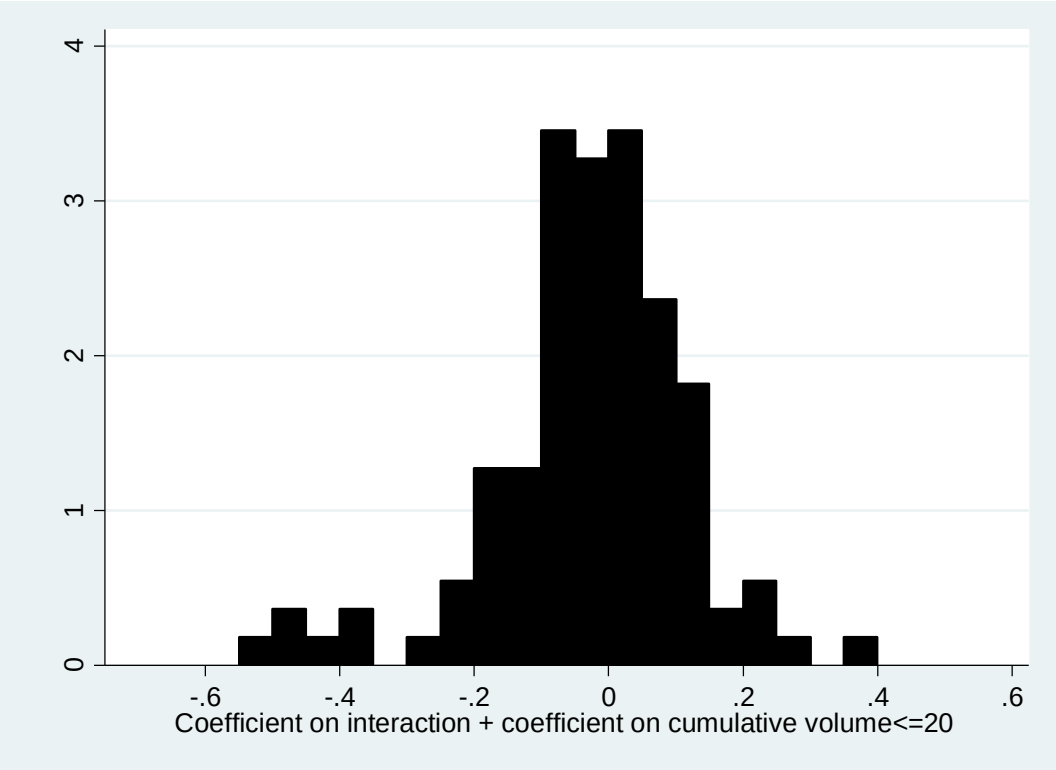


Figure 4: **Dummy variable versus Empirical Bayes' estimation**

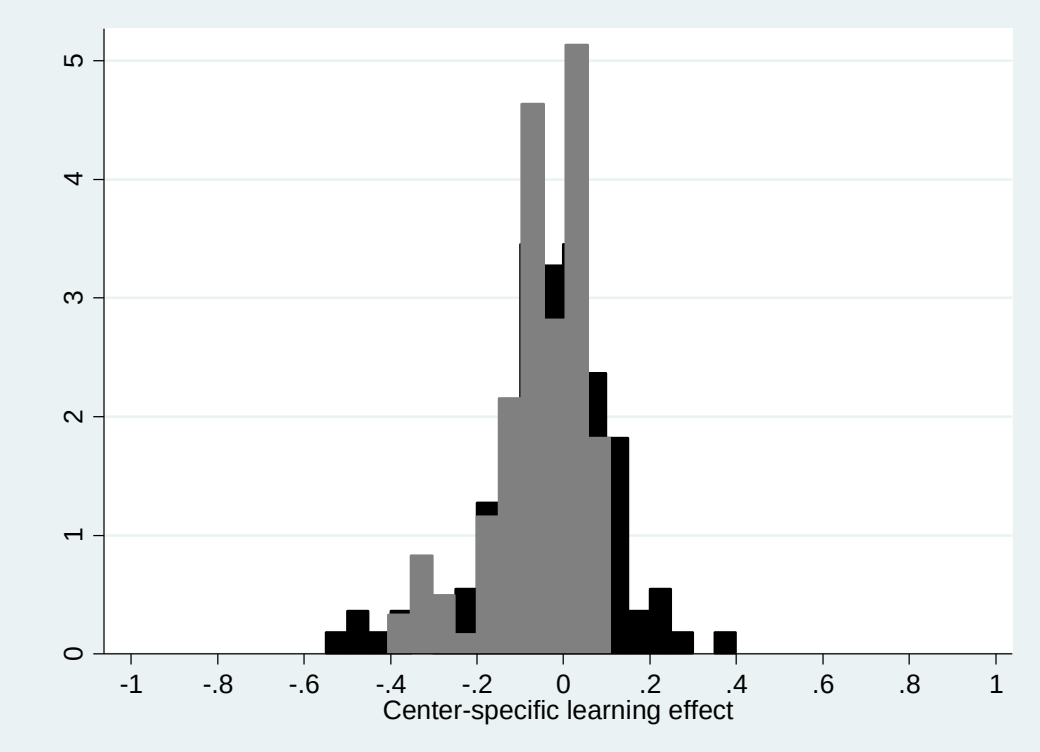


Figure 5: Pr(alive at six months) by cumulative volume

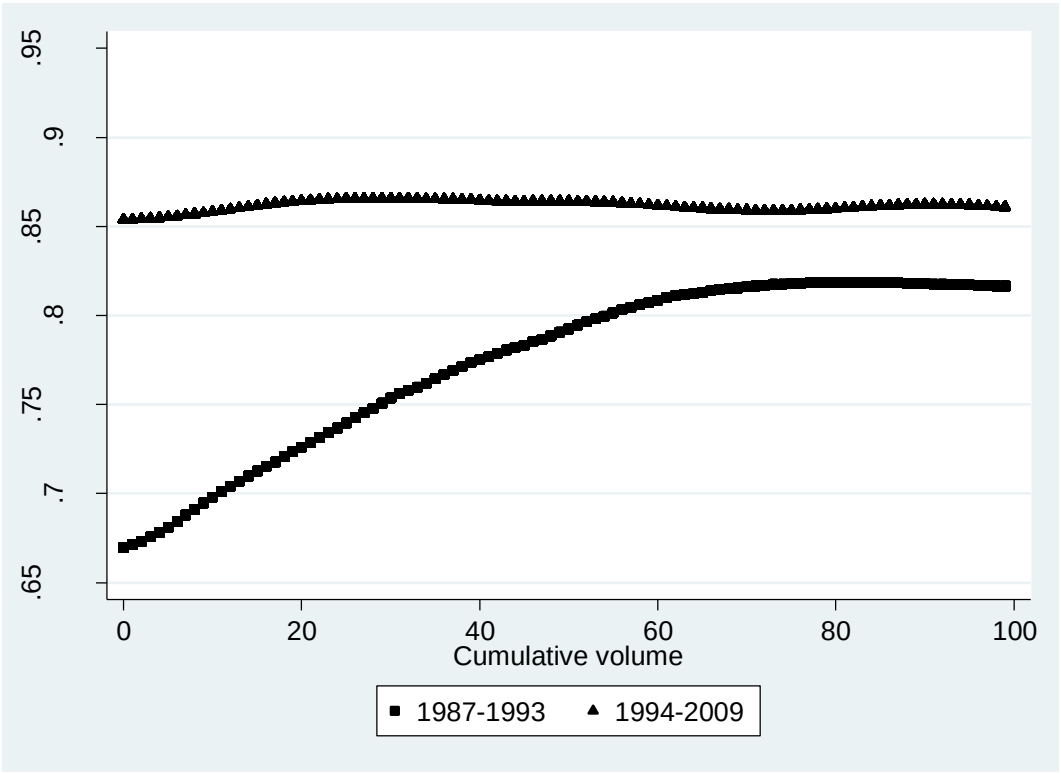


Figure 6: Six-month survival by cumulative volume (1988-2009)

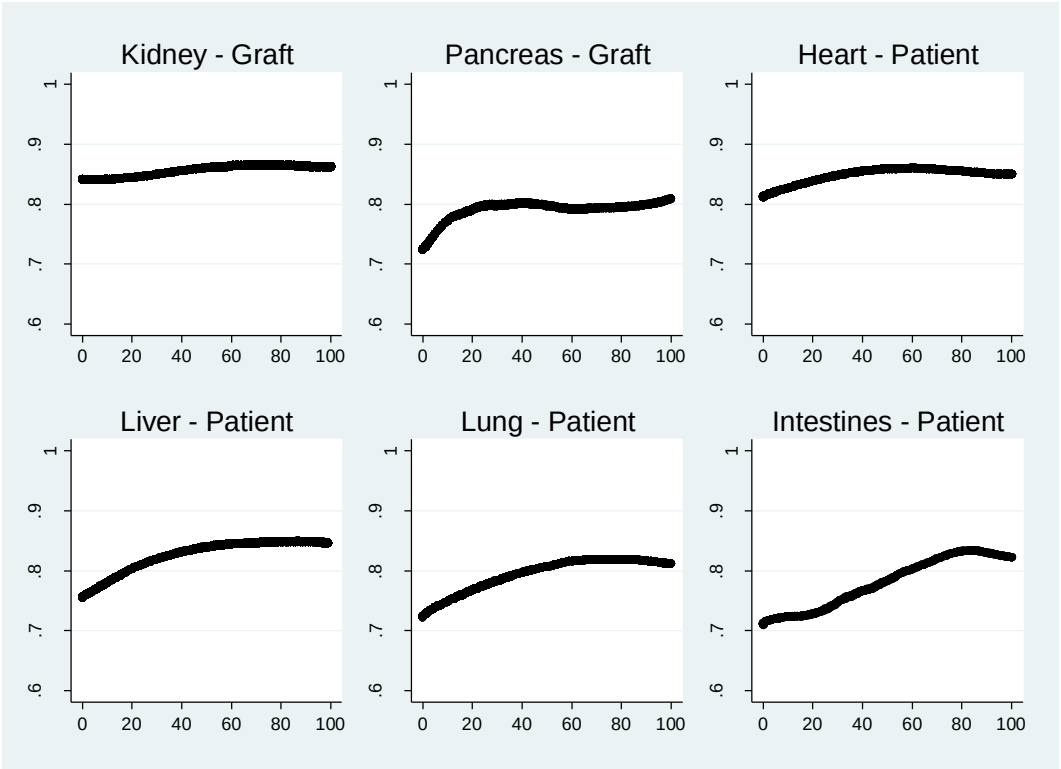


Figure 7: Intestinal transplant centers (2009)

Chapter 3:

Removing Financial Barriers to Organ and Bone Marrow Donation: The Effect of Leave and Tax Legislation in the U.S.

(joint work with Nicola Lacetera and Mario Macis)

1. Introduction

In virtually every country, the demand for organs and bone marrow far exceeds supply, leaving many patients to spend years and even die waiting for donated organs or bone marrow. In the U.S., for instance, the median wait-time until death or transplantation was 276 days for a liver and 547 days for a kidney in 2005, and only slightly over 60% of individuals waitlisted ever received an organ. Approximately 3,000 individuals die each year because they cannot find a matching bone marrow donor.[23] In addition to the implications for transplant candidates, a kidney transplant also saves at least $90,000 over the life of the individual relative to on-going dialysis treatment (Matas and Schnitzler, 2003). This supply shortage and the associated costs, loss in quality of life and even life itself drive the ongoing debate as to whether donors should receive some form of compensation in order to increase organ and bone marrow donation.

Concerns about exploitation of the poor and sick, adverse selection, motivational crowding out, and a general aversion or "repugnance" toward the commercialization of body parts have influenced the debate heavily (Frey, 1993; Roth, 2007; Titmuss, 1971). Some scholars

[23] These statistics are available from the Organ Procurement and Transplantation Network (OPTN) and the National Marrow Donor Program (NMDP) for organs and bone marrow, respectively.

and policymakers have manifested an aversion to any form of explicit reward for organ donors whereas others have advocated direct monetary payments. Becker and Elias (2007), for instance, estimate that amounts of $15,000 and $38,000 would enable markets for kidneys and livers, respectively, to clear.[24] Others see direct cash payments as potentially deleterious or socially unacceptable, but are open to considering some form of "in-kind" rewards to help reduce the supply shortage of human organs and tissue (Frey, 1993; Lacetera and Macis, 2010, 2012; Leider and Roth, 2010; Rodrigue et al., 2009; Roth et al., 2004).[25] Singapore and Israel have instituted priority rules for organ donors to reward those with signed donor cards and their families (Biyar, 2011; Duenwald and Shipley, 2011).[26] Israel also allows some direct payments to donor families to "memoralize" post-cadaveric donation, as well as more direct forms of compensation such as an exemption from health insurance premiums for living donors (Levush, 2010; Satel, 2010). Several European countries make organ donation an opt-out rather than an opt-in decision; according to some observers, this has led to significantly higher organ donation rates (Abadie and Gay, 2006).

In this paper, we present a comprehensive study of the impact of legislative efforts in the U.S. to mitigate the organ and bone marrow supply shortage by removing disincentives to donation without offering direct compensation, primarily through work leave legislation and tax credits and deductions. Specifically, between 1989 and 2009, a number of U.S. states passed legislation that grants paid or unpaid leave to state employees (and in some cases private

[24] The only country without an organ supply shortage is Iran, where the sale of kidneys has been legal since 1988. The Iranian government pays $1,200 and provides health insurance for one year to cover surgery-related conditions. In addition, the vendor receives between about $2,300 and $4,500 either from the recipient or one of several designated charitable organizations (Hippen, 2008). "Gray" market prices for kidneys posted by websites offering to coordinate procurement and transplantation internationally (a.k.a. "transplant tourism") range from $14,000 to $85,000 (Shimazono, 2007).

[25] Byrne and Thompson (2001) identify additional mechanisms that could lead to perverse effects of incentives, including time-inconsistency issues related to rewards for donor registration.

[26] New U.S. policies do provide priority for prior living donors on the transplant waitlist, effective 05/24/2012. http://optn.transplant.hrsa.gov/PoliciesandBylaws2/policies/pdfs/policy_172.pdf.

employees), tax deductions to individuals who donate their organs or bone marrow, and tax credits to employers for promoting donation.

We quantify the effects of these types of legislation on both organ and bone marrow donations. For organ donations, we focus on the two most commonly donated organs, livers and kidneys, which account for over 80% of all organs donated and almost 100% of all donations from live donors. In addition, the gap between supply and demand is much larger for kidneys and livers relative to hearts, lungs, pancreas, and intestines.[27] We also assess whether the impact of the legislation varies by gender and donor-recipient relationship. Even though the tax and leave legislation apply primarily to living donors, we assess whether cadaveric donations are affected as well. We do so for two main reasons: first, if donations from living and deceased donors follow a common time trend, the donations by deceased donors might be used as a "control" group. Second, these types of donations might actually be substitutes (Fernandez, Howard, and Stohr, 2012); if so, legislation targeting one type of donors might have effects on the other type as well. We also study whether these laws affect the distribution of organ quality, as measured by the state-level post-transplant graft survival rate. For bone marrow donations, we explore potential differential effects by donation method: aspiration or apheresis.[28]

A priori, if the incentives implied by the legislation were to have a positive impact on donation, we should expect these laws to influence bone marrow donors more than organ donors. Bone marrow donation has a much lower risk of complications and death than does organ donation, and is much less burdensome to the donor in terms of recovery time, pain, and

[27] The Organ Procurement and Transplantation Network. http://optn.transplant.hrsa.gov/latestData/advancedData.asp. Accessed 07/04/2012.

[28] In apheresis, a prospective donor undergoes five days of drug injections to stimulate the production of specialized blood cells, which are then filtered out of the donor's blood over the course of several hours, much as in plasma donation. The alternative method of aspiration requires removal of actual bone marrow from the hip of the donor, a more painful and risky procedure than apheresis.

suffering. Also, bone marrow regenerates and can be donated multiple times, whereas kidneys never re-grow. In the case of livers, which also regenerate, no cases of multiple donations are documented in the literature or the data and any prior hepatobiliary surgery complicates future transplant surgery should the donor ever need a liver transplant (Maddey and Van Thiel, 1988). In other words, bone marrow donation is less costly for a donor; therefore, at the margin, moderate incentives should tip the trade-off toward deciding to donate in the case of bone marrow more than they do for organs. For similar reasons, we differentiate between livers and kidneys within organ donation and, within bone marrow, aspiration and apheresis. The risk of complications or death and the recovery period are greatest for liver donation and lowest for apheresis donations (Confer et al., 2003; Karanes et al. 2003; Muzaale et al., 2011; Segev et al., 2010).

Our empirical strategy exploits the fact that different states have introduced legislation at different points in time, which provides us with several "natural experiments." We take advantage of the longitudinal nature of our dataset to lessen potentially important selection, endogeneity, and omitted variable problems. In our regression models, we include state fixed effects as well as state-specific time trends to ensure that we are controlling for omitted time-invariant factors and for selection into adopting the legislation based on the level and growth rate of the outcome variables (Ashenfelter and Card, 1985; Heckman and Hotz, 1989). To probe the validity of our identification strategy, we assess whether pre-existing trends in the demand for organs predict the adoption of legislation.

Our results indicate that the legislation had no overall effect on the number of organ donations. This result is robust across a variety of specifications and sub-samples, and holds also when we allow the legislation to affect outcomes with one- or two-year lags. In contrast, and

consistent with our prior, we do find a positive effect of leave legislation on bone marrow donation. Specifically, we find a positive effect of leave legislation for state employees on bone marrow donations, provided that a sufficient share of a state's labor force is state-employed (i.e., when the size of the population actually affected by the law is larger). Our estimated coefficient implies that leave legislation for state employees has a positive effect on bone marrow donations if state employees represent at least 5% of the labor force, which is the case for about 45% of our sample of state-years.

We have also considered the effects of the legislation on organ quality, as proxied by six-month and three-year post-transplant graft survival rates, to test if the legislation might be causing shifts in the underlying quality distribution of organs used for transplantation even in the absence of changes in the overall number of transplants. This could happen if the legislation has opposed effects on different types of living donors. For example, the laws might lead to increased donation among the less intrinsically motivated donors and decreased donation among the more intrinsically motivated. The latter types of donors may be of higher "quality" (Titmuss, 1971); therefore, the incentives implied by the legislation may lead to a shift in the overall quality of organs donated. We find an overall *positive* effect for three-year-survival from leave for state employees although the estimated coefficients are only marginally statistically significant. We also find a positive effect of leave for private employees on six-month survival rates of recipients of organs from male donors and positive effects of individual tax credits on six-month survival rates of recipients of organs from female donors. These results suggest that the laws may affect the distribution of organs donated or the distribution of organs used even in the absence of an overall effect on the quantity of organs.

Our study contributes to a small but growing literature in economics on organ and bone marrow donation. Two recent papers have looked at the effects of a variety of traffic safety laws on cadaveric organ donation, such as motorcycle helmet laws, primary seat belt enforcement laws, and speed limits (Dickert-Conlin, Elder, and Moore, 2012; Fernandez, Howard and Stohr, 2012). Kessler and Roth (2012) studied the effect of priority rules in a laboratory experiment. A number of studies (e.g., Roth et al., 2004, 2005a, 2005b) have analyzed the use of kidney exchanges, which cross-match incompatible donor and recipient pairs to create compatible donor-recipient pairs. Bagozzi et al. (2001) documented differences in bone marrow donation across different cultures, and Bergstrom, Garratt and Sheehan-Connor (2009 and 2012) analyzed the optimal size and racial composition of bone marrow registries. Although the effects of non-cash legislated incentives on many types of pro-social behavior, including health-related activities (e.g., blood donation), have now been studied extensively, the literature has just begun to study the effects of such legislation on the much more "costly" pro-social behavior involved in organ and bone marrow donation.

The overall scarcity of organ and bone marrow donors and the difficulty in matching between donors and recipients make natural experiments such as the ones exploited in this paper particularly important for determining how well such legislation performs in solving the severe organ and bone marrow shortage problem existing in the U.S. A few similar but more limited studies exist. Venkataramani et al. (2012) examined the effect of tax deductions for individuals on living organ donation. Bilgel (2011) and Wellington and Sayre (2011) studied tax deductions for individuals and leave legislation for state employees, but consider only organs and not bone marrow (Bilgel) and only kidneys (Wellington and Sayre). In addition to the types of legislation and donation considered by these papers, we analyze the effects of two similar types of

legislation granting leave to private employees and tax credits to employers for donation-promoting activities. Boulware et al. (2008) included all four types of legislation, but only consider kidney donations, and do not control for state-specific time-invariant factors, factors that vary over time but are common to all states, or pre-existing trends in state-level donation rates. We also explore whether these laws affected the quality of organs donated. Perhaps most importantly, our paper is the first to we examine the effects of these policies also on bone marrow donations, for which theoretical considerations lead us to anticipate stronger effects. In fact, like in our study, these other papers document no effect of the laws examined on *organ* donation. The positive effect we find on *bone marrow* donation, in addition to its relevance for policy and health consideration, supports an "incentive size" explanation for the zero result on organs, namely that the incentives may be too low for more "costly" donations but may work for less invasive procedures such as bone marrow donation. This is consistent with the positive effect found by Lacetera and Macis (2012) of paid leave on an even less invasive procedure, blood donation.[29]

In Section 2 we offer background information on the history of organ and bone marrow donation and the associated legislation. In Section 3 we describe the data, and in Section 4 we present and discuss our empirical strategy. We report the results in Section 5, and in Section 6 we discuss some implications of our results and conclude.

[29] Through utilizing the UNOS data request process rather than relying on OPTN's online data tool, we were able to obtain transplant-level data, which we aggregated at the state level. With the exception of Boulware et al. (2008) the prior studies cited above use data aggregated at the donation service area level, not the state level. Although donation service areas usually align with state boundaries, 32 of the 58 donation service areas in the U.S. include counties from more than one state.

2. Organ and bone marrow donation and associated legislation

2.1 Background[30]

In 1954, the first successful living donor kidney transplant was performed, followed by the first successful cadaveric donor kidney transplant in 1962. The first successful cadaveric liver transplant occurred in 1967 between identical twins. Bone marrow was first successfully transplanted in 1973. A living donor liver was not successfully transplanted until 1989.

Long-term dialysis treatment became available in 1960, greatly extending the life expectancy of individuals with renal failure and with that, the demand for kidney transplants. The Food and Drug Administration's approval of the immunosuppressant cyclosporine in 1983 transformed organ transplantation from a high-risk experimental procedure with almost certain organ rejection to a common treatment for organ failure. In the late 1990s, laparoscopic surgery greatly reduced the pain and recovery time for live kidney donors.[31]

As science and technological progress developed ever more effective transplantation methods, policymakers sought, in a variety of ways, to facilitate the use of these new methods and influence the exchange of organs. Medicare has paid for dialysis since 1972, kidney transplants since 1978, and liver transplants since 1990.[32] As for bone marrow, Medicare began coverage in 1978 and expanded it in 1985 and in 2010. Federal law increased the supply of deceased donor organs by expanding the definition of "death" to include "brain death" in 1981. In 1984, the National Organ Transplant Act banned the sale of organs and bone marrow, and the

[30] We focus here on the two human organs and one type of tissue included in this study: kidneys, livers, and bone marrow. Lungs, hearts, and intestines can be donated by living donors, but this occurs extremely rarely, so we drop these from our sample. (Deceased donors are required for heart transplants except for the case of domino transplants [i.e., a heart-lung recipient donates his or her heart to another recipient].)

[31] http://www.organtransplants.org/understanding/history/index.html

[32] Medicare approved liver transplantation for a limited number of conditions in 1990. This coverage was expanded to all end-stage liver disease patients except those with Hepatitis B or liver cancer. In 1996, Hepatitis B became covered, and in 2001 Medicare began covering hepatocellular carcinoma, but other forms of cancer remain uncovered.

Organ Procurement and Transplantation Network (OPTN) was established to promote organ donation, facilitate the allocation of organs, and serve as a central repository of organ-donation-related data. OPTN's bone marrow counterpart, the National Marrow Donation Program (NMDP) was established two years later in 1986. In 1994, a federal law was passed to provide leave of absence for bone marrow (5 days) and organ (30 days) donation by federal employees. Federal law also started requiring hospitals to notify organ procurement organizations of all eligible deaths in 1998, so that all might have the opportunity to donate.

Although organs from deceased donors are still the main source for transplants, this supply is inherently limited by the death rate, the type of deaths, and the decomposition process. Only a small percentage of deaths yield viable organs and, although improvements in storage and transportation of organs have occurred, kidneys are only viable for up to 24 hours and livers for up to 12 hours without a living blood supply. Despite over two million deaths in the U.S. in 2009, eligible deaths documented by UNOS totaled only 9,827.[33] These deaths yielded organs used in 11,285 kidney transplants and 6,098 liver transplants, supplemented with 6,387 live kidney donations and 219 live liver donations. Meanwhile, 33,663 people joined the kidney waitlist and 10,706 joined the liver waitlist in 2009. Bone marrow donations must come from living donors exclusively, but individual donors can donate more than once, making the bone marrow supply less inherently limited than the supply of donor organs.

Donating an organ or bone marrow exacts financial costs and at least some risk of pain and immediate and future health risks. Even though payers of organ and bone marrow transplants also pay the costs of recovery, both types of donors face costs in terms of time away from work, travel, and lodging. Prohibited by law from paying direct compensation to donors, states have

[33] This may be a lower bound since UNOS does not track information on all deaths. Gortmaker et al. (1996) estimated an eligible donor pool of 13,700 per year based on a study of sixty-nine acute care hospitals in the U.S.

attempted to address the organ shortfall by offsetting the incidental costs associated with donation and protecting employees from employer retaliation for leave taken to donate. The health risk remains: for kidney donors 3.1 deaths per 10,000 donors and as high as 17 per 10,000 for liver donors (Muzaale et al., 2011; Segev et al., 2010). In addition, donors may experience non-fatal complications including pain, infection, and hemorrhaging.[34]

2.2 Leave and tax legislation

States have attempted to address the organ and bone marrow shortfalls through a variety of methods that diminish the financial barriers to donation: leave for state employees, leave for private employees, tax credits for employers, and tax deductions for individuals. In general, laws granting leave offer up to 30 days for organ donation and up to one week for bone marrow donation. Tax deductions for individuals cover non-medical donation-related expenses up to a maximum of $10,000. Tax credits for employers cover donation-promoting activities, including the provision of paid leave to donors. Tables 19 (organs) and 20 (bone marrow) list the dates of passage for each type of legislation by state. (Legal references are listed in the appendix by state.) In 1989, Colorado passed the first relevant legislation providing state employees leave for the donation of an organ or bone marrow. Since then, most states have implemented legislation removing financial disincentives to donation through leave or tax legislation. For organ donation, thirty-one states offer leave for state employees, seven states offer leave for private employees, sixteen states give tax deductions to individuals and three states provide tax credits to employers. For bone marrow donations, thirty-three states offer leave for state employees, eleven states offer

[34] www.transplantliving.org/livingdonation/outcomes/risks.aspx., accessed 03/26/12.

leave for private employees, fifteen states give tax incentives to individuals and four states give employers tax credits for donation-promoting activities.[35]

3. Data and descriptive statistics

3.1 Organs

Patient-level data on kidney and liver transplants come from the Organ Procurement and Transplantation Network (OPTN).[36] From a total of 358,378 individual-level transplants, we obtained 1,071 state-year level observations with 51 observations per year from 1988, when OPTN began collecting data, through 2008.[37] Note that our data counts are transplants: we only count the organs actually used for transplantation, not organs recovered or donors consenting. However, because our main focus is on living donors, the number of organs recovered and the number of organs transplanted is the same.

Figures 2A and 2B describe how the volume and composition of organ donations have changed over time. Kidneys are the most common organ transplanted, followed by livers. Together these account for most of the organs transplanted in the U.S. and over 99% of all living donor organs. Kidney, liver and bone marrow donations generally increased until the late 2000s. This pattern, however, is much stronger for kidneys vis-à-vis livers and bone marrow. An overall upward trend in donations of both cadaveric and living donors exists until the late 2000s. Cadaveric donations far exceed those from living donors and underscore how infrequently

[35] Further details on the specifics of the laws are available at: http://sitemaker.umich.edu/sarah.stith/files/lms_organdonation_onlineappendix.pdf .

[36] "The data reported here have been supplied by the United Network for Organ Sharing as the contractor for the Organ Procurement and Transplantation Network. The interpretation and reporting of these data are the responsibility of the authors and in no way should be seen as an official policy of or interpretation by the OPTN or the U.S. Government." (http://optn.transplant.hrsa.gov/shareddownloadables/data_use_agreement.pdf)

[37] Total observations in the regressions considering livers only are lower because some state-years had no living donor transplants. For the regressions that analyzed organ quality changes, non-reporting of covariates leads to a reduction in observations. In the quality regressions using six-month and three-year survival rates as the outcome variable, the panel is shortened to give all recipients sufficient follow-up time.

compatible living donors come forward, although every human is born with two kidneys and a liver that can lose up to 70% of its size and still re-grow.

The highly detailed organ data include many variables associated with the medical procedure and demographics of both the transplant recipient and the donor. Table 21 reports summary statistics. On average, cadaveric donations dominate living donations with kidneys being the more common organ donated relative to livers. Males donate more organs overall, but this is due to more males donating cadaveric organs, while females dominate living donation. A variety of explanations could exist – men are more likely to die in accidents and tend to die earlier. Women may have more flexible work lives and might simply be more altruistic or more cautious about opting in to cadaveric organ donation. For livers, almost 94% of transplant recipients receive a cadaveric donor organ, while for kidneys about 30% receive a living donor organ. These differences suggest that we should break down our main analyses by both gender and organ. Table 22 shows the distribution of transplants by type of donor-recipient relationship. Most live donors are biologically related to the transplant recipient. This likely arises in part due to donor-recipient capability issues, which mean family members are more likely to match the recipient's blood type and other match factors than a random person from the general population. Approximately 18% of living donors are not spouses and are biologically unrelated.

3.2 Bone marrow

Bone marrow donation data were obtained from the National Marrow Donor Program (NMDP). We have a total of 14,463 transplants. The total number of donations omits approximately 30% of bone marrow donations by members of the military and for registrants for

whom no state of residence was recorded.[38] Table 23 contains descriptive statistics for bone marrow donations. The table reveals that both males and females donate at equal rates. Apheresis is a less common type of donation, largely due to its later uptake. Our data document no apheresis donations prior to 1999. By 2009, 0.7 apheresis donations occurred along with 0.3 aspiration donations, per one million population.

3.3 Legislation

The legislative data are compiled from donor program websites (www.optn.org and www.ncls.org), state government websites, and searches of state laws via Nexis®. We categorize the leave incentives into leave for employees of the state government (hereinafter "state employees") and leave for private sector employees (hereinafter "private employees"). Taxes fall into two categories: individual tax deductions of up to $10,000 or employer tax credits for donation-related expenses including promotional activities and paid leave for donation.[39]

4. Empirical strategy

Our empirical strategy exploits the fact that different states introduced legislation in different years; we use variation both across and within states over time to identify the effect of the legislation on a series of outcomes of interest. Specifically, we estimate a reduced-form model that takes the following form:

$$Y_{kt} = LEAVE_{kt}'\delta_{leave} + TAX_{kt}'\delta_{tax} + X_{kt}'\beta + \theta_k + \eta_t + \gamma_{kt} + \varepsilon_{kt}. \qquad (1)$$

[38] Although our organ data contain all organs transplanted, our bone marrow data are limited by the fact that only 36,800 of the total 54,140 requests for donations recorded include state-identifying information. Most omitted requests involve international and Department of Defense donors. Our outcome variables include only those 14,463 requests for donation that result in actual donation of bone marrow.

[39] Virginia does not set a maximum and Idaho allows for a tax *credit* of up to $5,000.

In Equation (1), Y_{kt} is the outcome variable in state k in year t, and we consider three main outcome variables: the number of organ donors standardized by one million population, the number of bone marrow donations per one million population, and post-organ transplant survival rates. $LEAVE_{kt}$ and TAX_{kt} are indicators for whether state k had leave legislation or tax legislation in place, respectively, in year t. More specifically, we include indicators for whether a state has leave provisions for state employees, leave provisions for private employees, tax deductions for individuals, and/or tax credits for employers. The vector of controls X_{kt} includes state-level income per capita and the unemployment rate, which could affect the availability and accessibility of transplant surgery. In the organ quality regressions, we also include donor, match, and patient characteristics to control for the differences in the types of donors, matches, and patients across states. Year fixed effects (η_t) account for aggregate factors that might affect the outcome variables, including nation-wide policy changes as well as secular trends in attitudes toward organ and marrow donation. θ_k are state fixed effects, γ_{kt} are state-specific time trends, and ε_{kt} is an error term. The main coefficients of interest, δ_{leave} and δ_{tax}, measure the within-state effect of passing a given type of legislation on the number of donations per million population, controlling for factors affecting all states in a given year, and state-specific fixed effects and time trends. In all regressions, standard errors are clustered at the state level to account for serial correlation in the state law indicators (Bertrand et al., 2004).[40]

Not all states have introduced such laws and different states have introduced the legislation at different times. This raises the question of whether the adopting states differ from the non-adopting states in fundamental ways that are correlated with our outcomes of interest. For instance, states with systematically *higher* levels of organ donations per capita might be

[40] In addition to the specifications described above, we used logs and other nonlinear variations and/or normalizations of the outcome variables. We also increased the frequency of the observations to months and quarters and manipulated the length of the balanced panel. None of these other approaches significantly altered our results.

more likely to introduce the legislation, perhaps due to greater familiarity with donation in the population or the transplant community's outreach efforts. In that case, a positive coefficient on the tax indicators might simply reflect this underlying heterogeneity rather than an effect of the law. The opposite is also possible; in other words, states with *lower* levels of organ or bone marrow donations per capita may be more likely to adopt the legislation in response to a shortage of organs. That case would bias our coefficient estimates downward. The inclusion of state fixed effects mitigates the bias that would occur if states adopted legislation based on the *level* of the outcome variable. Further, we include state-specific time trends to account for the possibility that states with systematically lower or higher *growth rates* of the outcome variable might be more likely to adopt the legislation.

To probe our identification strategy, we checked whether the passage of the legislation in a given state-year correlated with the lagged (one year) cumulative number of waitlist candidates per one million population; the lagged number of waitlist candidates year per one million population; the lagged number of waitlist candidates who died or were too sick for transplant, per one million population; and the lagged cumulative number of individuals who ever left the waitlist dead or too sick for a transplant. We use these variables to proxy for lagged values of cumulative demand, current demand, cumulative excess demand, and current excess demand. Table 24 reports summary statistics for these variables. On average, seventy individuals per one million population were awaiting an organ in a given state-year and four individuals per one million population die on the waitlist or are deemed too sick for transplantation each year.[41] We regress a dummy variable equal to one if a law was passed in the current year on lagged values (from the prior year) of the waitlist variables in Table 24. As shown in Table 25, the estimated

[41] The waitlist figure is larger for kidneys due primarily to better waitlist survival rates allowed for by dialysis. No similar life-extending pre-transplant therapy exists for end-stage liver disease.

coefficients are generally small and not statistically significant (with only two exceptions where the coefficients are small and marginally significant), indicating that prior values of these variables did not generally have any discernible effect on whether a state passed a law.[42] These results, together with our inclusion of year and state effects and state-level time trends in the regressions, make us confident about the validity of our identification strategy.

5. Results

5.1 Organ donations: Main results

We first estimate model (1) using total organ transplants per one million population as the dependent variable in columns [1] through [5] of Table 26, and living and cadaveric donor transplants separately in columns [6] and [7]. Although the tax and leave legislation generally target living donors, we consider donations from both living and deceased donors for two main reasons. First, one could postulate that donations from living and deceased donors follow a common time trend, and precisely because the legislation targets living donations, the donations by deceased donors might be seen as a benchmark, or "control" group. The second reason to study the effects on both living and deceased donations is that these types of donations might actually be substitutes, in which case donations from deceased donors could not be used as a control because under this hypothesis they would be affected by the legislation. For example, the waitlist only applies to potential recipients of cadaveric organs. If more living organs are donated, these individuals will drop from the waitlist, which might enable the donor-recipient matching process to be more selective as to which cadaveric organs are used in transplantation.[43]

[42] Specifications where we used two- or three-year lags deliver similar results.

[43] Organs vary in quality, so without an increase in the number of transplants, an increase in the number of living donors should lead to a smaller group of individuals accessing the same pool of cadaveric donor organs, thus allowing only the highest quality organs to be selected. Donor factors correlated with survival outcomes after liver transplantation include donors over 40 years old, donation after cardiac death rather than brain death, partial rather

Additionally, the employer tax credits could (in some states) apply to expenses incurred in promoting cadaveric donation as well as living donation. For these reasons, it is informative to study the effect of the legislation on both types of donations separately.

The results shown in column [1], which do not include state or year effects, indicate a positive correlation between the number of transplants and the existence of leave for state employees and leave for private sector employees; however, the coefficient estimates dramatically drop in magnitude and cease to be statistically significant when we introduce year and state fixed effects. In column [5] we add state-specific linear time trends, and again all of our coefficients of interest are estimated to be small and not statistically significant. These results underscore the importance of accounting for state-level heterogeneity and aggregate time effects, with the latter having the largest impact on our coefficient estimates of interest. Specifically, it would appear that the positive estimated coefficients on the legislation indicators in column [1] were reflecting a general trend of increasing donations over time.

Breaking down the analysis by live and cadaveric donations in columns [6] and [7] does not change the main results. We also consider the possibility that effects may differ for men and women due in part to men's greater attachment to the workforce, the target of the tax and, especially, the leave legislation, and report the results in Table 27. Again, we find no significant effects. Lastly, we differentiate between kidneys and livers in Table 28. Here, too, we obtain estimated coefficients that are both small and statistically insignificant. The single exception, in the absence of more defined patterns in the data, should, more plausibly, be attributed to random chance.

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than whole liver grafts, African-American race, less height, and cerebrovascular causes of death (Feng et al., 2006). For kidneys, donor characteristics associated with poorer transplant outcomes include age, cerebrovascular causes of death, renal insufficiency (serum creatinine over 1.5 mg/dL) and a history of hypertension (Port et al., 2002).

5.1a Organ donations: Additional analyses

We perform a number of further analyses to probe the (null) results described above.

Balanced Panel. First, our panel extends from 1/1/1988 to 12/31/2008. However, most of the legislation occurred around and after the year 2000. To reduce the influence of the long lags, in most cases, before the passage of legislation, we estimate model (1) using a panel including five years before passage of any tax or leave legislation and five years after the passage of that first legislation, omitting the year of introduction of the legislation.[44] Focusing on the period of time in which we can most confidently attribute differences in the number of live and cadaveric donors between states with and without legislation *to* the legislation, we still find no effect from the passage of these laws.[45]

Related vs. Unrelated Donors. Second, as described in Table 3, the vast majority of organ donations occur between biologically related individuals or between spouses. One could imagine that although leave and tax incentives might not play a major role in the decision of potential donors who are biologically related to the recipient, they might have a stronger impact on non-related potential donors. In Table 29, we run our main regressions on the number of donors who are biologically related, and on the number of donors who are not biologically related (both including and excluding spouses). Our results indicate insignificant effects of leave for state employees and tax deductions for individuals. Tax credits for employers seem to have a negative effect on biologically related donors and a (marginally statistically significant) positive effect on donations from non-biologically related donors, but the point estimates are very small in magnitude. We also detect a negative effect of leave for private employees on donations by

[44] These results are available upon request.

[45] In unreported results, the estimated coefficients on tax credits for employers are negative and statistically significant, but we do not include them due to the very small sample size of the balanced panel (only 30 observations). (These results are available upon request.)

non-biologically related donors, but again the estimated effect is negligible in magnitude. The most prevalent laws (i.e. leave for state employees and tax deductions for individuals) do not seem to affect biologically related and non-biologically related donors differently. Therefore, we find only weak evidence for the hypothesis that non-biologically related donors are more sensitive to the financial disincentives to donation.

State employees as a share of the labor force. Third, we note that leave for state employees should only affect the incentives of state employees. We, therefore, re-run our main regressions controlling for the number of state employees, both total and full-time, normalized by the total labor force at the state-year level (to parallel the construction of the left-hand side variable), and interact this variable with the law indicator. These results are reported in Table 30. Even though the estimated interaction effects are not statistically significant, their positive sign and considerable magnitude suggest that perhaps the laws have some positive effect increasing with the size of the population affected by the law.

5.2 Bone marrow donations: Main results

As described in Section 2.2, many states have passed legislation for bone marrow donors that is separate from that for organ donors, but the legislation is similar in spirit. The main difference is that leave allowances tend to be shorter for bone marrow donors. Because the bone marrow donation procedure is less costly to the donor relative to organ donation (in terms of risk of complications, pain and suffering, recovery time, and the possibility of future donation), such incremental measures as these laws might have a greater impact, at the margin, for bone marrow

donors than they do for organ donors.[46] In addition, two methods of donation exist—apheresis and aspiration, with the former being a much less invasive procedure.

The results are presented in Tables 31 through 33. Once again, in our most stringent specification (including year and state fixed effects and state time trends) we find no evidence that leave or tax legislation had any impact on the number of bone marrow donations (normalized by one million population). Given the evidence discussed in Section 4, including time trends is particularly relevant here.

If we break down donations by gender (Table 32), we again find no effect from such laws. In Table 33C, we split our regressions between donations by apheresis versus donations by aspiration. Apheresis as a form of donation first appears in our data in 1999, so we run our regressions using just the observations for those individuals donating after 1999. Although apheresis is significantly less burdensome for the donor, some authors still consider bone marrow donation via aspiration preferable (Seitz et al., 2012.) Yet, because the financial and physical barriers to apheresis are lower than for aspiration, one might expect an increase in this type of donation, in particular from donors on the margin between donating and not donating. On the other hand, the introduction of leave and tax deductions for donation may allow donors to choose the more burdensome option of aspiration, which would not have been feasible without the leave laws and tax deductions to cover incidental expenses associated with donation. Only leave for private employees appears to have a marginally significant effect on the method of donation; it reduces donation by aspiration. This negative coefficient may be somewhat counterbalanced by the positive (but insignificant) coefficient for apheresis donations. It appears that although these laws have no effect on overall donations, they may have some effect on how individuals chose to

[46] We performed similar analyses using year-to-year changes in donations, finding very similar results.

donate. The other laws also yield opposite signed coefficients, although in favor of more "costly" aspiration. Again the estimates are not statistically significant.

5.2b Bone marrow donations: Additional analyses

Balanced Panel. As with organs, we also consider the possibility that the main effect of these laws will occur shortly after their passage. Again, we take observations from five years before and five years after the passage of a law, omitting the year of passage, to determine if a more immediate, and perhaps less long-term, effect exists.[47] Again, we find no effect from these types of legislation on the number of bone marrow donations.

State employees as a share of the labor force. We also re-run our analysis controlling for the number of state employees, both total and full time, normalized by the state labor force to parallel the way we constructed the left-hand side variable. The results are reported in Table 34. Unlike with organs, this analysis does indicate a positive and significant effect from leave for state employees on bone marrow donations. In fact, although the main effect of leave for state employees is negative and usually insignificant, we find that the interaction between the rate of employment by the state and the existence of leave for state employees is positive and significant. The coefficient estimates of about -1.5 on leave for state employees and of 37.2 on the interaction term imply that leave for state employees has a positive effect if state employees represent at least 4.1 percent of the labor force, which is true for almost 48 percent of state-year observations in the data. Using just full-time employees (which account for 72% of state employees) yields similar results: the effect of leave legislation on bone marrow donations is positive if full-time state employees are at least 1.8 percent of the state labor force, which holds for 98% of state-year observations in our sample.

[47] These results are available upon request.

5.3 Effect on the quality of organs

Although we found no effect of these types of legislation on the *quantity* of organ donation, we explore the possibility that these laws could have shifted the *quality* composition of organs used for transplant. One way this could happen is if the legislation has opposed effects on different types of living donors. For example, the laws might have led to increased donations among less intrinsically motivated donors and decreased them among the more intrinsically motivated and the latter are donors of higher "quality," on average (Titmuss, 1971).[48] Another possibility is that the laws are affecting living and deceased donations differently. Fernandez et al. (2012) measure a substitution effect between live and cadaveric donors. A shift in the distribution of donors between living and cadaveric could also lead to a shift in the quality distribution if those two donor sources lead to systematically different survival outcomes. Both medical and social factors could lead to differences in the outcomes yielded by these two donor sources. Although living donors do tend to be older and, therefore, less likely to yield high-quality organs, the timing of donation can be optimized with living donors. The timing is important since the organ rapidly deteriorates without a blood supply and because this ensures that the recipient and donor are in the best health possible at the time of transplantation rather than allowing the timing of the transplant to be entirely determined by the time of death of the donor. Regarding social factors, living donation may proxy for a better social support network, which could improve longer term survival.[49]

[48] Note that the opposite could also happen, with the more intrinsically motivated donors being lower-quality donors (Healy, 2006). If these donors have lower motivation to give in the presence of incentives, the quality of the resulting pool of organs will actually increase.

[49] In a study of 289 transplant centers, the lack of a support person available to the transplant recipient was viewed as an absolute contraindication to transplantation by 6.5% and 2.6% of kidney and liver transplant centers, respectively. The relative contraindication percentages are 67.4% and 33.5% for kidneys and livers, respectively (Levenson and Olbrisch, 1993)., Although we are unaware of any studies directly testing the effect of social

We consider, as a measure of the quality of the organ transplanted, the total number of grafts functioning for at least six months (or for three years in some regressions) as a share of the total number of transplants. In all of our regressions, we include a range of match, donor, and recipient characteristics that could affect survival as specified in Table 35.[50] Because survival data on bone marrow transplants are not available, we must limit the following analysis to just organ donations. Re-running the main regressions for this time period does not change the null effect of these types of legislation on the donor supply. Table 36 shows descriptive statistics for the quality outcome variables. Obviously, longer time periods are associated with higher death rates. Also, it appears that survival for recipients of living donations is higher than for recipients of cadaveric donors.

The regression results (from a linear probability model) are shown in Tables 37 through 40. Overall, we find no effect of these laws on the quality of the organs donated as measured by the six-month state-level survival rate. When we consider the three-year survival period, however, we find some marginally significant evidence of a positive effect from leave for state employees. Since the pattern of coefficients is similar for six-months and three-years, and because significant factors external to transplantation can affect longer term survival, we focus predominantly on the six-month survival rates as the more accurate measure of quality.

We do find statistically significant differences among some subpopulations, which may indicate a shift in the distribution of organs used, even if overall we find no quality impact. In Table 38 we look at survival rates of recipients of female and male organs separately, further

networks on post-transplant survival among liver and kidney recipients, authors have documented its importance in heart transplantation (Bohachick et al., 2002) and long-term dialysis outcomes (Thong et al., 2007). A review of 122 studies across medical fields suggests that social support is important for patient adherence to medical treatment (DiMatteo, 2004).

[50] The controls used mirror those used by the Scientific Registry of Transplant Recipients to calculate transplant-center-level expected survival rates and include age, gender, race, and underlying diagnosis.

distinguishing between live and cadaveric organs. Leave for private employees increases the survival rate for recipients of live male organs by 5.5 percentage points (for comparison, the average six-month survival rate is 86 percent), whereas tax deductions for individuals increases the live female donor survival rate by almost 7 percentage points (compared to an average of 92 percent). The latter effect seems to be offset by a negative, marginally significant effect on recipients of live male organs.

Finally, we look at kidneys (Table 39) and livers (Table 40) separately. We find little or no effects for kidneys or livers when analyzed separately for six-month survival. For three-year survival rates, we find some marginally significant positive effects from leave for state employees and individual tax deductions for liver transplant recipients, which parallel in sign the coefficients for six-month survival. Leave for state employees leads to a 3.1 percentage point increase, and tax deductions for individuals leads to a 7.3 percentage point increase in the three-year survival rate of liver transplant recipients. The average survival rate among this population is 56 percent.

Overall, there is some evidence of a positive effect of leave for state employees on three-year survival rates, although the estimates are only marginally significant. Slightly stronger evidence of some positive effects on quality of leave for private employees and individual tax deductions also exists. Thus, the legislation might be inducing quality improvements in survival rates by changing the composition of the donor pool even though it does not increase overall organ donations.

6. Discussion and conclusions

Policymakers and scholars have long debated how to overcome the shortage of organs and bone marrow in the U.S. In this and in other systems based exclusively on altruistic donors,

the supply is insufficient to cover the need, and legal rules and social norms prevent direct compensation. We analyzed a third option, tax and leave laws, which allow donors of organs or bone marrow to be, at least financially, not significantly worse off than before donating. Donating an organ is a costly decision for the living donor, and one that may hinge on financial (and work-related) considerations. Because of these costs, the efficacy of these laws is certainly not guaranteed. Donating bone marrow is also not likely a decision that is made lightly, but it is less burdensome. On this basis, if incentives have a positive impact on donation, we anticipated that the incentives examined would have a stronger effect on bone marrow than on organs.

Our results are consistent with this interpretation; we documented no impact of the legislation on the number of organ donations, and a positive impact on bone marrow donations. We also found some marginally significant evidence of a positive effect of the legislation on organ quality. This suggests that only focusing on changes in quantity may overlook shifts in the underlying quality distribution of organs used for transplantation.

A few explanations could exist for the lack of an effect of the legislation on the quantity of organs. First, it is possible that not enough people are aware of the existence of the legislation. UNOS, for example, does not mention these types of legislation in its summary of information for prospective living organ donors.[51] (The NMDP does, however, mention the existence of laws providing leave to donors, which also could help explain the stronger effect of these types of legislation on bone marrow donations.[52]) Second, the results could be confounded by the existence of grant programs, which already may be providing the same cost reimbursement as the tax laws. Employer-specific paid leave programs could further be diminishing the effect of

[51] http://www.unos.org/docs/Living_Donation.pdf
[52] http://marrow.org/Registry_Members/Donation/Now_that_you_are_a_match_%28PDF%29.aspx

leave laws.[53] Third, a composition effect might be occurring, whereby some subsets of the population are positively motivated by these additional incentives to donate (on top of their intrinsic motives) whereas others are "crowded out" (because their self or social image may be tainted [Benabou and Tirole, 2006] or because they consider the presence of material incentives repugnant [Roth, 2007]). Fourth, the incentives put in place by these types of legislation might not be strong enough to induce an individual, who is not otherwise sufficiently altruistically motivated, to endure the pain, suffering, scarring, time away from work and leisure, and undocumented long-term donor health effects implied by an organ donation. Some evidence also exists that donors occasionally have difficulty obtaining life and health insurance post-donation (Rudow et al., 2006; Spital and Jacobs, 2002).[54] Untangling these explanations is of importance for policymakers interested in increasing and enhancing the supply of organs for transplantation.

The positive effect of the legislation on bone marrow donations leads us to favor the fourth explanation: although tax breaks and leave provisions may be sufficient to induce, at the margin, individuals to undergo a moderately invasive procedure such as a bone marrow donation, they may be too low for the more "costly" organ donations. Similarly, there may be enough individuals *at the margin* between being willing to donate bone marrow or not, such that the incentives analyzed here tip their decision, but this may not be the case for organs. In other words, and following the terminology of Gneezy and Rustichini (2000), the incentives described here may be "large enough" for bone marrow donations, but not for organ donations. The

[53] For the particularly financially constrained, organizations such as The National Living Donor Assistance Center (www.livingdonorassistance.org) provide grants to cover the costs of donation, which may leave the legislation with little room to have an impact. In addition, the American Society of Transplantation publishes an incomplete list of the names of private companies, including large organizations such as major state universities (Iowa, Minnesota, Ohio, and Wisconsin) offering paid leave to donate to their employees. Such initiatives could be obscuring the effects of legislation mandating unpaid leave.

[54] Perhaps suggestive of the issues with insuring organ donors, The Living Organ Donor Protection Act, which would have ensured donors could not be denied coverage or charged surcharges by health insurers, died in Committee. http://www.govtrack.us/congress/bills/111/hr1558

findings from Lacetera and Macis (2012) and Lacetera, Macis and Slonim (2011, 2012) of a positive effect of leave legislation and $5-$15 gift cards on an even less invasive procedure, blood donation, further corroborate our interpretation.

If this interpretation is correct, then we would expect larger incentives to have positive effects on bone marrow donations, and potentially also on organ donations. More systematic analyses from contexts where such stronger incentives are provided would be needed to reach firmer conclusions, however. The recent decision on December 1, 2011 by the 9th U.S. Circuit Court of Appeals that bone marrow apheresis can be compensated will provide researchers with an opportunity to further our understanding of which policies are effective in reducing the organ and bone marrow demand-supply imbalance.[55]

[55] The apheresis technique did not exist at the time of the National Organ Transplant Act in 1984 (Korbling and Freireich, 2011). This highlights the importance of legislative evolution to match scientific innovation.

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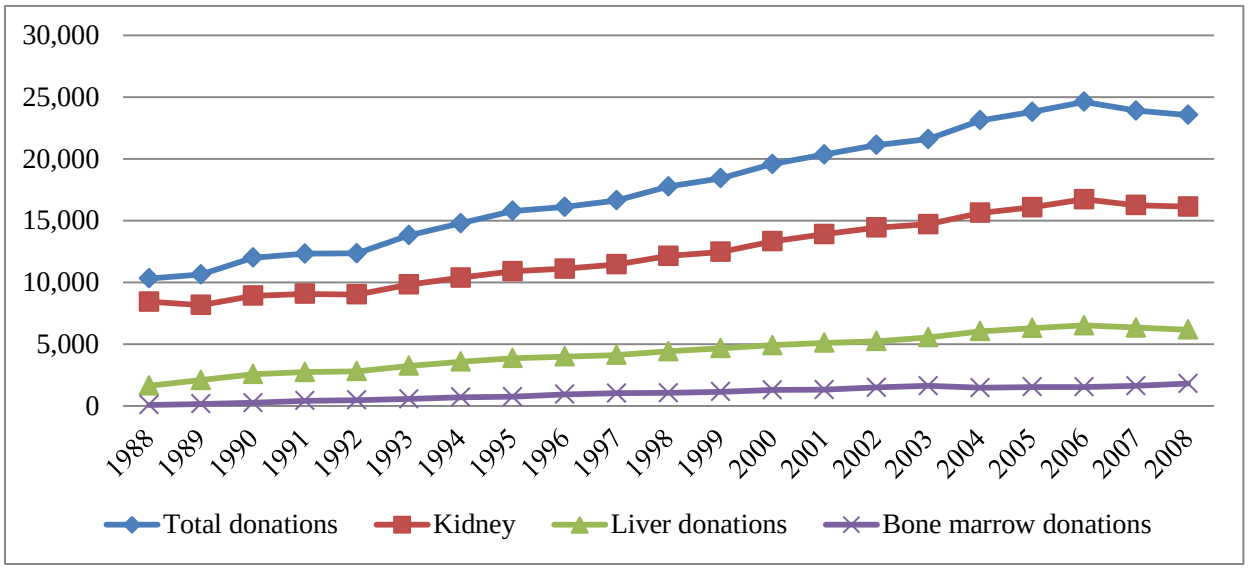
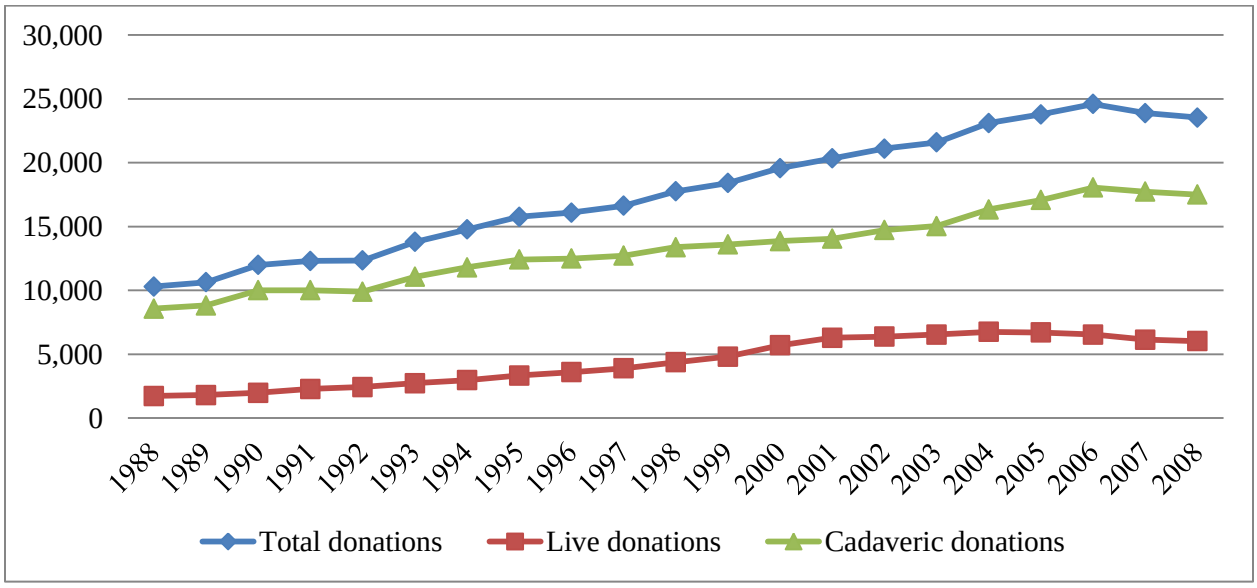
United States Renal Data System (www.usrds.org)

Figure 8: Total donations by type of donation



Notes: OPTN data through 12/31/2008; NMDP data through 12/31/2008.

Figure 9: Total donations by type of donor



Notes: OPTN data through 12/31/2008.

Table 19: State laws for organ donors

State	Leave for state employees	Leave for private employees	Tax deduction for individuals*	Tax credit for employers
Alaska	2008			
Arkansas	2003	2005	2005	2005
California	2002			
Colorado	1989			
Connecticut	2007	2004		
Delaware	2001			
Georgia	2002		2004	
Hawaii	2005			
Idaho	2006		2006	
Illinois	2002	2005		
Indiana	2002			
Iowa	2003		2005	
Kansas	2001			
Louisiana			2005	
Maine	2002	2002		
Maryland	2000			
Massachusetts	2005			
Minnesota	2006		2005	
Mississippi	2004	2004	2006	
Missouri	2001			
New Mexico	2007		2005	
New York	2001		2006	
North Carolina				
North Dakota	2005		2005	
Ohio	2001		2007	
Oklahoma	2002		2008	
Oregon				1991
Pennsylvania		2006		2006
Rhode Island			2009	
South Carolina	2002	2006		
Texas	2003			
Utah	2002		2005	
Virginia	2001		2007	
Washington	2002			
West Virginia	2005			
Wisconsin	2000		2004	

*Idaho has an individual tax credit rather than tax deduction.

The following states have none of the above laws: AL, AZ, FL, KY, MI, MT, NE, NV, NH, NJ, SD, TN, VT, WY.

Table 20: State laws for bone marrow donors

State	Leave for state employees	Leave for private employees	Tax deduction for individuals*	Tax credit for employers
Alaska	2008			
Arkansas	2003	2005	2005	2005
California	2002			
Colorado	1989			
Connecticut	2004	2004		
Delaware	2001			
Georgia	2002		2004	
Hawaii	2005			
Idaho	2006		2006	
Illinois	2002	2005		
Indiana	2002			
Iowa	2003		2005	
Kansas	2001			
Louisiana	1992	1992		1992
Maryland	2000			
Massachusetts	2005			
Minnesota	1990	2004	2005	
Mississippi	2004	2004	2006	
Missouri	2001			
Nebraska	1992	1992		
New Mexico	2007		2005	
New York	2001	2007	2006	
North Dakota	2005		2005	
Ohio	2001		2007	
Oklahoma	2002		2008	
Oregon	1991	2002		1991
Pennsylvania		2006		2006
Rhode Island			2009	
South Carolina	2002	2002		
Texas	2003			
Utah	2002		2005	
Virginia	2001		1997	
Washington	2002			
West Virginia	2005			
Wisconsin	2000		2004	

*Idaho has an individual tax credit rather than tax deduction.

The following states have none of these laws: AL, AZ, FL, KY, ME, MI, MT, NV, NH, NJ, NC, SD, TN, VT, WY.

Table 21: Descriptive statistics – Organ transplants per 1M population

Variable	State-year observations	Mean	Standard deviation	Minimum	Maximum
Total	1071	66.8	19.7	0.0	157.5
Live	1071	16.8	8.4	0.0	59.2
Cadaveric	1071	50.0	15.3	0.0	126.3
Male	1071	37.6	11.9	0.0	88.1
Female	1071	29.2	10.2	0.0	76.9
Livers	1069	16.1	6.2	0.9	48.5
Kidneys	1071	46.7	12.5	13.0	99.4
Live - male	1071	7.1	3.9	0.0	32.7
Dead - male	1071	30.5	10.4	0.0	78.1
Live - female	1071	9.7	5.1	0.0	36.1
Dead - female	1071	19.5	7.3	0.0	55.1
Live - Livers	1069	0.6	0.9	0.0	6.9
Dead - Livers	1069	15.5	6.0	0.9	46.7
Live - Kidneys	1071	16.2	8.0	0.0	59.2
Dead - Kidneys	1071	30.5	8.4	10.9	70.1

Notes: Data are from OPTN and cover the period from 1/1/1988 through 12/31/2008.

Table 22: Descriptive statistics – Live donor-recipient relationships

Variable	All	Kidneys	Livers
Total donations	77,760	74,363	3,397
Biological, blood-related parent	16%	15%	25%
Biological, blood-related child	17%	17%	25%
Biological, blood-related identical twin	0%	0%	0%
Biological, blood-related sibling	31%	32%	15%
Biological, blood-related half-sibling	1%	1%	1%
Biological, blood-related other relative	7%	7%	10%
Non-biological, spouse	10%	11%	6%
Non-biological, life partner	0%	0%	0%
Non-biological, unrelated: paired exchange	1%	1%	0%
Non-biological, unrelated: anonymous donation	1%	1%	1%
Non-biological, living/deceased donor exchange	0%	0%	0%
Non-biological, unrelated: domino	0%	0%	2%
Non-biological, other directed donation	15%	15%	16%

Notes: Data are from OPTN and cover the period from 1/1/1988 through 12/31/2008.

Table 23: Descriptive statistics – Bone marrow

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Bone marrow transplants per 1m population					
Total	1173	3.7	3.3	0.0	21.3
Female	1173	1.6	1.7	0.0	13.7
Male	1173	2.1	2.0	0.0	15.2
% of donation requests resulting in donation					
Total	1173	61%	27%	0%	100%
Female	1173	48%	32%	0%	100%
Male	1173	51%	31%	0%	100%
Apheresis versus aspiration per 1m population					
Apheresis	1049	2.4	3.4	0.0	22.7
Aspiration	1049	3.8	3.0	0.0	33.0
% of donations requests resulting in X type of donation					
Apheresis	1049	28%	32%	0%	100%
Aspiration	1049	72%	32%	0%	100%

Notes: The data for this table come from the NMDP and cover the period from 1/1/1987 through 12/31/2009.

Table 24: Descriptive statistics – Waitlist

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
Cumulative waitlist per 1m population	1020	480	352	4	1711
Cumulative waitlist per 1m population minus cumulative removals from waitlist per 1m population	1020	64	53	0	308
Cumulative candidates dying on waitlist or deteriorating until too sick for transplant per 1m population	1020	35	36	0	170
Yearly number of candidates dying on waitlist or deteriorating until too sick for transplant per 1m population	1016	5	4	0	21

Notes: Data are from OPTN and cover the period from 1/1/1988 through 12/31/2008.

Table 25: Probability of legislation passing

(Outcome = probability of law passing)

	(1)	(2)	(3)	(4)
	Leave for private employees	Leave for state employees	Tax deductions for individuals	Tax credits for employers
Cumulative waitlist per 1m population	-0.0149	0.0106	-0.00769	-0.0113
	(0.0242)	(0.0102)	(0.0154)	(0.0109)
Observations	1,020	1,020	1,020	1,020
R-squared	0.120	0.125	0.147	0.149
Cumulative waitlist per 1m population minus cumulative removals from waitlist per 1m population since October 1987	0.0741	-0.0518	0.0882*	0.000502
	(0.0961)	(0.0396)	(0.0525)	(0.0329)
Observations	1,020	1,020	1,020	1,020
R-squared	0.120	0.125	0.148	0.148
Cumulative candidates dying on waitlist or deteriorating until too sick for transplant per 1m population	-0.170	0.0438*	-0.0311	-0.0152
	(0.123)	(0.0238)	(0.0724)	(0.0340)
Observations	1,020	1,020	1,020	1,020
R-squared	0.121	0.125	0.147	0.148
Yearly number of candidates dying on waitlist or deteriorating until too sick for transplant per 1m population	-0.226	0.0362	0.253	-0.0990
	(0.289)	(0.131)	(0.161)	(0.0956)
Observations	1,016	1,016	1,016	1,016
R-squared	0.120	0.124	0.148	0.149

Notes: The data include the full unbalanced panel. State-level controls include unemployment rate and income per capita. All regressions include state and year fixed effects and state time trends. State-level clustered standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

Table 26: Organs -- Main results

(Outcome = organ transplants per one million population)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Type of donations	All	All	All	All	All	Cadaveric	Live
Leave for state employees	11.46***	-1.041	6.003***	-0.236	-1.204	-1.566	0.362
	(3.731)	(2.848)	(2.178)	(1.762)	(2.293)	(2.061)	(1.008)
Leave for private employees	10.91*	2.665	11.15*	6.466	4.428	5.357	-0.927
	(5.782)	(5.610)	(5.702)	(4.608)	(6.333)	(6.327)	(1.303)
Tax credits for employers	5.502	-3.641	-7.104	-4.188	-2.418	-1.655	-0.763
	(4.861)	(4.442)	(6.848)	(5.106)	(6.823)	(7.497)	(1.172)
Tax deductions for individuals	8.139	1.153	-0.578	0.240	-1.419	-0.0303	-1.387
	(4.998)	(3.670)	(4.006)	(2.419)	(3.761)	(3.452)	(1.292)
Year fixed effects		X		X	X	X	X
State fixed effects			X	X	X	X	X
State-year fixed effects					X	X	X
Observations	1,071	1,071	1,071	1,071	1,071	1,071	1,071
R-squared	0.160	0.458	0.562	0.693	0.734	0.624	0.830

Notes: The data include the full unbalanced panel. State-level controls include unemployment rate and income per capita. State-level clustered standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

Table 27: Organs -- Results by gender

(Outcome = organ transplants per one million population)

	(1)	(2)	(3)	(4)	(5)	(6)
		Cadaveric	Live -		Cadaveric	Live -
Type of donation	Male	- Male	Male	Female	- Female	Female
Leave for state employees	-1.479	-1.874	0.395	0.275	0.308	-0.0331
	(1.425)	(1.302)	(0.460)	(1.228)	(1.210)	(0.652)
Leave for private employees	4.260	5.214	-0.952	0.167	0.143	0.0252
	(3.961)	(3.950)	(0.839)	(3.322)	(3.161)	(0.839)
Tax credits for employers	-1.666	-2.475	0.809	-0.752	0.820	-1.572
	(3.197)	(3.886)	(1.166)	(4.152)	(3.955)	(1.068)
Tax deductions for individuals	-0.0578	0.244	-0.301	-1.361	-0.274	-1.086
	(2.395)	(2.291)	(0.663)	(1.738)	(1.615)	(0.756)
Observations	1,071	1,071	1,071	1,071	1,071	1,071
R-squared	0.615	0.552	0.725	0.673	0.481	0.766

Notes: The data include the full unbalanced panel. State-level controls include unemployment rate and income per capita. All regressions include state and year fixed effects and state time trends. State-level clustered standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

Table 28: Organs -- Results for livers and kidneys separately

(Outcome = organ transplants per one million population)

	(1)	(2)	(3)	(4)	(5)	(6)
Type of donation	Liver	Live - liver	Cadaveric - liver	Kidney	Live - kidney	Cadaveric - kidney
Leave for state employees	-0.342	0.0362	-0.378	-0.979	0.295	-1.276
	(0.730)	(0.165)	(0.736)	(1.633)	(1.051)	(1.280)
Leave for private employees	1.780	-0.479**	2.259	2.124	-0.509	2.635
	(2.530)	(0.230)	(2.515)	(3.620)	(1.319)	(3.538)
Tax credits for employers	-0.403	0.804	-1.207	-2.213	-1.527	-0.687
	(3.035)	(0.545)	(3.421)	(3.487)	(1.255)	(4.049)
Tax deductions for individuals	-0.0744	0.315	-0.389	-0.494	-1.692	1.200
	(1.217)	(0.298)	(1.184)	(2.307)	(1.370)	(1.956)
Observations	1,069	1,069	1,069	1,071	1,071	1,071
R-squared	0.735	0.575	0.722	0.704	0.814	0.523

Notes: The data include the full unbalanced panel. State-level controls include unemployment rate and income per capita. All regressions include state and year fixed effects and state time trends. State-level clustered standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

Table 29: Organs -- Results by donor-recipient relationship

(Outcome = organ transplants per one million population)

	(1)	(2)	(3)
	Biologically related donors	Not biologically related donors (including spouses)	Not biologically related donors (excluding spouses)
Leave for state employees	0.000365	0.00414	0.0142
	(0.0137)	(0.0156)	(0.0163)
Leave for private employees	0.0117	-0.0281**	-0.0263*
	(0.0142)	(0.0106)	(0.0141)
Tax credits for employers	-0.0453**	0.0266*	0.0233
	(0.0214)	(0.0134)	(0.0223)
Tax deductions for individuals	0.00499	-0.0122	-0.00161
	(0.0147)	(0.0124)	(0.0111)
Observations	1,070	1,070	1,070
R-squared	0.978	0.621	0.468

Notes: The data include the full unbalanced panel. State-level controls include unemployment rate and income per capita. All regressions include state and year fixed effects and state time trends. State-level clustered standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

Table 30: Organs – Results controlling for and interacting with state employment rate

(Outcome = organ transplants per one million population)

	(1)	(2)	(3)	(4)	(5)	(6)
Type of donor	All	All	Live	Live	Cadaveric	Cadaveric
Leave for state employees	-6.211	-8.371	1.469	1.019	-7.682	-9.392
	(6.432)	(6.309)	(3.328)	(2.909)	(5.622)	(5.825)
Leave for private employees	1.377	1.810	-0.686	-0.586	2.063	2.396
	(8.737)	(8.840)	(1.833)	(1.869)	(8.018)	(8.132)
Tax credits for employers	2.444	2.011	-0.341	-0.467	2.785	2.478
	(14.05)	(13.87)	(1.852)	(1.876)	(13.91)	(13.73)
Tax deductions for individuals	-1.012	-0.982	-1.552	-1.581	0.540	0.599
	(4.103)	(4.211)	(1.435)	(1.462)	(3.786)	(3.856)
State employees/labor force	-54.42		53.92		-108.3	
	(241.6)		(125.2)		(207.5)	
Leave for state employees*						
(state employees/labor force)	98.75		-19.28		118.1	
	(174.2)		(82.43)		(148.8)	
Full-time state employees/labor force		311.1		115.7		195.5
		(327.4)		(182.6)		(360.5)
Leave for state employees *						
(full-time state employees/labor force)		205.1		-13.37		218.5
		(232.5)		(97.99)		(210.4)
Observations	784	784	784	784	784	784
R-squared	0.716	0.717	0.812	0.812	0.654	0.655

Notes: The data include the full unbalanced panel. State-level controls include unemployment rate and income per capita. All regressions include state and year fixed effects and state time trends. State-level clustered standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

Table 31: Bone marrow – Main results (donations)

(Outcome = bone marrow donations per one million population)

	(1)	(2)	(3)	(4)	(5)
Leave for state employees	1.611***	-0.585	2.370***	-0.922*	0.0788
	(0.345)	(0.626)	(0.284)	(0.470)	(0.397)
Leave for private employees	-0.676*	-1.252**	0.321	-0.749	0.165
	(0.392)	(0.611)	(0.320)	(0.509)	(0.523)
Tax credits for employers	-1.288	-0.538	0.0487	-0.115	0.869
	(0.800)	(0.951)	(0.884)	(0.650)	(0.825)
Tax deductions for individuals	0.222	-1.233*	0.166	-1.066**	-0.313
	(0.377)	(0.630)	(0.378)	(0.431)	(0.441)
Year fixed effects		X		X	X
State fixed effects			X	X	X
State-level time trends					X
Observations	1,173	1,173	1,173	1,173	1,173
R-squared	0.038	0.380	0.356	0.650	0.780

Notes: The data include the full unbalanced panel. State-level controls include unemployment rate and income per capita. State-level clustered standard errors in parentheses *** $p < .01$, ** $p < .05$, * $p < .1$

Table 32: Bone Marrow -- Donations by gender

(Outcome = bone marrow donations per one million population)

	(1)	(2)
Type of outcome	Donations - female	Donations - male
Leave for state employees	0.126	-0.0474
	(0.248)	(0.193)
Leave for private employees	0.201	-0.0358
	(0.268)	(0.302)
Tax credits for employers	-0.210	-0.103
	(0.277)	(0.247)
Tax deductions for individuals	0.116	0.752
	(0.390)	(0.460)
Observations	1,173	1,173
R-squared	0.615	0.715

Notes: The data include the full unbalanced panel. All regressions include state and year fixed effects and state-level time trends. State-level clustered standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

Table 33: Bone marrow -- Donations by method

(Outcome = bone marrow donations per one million population)

	(1)	(2)
	Apheresis donations	Aspiration donations
Leave for state employees	-0.202	0.253
	(0.471)	(0.363)
Leave for private employees	0.634	-0.651*
	(0.403)	(0.379)
Tax credits for employers	-0.652	0.562
	(0.830)	(0.648)
Tax deductions for individuals	0.879	0.387
	(0.659)	(0.568)
Observations	507	507
R-squared	0.844	0.788

Notes: The data include the full unbalanced panel. All regressions include state and year fixed effects and state-level time trends. State-level clustered standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

Table 34: Bone marrow – Results controlling for and interacting with state employment rate

(Outcome = bone marrow donations per one million population)

	(1)	(2)	(3)	(4)	(5)	(6)
Type of donor	All	All	Female	Female	Male	Male
Leave for state employees	-1.521*	-1.382*	-0.929	-0.855	-0.592	-0.527
	(0.813)	(0.749)	(0.709)	(0.637)	(0.374)	(0.358)
Leave for private employees	0.120	0.0329	0.130	0.0741	-0.00958	-0.0412
	(0.512)	(0.501)	(0.269)	(0.271)	(0.300)	(0.299)
Tax credits for employers	0.866	0.898	0.129	0.148	0.737	0.750*
	(0.840)	(0.808)	(0.413)	(0.393)	(0.454)	(0.443)
Tax deductions for individuals	-0.235	-0.197	-0.224	-0.197	-0.0118	-0.000537
	(0.413)	(0.399)	(0.263)	(0.250)	(0.233)	(0.231)
State employees/labor force	-32.27		-16.34		-15.93	
	(33.52)		(22.77)		(39.20)	
Leave for state employees*						
(state employees/labor force)	37.16**		23.99		13.17*	
	(17.66)		(17.12)		(6.772)	
Full-time state employees/labor force		-77.54*		-45.52		-32.01
		(39.96)		(38.55)		(45.19)
Leave for state employees *						
(full-time state employees/labor force)		47.37**		31.04		16.32*
		(22.47)		(21.53)		(9.331)
Observations	1,122	1,122	1,122	1,122	1,122	1,122
R-squared	0.789	0.789	0.626	0.626	0.727	0.727

Notes: Includes the full unbalanced panel. State-level controls include unemployment rate and income per capita. All regressions include state and year fixed effects and state-level time trends. State-level clustered standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

Table 35: Descriptive statistics – Donor, match, and patient characteristics

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
% incompatible recipient-donor blood types	1071	14%	12%	0%	68%
% pediatric patients (<18 years)	1071	8%	3%	0%	30%
% multi-organ recipients	1071	2%	2%	0%	15%
% with diabetes diagnosis	1071	16%	5%	0%	38%
% with non-cholestatic liver disease	1067	55%	12%	0%	100%
Cold ischemia time	1071	13	3	6	26
Recipient age	1071	44	4	32	55
Days on waitlist	1071	395	132	55	907

Notes: These percentages and averages are calculated for the whole sample. Subsample rates are used in subsample analyses.

Table 36: Descriptive statistics – Quality outcome variables

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
% survive six months - all donor types	1071	86%	7%	36%	100%
% survive three years - all donor types	1071	62%	24%	0%	100%
% survive six months - live donors	1068	93%	8%	0%	100%
% survive six months - cadaveric donors	1071	84%	7%	41%	100%
% survive six months - female donors	1071	86%	8%	33%	100%
% survive six months - male donors	1071	86%	8%	17%	100%
% survive six months - live female donors	1062	92%	9%	0%	100%
% survive six months - cadaveric female donors	1069	83%	11%	0%	100%
% survive six months - live male donors	1056	93%	10%	0%	100%
% survive six months - cadaveric male donors	1070	85%	8%	0%	100%
% survive six months - kidney donors	1071	89%	7%	40%	100%
% survive three years - kidney donors	1071	65%	25%	0%	100%
% survive six months - live kidney donors	1068	93%	8%	0%	100%
% survive six months - cadaveric kidney donors	1071	87%	7%	43%	100%
% survive six months - liver donors	1067	78%	12%	0%	100%
% survive three years - liver donors	1067	56%	24%	0%	100%
% survive six months - live liver donors	579	80%	30%	0%	100%
% survive six months - cadaveric liver donors	1067	78%	12%	0%	100%

Table 37: Tax and leave effects on quality – All organs

(Outcome = state-level survival rate)

	(1)	(2)	(3)	(4)
Survival time	Six months	Three years	Six months	Six months
Type of donor	All	All	Live	Cadaveric
Leave for state employees	0.198	1.509*	0.444	-0.0627
	(0.506)	(0.761)	(0.794)	(0.614)
Leave for private employees	-0.0366	-1.042	0.402	0.323
	(0.838)	(1.187)	(1.387)	(1.474)
Tax credits for employers	0.220	2.182	1.127	0.262
	(0.690)	(1.733)	(1.012)	(0.874)
Tax deductions for individuals	0.827	1.561	2.985	0.579
	(0.953)	(1.025)	(2.536)	(1.395)
Observations	1,067	965	579	1,067
R-squared	0.723	0.887	0.556	0.676

Notes: The data include the full unbalanced panel. All survival rates are multiplied by 100 so the coefficients can be read as percentage changes. All regressions include state and year fixed effects and state-level time trends. Case mix controls: recipient age, recipient gender, diagnosis = noncholestatic v. other (livers), diagnosis=diabetes v. other (kidneys), live donor, and pediatric recipient. State-level clustered standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

Table 38: Tax and leave effects on quality - Organs by gender

(Outcome = state-level six-month survival rate)

	(1)	(2)	(3)	(4)	(5)	(6)
			Live -	Live -	Cadaveric -	Cadaveric -
Type of donor	Female	Male	female	male	female	male
Leave for state employees	1.172*	-0.629	-0.148	0.648	1.407	-1.031
	(0.599)	(0.807)	(1.411)	(0.843)	(0.973)	(0.869)
Leave for private employees	-0.648	0.983	-1.106	5.516**	-0.487	1.062
	(1.138)	(1.220)	(2.656)	(2.118)	(1.863)	(1.862)
Tax credits for employers	0.649	0.0985	1.109	-0.136	1.012	-0.0194
	(1.019)	(0.802)	(2.030)	(1.243)	(1.199)	(0.920)
Tax deductions for individuals	-1.067	1.495	6.924**	-4.020*	-1.847	2.045
	(1.129)	(1.534)	(3.112)	(2.154)	(2.218)	(2.384)
Observations	1,055	1,064	449	442	1,055	1,064
R-squared	0.563	0.583	0.579	0.613	0.465	0.540

Notes: The data include the full unbalanced panel. All survival rates are multiplied by 100 so the coefficients can be read as percentage changes. All regressions include state and year fixed effects and state-level time trends. Case mix controls: recipient age, recipient gender, diagnosis = noncholestatic vs. other (livers), diagnosis=diabetes v. other (kidneys), live donor, and pediatric recipient. State-level clustered standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

Table 39: Tax and leave effects on quality - Kidneys

(Outcome = state-level survival rate)

	(1)	(2)	(3)	(4)
Survival time	Six months	Three years	Six months	Six months
Type of donor	All	All	Live	Cadaveric
Leave for state employees	-0.121	0.726	0.872	-0.516
	(0.478)	(0.786)	(0.955)	(0.657)
Leave for private employees	-0.0557	-0.780	0.847	-0.590
	(0.950)	(1.647)	(1.214)	(1.371)
Tax credits for employers	-0.417	2.247	-0.366	-0.615
	(0.625)	(1.875)	(1.006)	(1.109)
Tax deductions for individuals	-0.429	-0.918	-0.140	-0.631
	(0.943)	(1.543)	(1.496)	(1.073)
Observations	1,071	969	1,021	1,071
R-squared	0.663	0.855	0.356	0.592

Notes: The data include the full unbalanced panel. All survival rates are multiplied by 100 so the coefficients can be read as percentage changes. All regressions include state and year fixed effects and state-level time trends. Case mix controls: recipient age, recipient gender, diagnosis = noncholestatic v. other (livers), diagnosis=diabetes v. other (kidneys), live donor, and pediatric recipient. State-level clustered standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

Table 40: Tax and leave effects on quality - Livers

(Outcome = state-level survival rate)

	(1)	(2)	(3)	(4)
Survival time	Six months	Three years	Six months	Six months
Type of donor	All	All	Live	Cadaveric
Leave for state employees	1.502	3.089*	-1.339	1.382
	(1.266)	(1.689)	(4.603)	(1.294)
Leave for private employees	0.895	-1.320	-8.292	1.758
	(2.223)	(3.928)	(13.57)	(2.411)
Tax credits for employers	1.910	0.236	-4.518	2.005
	(1.426)	(3.106)	(10.44)	(1.401)
Tax deductions for individuals	3.092	7.318*	1.747	1.639
	(3.556)	(3.981)	(21.92)	(3.992)
Observations	1,067	963	490	1,067
R-squared	0.534	0.652	0.428	0.527

Notes: The data include the full unbalanced panel. All survival rates are multiplied by 100 so the coefficients can be read as percentage changes. All regressions include state and year fixed effects and state-level time trends. Case mix controls: recipient age, recipient gender, diagnosis = noncholestatic v. other (livers), diagnosis=diabetes v. other (kidneys), live donor, and pediatric recipient. State-level clustered standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$

Table 41: Legal references

State	References
Alaska	HB 252
Arkansas	A.C.A. § 11-3-205; HB 2779; A.C.A. §21-4-215; HB 1393
California	Cal Ed Code §89519.5; Cal Lab Code §1510
Colorado	CRS 24-50-104; HB 1250
Connecticut	SB 1447; Conn Gen Stat § 17b-288; SB 327
Delaware	14 Del. C § 1318B; 29 Del. C. § 5122;
Georgia	OCGA § 47-7-27; OCGA § 45-20-31
Hawaii	HRS §78-23.6
Idaho	Idaho Code §59-1608; Idaho Code §63-3029K; Idaho Code §67-5343
Illinois	HB0324
Indiana	2002 Ind. PL 94
Iowa	Iowa Code §422.7; Iowa Code §70A.39
Kansas	Exec Order No. 2001-02
Louisiana	La RS 47:297; La RS 47:287.758; 1992 HB 428
Maine	26 MRSA §843
Maryland	Md State Personnel and Pensions Code Ann §9-1106
Massachusetts	ALM GL ch 62, §3; 2005 Acts Chapter 99 §1.33E
Minnesota	Minn Stat §181.945; Minn Stat §181.9456; S.F. No. 2840
Mississippi	Miss. S.B. 2981; Miss Code Ann §27-7-18; Miss Code Ann §25-3-103
Missouri	HB 679 (2001)
Nebraska	RRS Neb §71-4820; 1992 Neb LB 1099
New Mexico	NM Stat Ann §24-28-3; NM Stat Ann §7-2-36
New York	NY CLS Labor §202-b; NY CLS Tax §612
North Dakota	SB 2298, Ch 476; ND Cent Code §57-38-30.3
Ohio	ORC Ann 5747.01; ORC 124.139
Oklahoma	68 Okl St §2358; 74 Okl St §840-2.20B
Oregon	ORS §659A.312; ORS §315.604
Pennsylvania	35 PS §6120.2; 35 PS §6120.3
Rhode Island	2009 RI SB 76
South Carolina	S.C. Code §8-11-65; S.C. R. 61; 2005 SC R 373; 1992 S.C. R. 642
Texas	Tex Govt Code §661.916
Utah	Utah Code Ann §59-10-1015; Utah Code Ann 1953 §67-19-14.5; 2002 Ut. SB 125
Virginia	Va Code Ann §2.2-2821.1; Va Code Ann §58.1-322
Washington	Exec Order 02-01
West Virginia	W.Va Code §29-6-28
Wisconsin	2003 AB 477; Wis Stat §71.05; Wis. Stat §230.35