Externalities from Medical Innovation: Evidence from Organ Transplantation*

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Abstract

We evaluate the introduction of direct-acting antiviral (DAA) therapy for hepatitis C (HCV) on liver transplant allocation in the United States. We hypothesize that DAAs obviate the need for transplant for some HCV-positive patients, which shortens the waiting list, potentially benefiting HCV-negative registrants and inducing marginal HCV-negative patients to register. Using data from the universe of transplants between 2005 and 2019, we find that DAA availability resulted in an additional 5,682 liver transplants to HCV-negative end-stage liver disease patients between 2014 and 2019, generating a positive externality of $7.52 billion. Our result is driven in part by a 37% average annual increase in HCV-negative waiting list registrations. In the absence of this behavioral response, DAA therapies would have eliminated the liver transplant waiting list.

Keywords: Medical Innovation, Externalities, Liver Transplantation; Direct-Acting Antivirals

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1 Introduction

The value of medical innovations partly relies on the incentives they generate. Across most health conditions, medical innovation is enormously valuable (Dranove et al., 2022; Hall & Jones, 2007; Murphy & Topel, 2006; Cutler & McClellan, 2001; Newhouse, 1992). However, an important contribution of economics has been to identify instances where innovation-generated incentives shift behavior that aligns with, or works against, their direct social welfare implications. For example, Papageorge (2016) shows that a significant benefit of HIV treatments (HAART) was to raise productivity and increase labor supply. Conversely, Kaestner et al. (2014) present evidence of technological substitution away from diet and exercise when statin medications were introduced to lower cholesterol. Medical innovation may also shift incentives (and subsequent behaviors and outcomes) for individuals who are not their primary beneficiaries. We refer to such instances as *innovation-induced externalities*. Especially in cases where new innovations are extremely costly relative to existing technology, valuing innovation-induced externalities may influence payer coverage decisions and research and development investment choices (Chernew & Newhouse, 2011; Philipson, 2000; Fendrick et al., 1996).

In this paper, we quantify the innovation-induced externalities associated with the recent introduction of a breakthrough medical treatment that dramatically improved health outcomes. Specifically, in December 2013, the Food and Drug Administration approved sofosbuvir, a direct-acting antiviral (DAA), for the treatment of chronic hepatitis C (HCV). Prior to the availability of DAAs, HCV was the leading cause of infectious-disease-related death in the United States and accounted for nearly half of all liver transplant waiting list registrations (Powell et al., 2019). However, DAA therapy, which achieves sustained viral clearance rates in over 90% of HCV patients, mechanically reduces liver demand to the extent that, for many, therapy obviates the need for a transplant. We conceive of those with end-stage liver disease (ESLD) resulting from conditions *other* than HCV (e.g., alcohol-associated liver disease, nonalcoholic steatohepatitis, etc.) to be external to the market for HCV pharmaceuticals, and we quantify the innovation-induced externalities to these individuals resulting from DAA-induced changes in the demand for livers.

We study the universe of patients wait-listed for a liver transplant between 2005 and 2019 from the Scientific Registry of Transplant Recipients (SRTR). The raw data highlight several clear implications of DAA availability. First, between 2014 and 2019, transplants to HCV^+ individuals declined sharply, while transplants to HCV^- individuals increased. As a result, the annual percentage of HCV^-

waiting list registrants who received a transplant increased from 33% in 2014 to 65% by 2019. Second, mirroring the transplant dynamics, during this period, the data indicate a sharp reduction in the number of HCV^+ individuals, and an increase in the number of HCV^- individuals, added to the liver transplant waiting list. Third, following DAA availability, both HCV^+ and HCV^- patients receiving a transplant were healthier at the time of transplant, as measured by the Model for End-Stage Liver Disease (MELD) score. Finally, the data indicate an overall increase in liver transplants from 2014 through 2019 (see Figure 1). While we focus on demand-side responses to DAA availability, this increase in liver transplants can only be explained by an increase in the supply of organs available for transplant, and we examine several potential explanations for this supply increase, including waiting list registrants' increased willingness to accept HCV^+ organs in the post-DAA era. The raw data suggest considerable welfare improvements to both HCV^+ and HCV^- individuals resulting from the availability of DAAs: many HCV^+ patients were cured of liver disease, and both marginal and inframarginal HCV^- patients gained access to livers.

While trends in the raw data imply significant innovation-induced externalities to HCV^- individuals with ESLD, our main parameter of interest is the number of new transplants to HCV^- individuals resulting from DAA availability. That is, the relevant counterfactual is the trend in HCV^- transplants in the absence of DAAs. Changes in descriptive trends may be due to DAAs, but they may also be due to concurrent shocks, such as the rise of fentanyl, which significantly increased HCV transmission, opioid overdose deaths, and the supply of transplantable organs (Dickert-Conlin et al., In press; Maclean et al., 2021; Powell et al., 2019), or by the full implementation of the Affordable Care Act, which expanded health insurance coverage and increased transplant wait-listing (Lemont, 2023). To address these concurrent shocks, our identification strategy compares trends in HCV^- liver transplants and wait-listing behaviors before and after the introduction of DAAs to similar trends for kidneys. The basis for this approach is that a comparison between liver and kidney behaviors and outcomes will net out common shocks to the demand and supply of organs for transplant, leaving changes induced by DAAs. Threats to the validity of our research design primarily involve spillovers from DAA availability to kidney waiting list registrants, but we show extensive evidence that spillover effects are negligible in our setting.

Using a traditional difference-in-differences (DiD) design, we estimate a 35.8% average annual increase in HCV^- liver transplants and a 39.1% decrease in HCV^+ liver transplants following the availability of DAAs, representing a total of 5,682 additional transplants to HCV^- individuals with ESLD from 2014 through 2019. We show that many newly transplanted HCV^- individuals would

have remained unlisted had they not been induced to join by the reduction in demand from HCV^+ individuals; our estimates imply an average annual increase in HCV^- waiting list registrations of 37% following the introduction of DAAs. Combined with an estimated reduction in HCV^+ waiting list registrations of 45%, we conclude that DAA availability would have eliminated the liver transplant waiting list had marginal HCV^- patients not been induced to join. Lending further credence to our research design, our estimates of the externality effect of DAAs on HCV^- transplants and waiting list registrations are larger in areas with higher baseline HCV rates.

Because many HCV^+ patients were cured of liver disease, additional HCV^- transplants did not crowd-out HCV^+ transplants, and so these gains added to the overall welfare benefits of DAAs. Under standard value of life assumptions, and assuming an additional 10.1 life-years per transplant (Rana et al., 2015), the net value of the additional 5,682 HCV^- transplants amounts to $1.25 billion per year, or $7.52 billion in total from 2014 through 2019. This calculation also depends on characteristics of the marginal HCV^- patient to be transplanted. We show that the time from wait-listing to transplant for HCV^- patients declined by 16% following the introduction of DAAs. Indeed, examining transplant rates conditional on listing, we find that the growth in HCV^- transplants outpaced the growth in waiting list demand, which suggests more frequent and/or earlier liver offers for HCV^- individuals. Furthermore, interrupted time series estimates suggest that the average MELD score at transplant for HCV^- recipients fell (improved) by three points (12.8%).[1] Both of these findings suggest our externality estimate represents a lower bound, as healthier patients will likely live longer post-transplant. We also detect a composition shift in the causes of liver disease among HCV^- patients joining the waiting list. In our data, the proportion of HCV^- registrants with alcohol-associated liver disease (ALD) increased following DAAs, which may affect expected longevity and thus our value estimate. However, this composition effect does not explain the increase in HCV^- waiting list registrations — using National Health and Nutrition Examination Survey (NHANES) data, we show that the prevalence of ALD in the population was flat from 2014 through 2018. In summary, we conclude that DAAs represented an innovation-induced externality that equates to roughly 11.5% of the total potential HCV^+ therapeutic market as of 2014.

We also conclude that the reallocation of livers from HCV^+ to HCV^- individuals resulted largely from an endogenous change in the HCV composition of the waiting list. Prior studies suggest that there was considerable room for such endogenous listing, as rates of waiting list referrals are quite low,

[1] Because MELD score is specific to liver disease, we cannot derive difference-in-differences estimates of MELD score at transplant relative to kidneys.

even among qualified ESLD candidates.[2] Furthermore, prior work has documented strategic behavior in organ transplant markets (Sweat, 2023; Agarwal et al., 2021, 2018; Zhang, 2010). A key finding of these studies is that organ allocation simulation models that ignore strategic behavior generate biased predictions. For example, our estimate of the positive externality to HCV^- liver transplant recipients resulting from DAAs is larger than the estimate from an epidemiological simulation model that did not account for behavioral listing responses (Jena et al., 2016). Our results also complement prior studies that have documented a wait-listing response to organ supply shocks including the opioid epidemic and the repealing of state motorcycle helmet laws (Dickert-Conlin et al., In press, 2019; Fernandez et al., 2013). However, unlike these studies, our analysis focuses on the implications of a demand shock (i.e., reduced demand for liver transplant among HCV^+ individuals and increased demand among HCV^- individuals) rather than a supply shock. This difference is notable in that behavioral responses to a negative demand shock can provide insight into potential effects of a broader reduction in the demand for organs if alternative treatments for conditions contributing to organ failure were to be developed (e.g., improved hypertension control or diabetes treatment reducing demand for kidneys).

Our study contributes to the larger literature on technological innovation by modeling and estimating behavioral responses to treatment innovations (Baranov et al., 2015; Peltzman, 2011; Dow et al., 1999), and adds to recent examples of innovation-induced behavioral responses, including statin medications and diet and exercise (Kaestner et al., 2014), HAART therapy and risky sex (Papageorge, 2016; Chan et al., 2015), cancer treatments and labor supply (Jeon & Pohl, 2019), immunization and disease screening (Moghtaderi & Dor, 2021), and immunotherapy and life insurance (Koijen & Van Nieuwerburgh, 2019). Our findings also contribute to the literature that has examined technological change in medical and pharmaceutical treatments, its impacts on value, and whether the surplus generated by that change has primarily been captured by the innovators or by consumers (Hult & Philipson, 2023; Jena & Philipson, 2008). For example, Hult et al. (2018) found that, among the more than 6,000 innovations they studied, 68% of new technologies had higher quality-adjusted prices than the incumbent technologies they sought to replace. Dunn et al. (2023) reported similar findings and concluded that much of the total surplus generated by pharmaceutical innovation accrues to innovators rather than consumers but pointed to DAAs for HCV treatment as a clear

[2]For example, Goldberg et al. (2016) found the 3-year incidence rate of wait-listing to be 15.8% among privately insured ESLD patients who met the clinical guidelines to join the waiting list and 10.0% among those with Medicaid coverage. Further, conditional on receiving an evaluation, between 30%–50% of candidates do not end up joining the liver transplant waiting list (Jesse et al., 2019; Bryce et al., 2010, 2009).

exception. Our results imply that, in addition to the surplus captured by those treated with DAAs, welfare gains also extended to HCV^- individuals with ESLD — consumers who were not the direct beneficiaries of the technological innovation, and whose gains are not considered in current estimates of DAA cost-effectiveness.

Specialty drugs, like those we study, have been responsible for driving the largest increases in pharmaceutical spending and have strained the budgets of public payers (ASPE, 2022; Hernandez et al., 2019). Our estimate of the innovation-induced externality of DAAs to HCV^- individuals changes the benefit-cost ratio from a public-payer perspective. Valuing externalities may also play an important role in generating new ideas and innovations (Dranove et al., 2022), where pharmaceutical revenue models have moved away from relying on "blockbuster" medications and toward higher-cost drugs with smaller patient populations (van der Gronde et al., 2017; Song & Jeung-Whan, 2016).

Finally, looking forward, two states in the U.S., Louisiana and Washington, have adopted innovative subscription models to finance DAA medications for their Medicaid and incarcerated populations, with policymakers in other states expressing interest in similar arrangements (Auty et al., 2022). The Biden administration has also recently introduced the "National Hepatitis C Elimination Program," which provides significant funding for the diagnosis and treatment of HCV (Fleurence & Collins, 2023). Our findings suggest that these programs, aimed at expanding access to DAA therapies, will significantly benefit HCV^- individuals with ESLD.

2 Background

2.1 Hepatitis C and Treatment Innovation

HCV is a chronic viral infection that leads to cirrhosis of the liver and its complications, including hepatocellular carcinoma (Kamal, 2008). Approximately 2.5 million people are living with HCV in the U.S., and prevalence rates have tripled over the past decade, largely as a consequence of the opioid epidemic and increased intravenous drug use (Powell et al., 2019; Zibbell et al., 2018). Traditional treatments for HCV have had limited effectiveness and are associated with debilitating side effects (Burstow et al., 2017). However, in December 2013, the Food and Drug Administration (FDA) approved sofosbuvir for the treatment of HCV. Sofosbuvir is a DAA that inhibits the replication of HCV's viral RNA and has shown a high resistance barrier. During the following year, three new DAAs were approved for HCV treatment, and since then, treatment with a combination of sofosbuvir (a NS5B protein inhibitor) and NS5A protein inhibitors has vastly improved sustained viral response

in HCV^+ patients (Burstow et al., 2017).

The 2013 FDA approval of the DAA NS5B inhibitor sofosbuvir and the 2016 approval of a sofosbuvir/velpatasvir regimen marked a new era for HCV treatment (Burstow et al., 2017). With cure rates approaching 100%, DAAs are now the frontline recommendation for treating HCV. They are also widely considered to be cost-effective (Dunn et al., 2023; Chhatwal et al., 2017; He et al., 2017). However, despite these benefits, the high cost of DAA medications has led to significant barriers to access (Henry, 2018). Though the actual price paid for medications such as DAAs depends on a variety of factors, the wholesale acquisition cost (i.e., list price) of a 12-week course of sofosbuvir treatment was $84,000 after its initial approval in 2013 (Roshenthal & Graham, 2016). By 2019, the median price for a course of DAA treatment fell to approximately $37,000 as competing medications were introduced. The high cost associated with DAA treatment, along with the fact that many of those living with HCV are unaware of their disease, have led to projections of sustained HCV disease prevalence in the era of DAAs (Chhatwal et al., 2016). In fact, despite the introduction of a curative therapy for HCV, U.S. deaths attributed to the virus in 2018 (3.7 per 100,000) had declined only modestly from 2013 levels (5.3 per 100,000) (CDC, 2020).

2.2 Hepatitis C, Wait-Listing, and Liver Transplant

Between 15% and 30% of those with an HCV infection experience spontaneous viral clearance (Kamal, 2008). However, for those who cannot clear the virus on their own, HCV becomes a chronic illness. Delaying treatment for HCV has serious health consequences (Erman et al., 2020). Left untreated, chronic HCV can lead to cirrhosis and its complications, eventually necessitating liver transplant (Zoulim et al., 2003). In fact, prior to the availability of DAAs, HCV was the leading cause of infectious-disease-related deaths in the United States (Powell et al., 2019) and accounted for nearly half of all liver transplant waiting list registrations.

Joining the liver transplant waiting list requires prospective candidates to first be referred to a transplant center where they undergo a thorough medical workup along with an evaluation of financial and psychosocial factors, including degree of social support, psychiatric illness, and whether the candidate uses alcohol, tobacco, or other substances (Wahid et al., 2021). While the process from evaluation to listing is informed by practice guidelines, transplant centers have latitude in how they evaluate candidates and assess transplant risk, with the center's transplant team ultimately responsible for waiting list determinations (Martin et al., 2014). Prior studies have documented low rates of evaluation referrals and wait-listing among qualified ESLD candidates, including Goldberg

et al. (2016) which reported the 3-year incidence rate of wait-listing to be 15.8% among privately insured ESLD patients who met the clinical guidelines to join the waiting list and 10.0% among those with Medicaid coverage. Of those who are evaluated for the waiting list, between 30%–50% of candidates fail to join (Jesse et al., 2019; Bryce et al., 2010, 2009).

Within three years of wait-listing, more than 10% of liver transplant candidates will die before receiving a transplant and 20% will be removed from the waiting list without undergoing transplant—primarily due to their disease progressing to the extent that they are no longer viable transplant candidates (Kwong et al., 2020). Nearly 30% of those receiving a liver transplant will experience graft failure within five years. Further complicating these issues is that untreated HCV leads to universal recurrence of infection after transplant, potentially resulting in graft loss and necessitating re-transplantation (Ciesek & Wedemeyer, 2012). HCV has historically limited the supply of transplantable livers as HCV^+ livers were commonly discarded (Levitsky et al., 2017). However, since the introduction of DAAs, there has been a shift toward more frequent transplantation of HCV^+ livers, and patients have shown an increased willingness to accept an HCV^+ liver (Kwong et al., 2020; Axelrod et al., 2018).

2.3 Conceptual Framework

To motivate our empirical work, we envision a simple discrete time model of a representative end-stage liver disease patient/physician team.[3] Each period of the model contains two stages. In the second-stage, conditional on being on the liver transplant waiting list, the probability that the patient receives an offer of a liver for transplant is a function of their health and the number of waiting list patients ahead of them on the list. Conditional on receiving a liver offer, the patient must decide whether to accept or refuse the organ for transplant. A patient may refuse an offer of a liver if they believe that they will receive an offer of a higher quality liver in the future. In the first-stage of a given period, clinically eligible liver patients must decide whether to join the waiting list. Because between 40% and 50% of those referred to transplant evaluation report concern over affording the costs of travel, visits, and testing (Harding et al., 2021; Dageforde et al., 2015), waiting list participation is a repeated choice (i.e., each period) even if the patient was previously on the list. The model takes the form of an optimal stopping problem conditional on being wait-listed for an organ, where the decision to join the waiting list is endogenous. In this sense, the model aligns with the framework of Howard

[3](Agarwal et al., 2020) highlight important agency issues faced by the patient/physician team, which we abstract from here.

(2002), who focuses on the decision to accept an organ offer, and Agarwal et al. (2021), who develop methods for evaluating alternative mechanisms with respect to efficiency and equity. The common thread in all these models is that individuals are allowed to endogenously respond to changes in the environment.

In our case, the change in the environment is a dramatic and curative innovation for a subset of individuals on the waiting list. DAAs cause both HCV^+ attrition from the waiting list and stem the flow of new HCV^+ registrants to the waiting list because the prevalence of HCV falls in the population. The implications are a shorter waiting list and a list whose composition shifts towards HCV^- registrants. For a given supply of organs, liver transplant offers increase for HCV^- registrants, and, as a direct result, the value of wait-listing increases for marginal HCV^- ESLD patients. The model clarifies the mechanisms by which DAAs will affect the welfare of HCV^+ and HCV^- individuals with liver disease. It highlights that changes in *levels* of equilibrium transplants will depend on the endogenous listing behavior of each group. This suggests that regressions of equilibrium transplant levels, which depend on both transplant acceptance probabilities and waiting list enrollment decisions, may generate different results than regressions of equilibrium transplant rates, which are conditional on waiting list size. Furthermore, the model highlights how HCV^- individuals, who are external to the market for DAAs, may still be affected by their introduction. That is, while the health of HCV^- individuals is not directly affected by DAAs, transplant offers change because of the direct health effects to HCV^+ individuals, and changes in transplant offers change HCV^- listing behavior.

Our data are well-suited to capture these changes. In what follows, we document raw trends in liver transplants and waiting list additions. We also describe changes in the health composition of the liver transplant waiting list by examining trends in MELD scores, time from listing to transplant, and waiting list exits due to condition improvement or death. Finally, our data also allow us to investigate an unmodeled, but potentially important, dynamic in the willingness of waiting list registrants to accept an HCV^+ liver for transplant. DAA availability may result in an increase in the supply of donors, and shift candidate preferences such that HCV^+ livers become more attractive, which would affect the number of livers available for transplant. The implication of such a change would be to increase liver offers, allowing for greater selectivity among transplant candidates. Following our presentation of the raw data, we present plausibly causal evidence on the comparative dynamics suggested by our theory from a research design in which we compare trends in liver transplant waiting list behavior and transplant outcomes to similar trends for kidneys.

3 Data and Descriptive Trends

3.1 Data Description and Summary Statistics

We use data from the Scientific Registry of Transplant Recipients (SRTR) from 2005 to 2019.[4] SRTR collects individual-level data on the universe of organ transplant waiting list registrants, donors, and transplant recipients from the United Network for Organ Sharing (UNOS) (Wright, 2022).[5] Using the SRTR data, we can calculate changes to the extensive margin of the liver transplant waiting list, including the number of registrants currently wait-listed and the number of those added and removed from the waiting list. We can also observe waiting list registrant characteristics including age, sex, race, ethnicity, source of insurance coverage, and the donation service area (DSA) where each registrant wait-lists.[6] In addition, the data allow us to track the severity of registrants' liver disease through their MELD score, where a higher score indicates a higher mortality risk. Throughout the analysis, we exclude individuals younger than 18 years at time of wait-listing or receiving a transplant since minors face different allocation rules and procedures than adults.

While the SRTR data do not allow us to observe HCV status at the time of waiting list registration, they do include HCV status determined by an antibody test for those receiving a transplant. We use this information to infer the HCV status of waiting list registrants by examining the prevalence of primary diagnosis codes commonly found among HCV^+ but not HCV^- liver transplant recipients, and vice versa. For example, 59% of HCV^+ transplant recipients have a diagnosis of "cirrhosis: type C" (SRTR code 4204) compared to only 2.2% of HCV^- recipients. Similarly, "alcoholic cirrhosis with hepatitis C" (SRTR code 4216) is observed in 13.3% of HCV^+ transplant recipients and only 0.6% of HCV^- recipients. Conversely, "cirrhosis: fatty liver (NASH)" (SRTR code 4214) is found among 14.3% of HCV^- transplant recipients compared to only 0.6% of HCV^+ recipients. Likewise, "alcoholic cirrhosis" (SRTR code 4215) is present in 26.7% of HCV^- transplant recipients and only 3.5% of HCV^+ recipients. We take a conservative approach and classify a diagnosis code as HCV-

[4] The SRTR data system includes data on all donors, waiting list registrants, and transplant recipients in the U.S., submitted by the members of the Organ Procurement and Transplantation Network (OPTN). The Health Resources and Services Administration of the U.S. Department of Health and Human Services provides oversight to the activities of the OPTN and SRTR contractors.

[5] A small number of people receive a liver transplant without being wait-listed. Our transplant measure includes those receiving a transplant whether they are wait-listed or not.

[6] Due to changes over time in the existence and services of certain DSAs, we use modified DSA identifiers throughout our analyses and proceed in three steps. First, we combine the Sierra Donor Services DSA into the Donor Network West DSA in California since Sierra Donor Services ended their liver program in 2008/2009 and was geographically entirely surrounded by Donor Network West. Second, the Mississippi Organ Recovery Agency began operating in 2013, so we combine that DSA with their pre-existing contiguous DSAs in Tennessee and north Mississippi, Louisiana, and Alabama. Third, because Lifelink of Southwest Florida ended in 2004, OurLegacy in Florida started in 2007, and Lifelink Puerto Rico started in 2012, we combine all Florida and Puerto Rico DSAs into one DSA unit.

related if its rate of occurrence among HCV^+ transplant recipients is at least four times greater than its rate of occurrence among HCV^- recipients, and vice versa. After assigning registrants based on their primary diagnosis codes, we identify additional HCV^+ waiting list registrants using an optional diagnosis text description field. The strings in this description field include terms such as "HCV," "Hepatitis C," "Hep C," as well as variations that may include periods, dashes, slashes, or minor typos.[7] Although we know the actual HCV status of transplant recipients, for consistency, we use inferred status in all regression analyses. In practice, our estimates using inferred HCV status are likely to be conservative, since we expect that misidentifying some HCV^+ individuals as HCV^- and vice versa would bias our estimates toward zero.[8] Also, since HCV antibodies remain even after achieving viral clearance, we are able to use HCV antibody status at time of transplant to assess whether our HCV^- classification might capture those with a cured HCV infection, thus potentially overstating DAA-associated changes in HCV^- wait-listing. We find no evidence of this. For example, in 2014, 99 (3.2%) of the 3,128 liver transplant recipients that we categorized as HCV^- based on diagnosis codes tested positive for HCV antibodies at the time of transplant, compared to 206 (3.3%) of the 6,180 liver transplant recipients categorized as HCV^- in 2019. For approximately 15% of waiting list registrants, neither the diagnosis code nor the text description allow us to assign an HCV status, so we exclude those individuals from our analyses.

Table 1 presents descriptive statistics for liver transplant waiting list registrants by HCV status and over time. Waiting list registrations among HCV^+ individuals with ESLD dropped from an average of 3,896 per year (35,068 total) over the 9 pre-DAA years in our sample to an average of 2,405 per year (14,431 total) across the 6 post-DAA years. The number of waiting list removals and transplants among HCV^+ registrants also dropped after DAAs became available, from 4,017 per year (36,157 total) to 2,984 per year (17,901 total). In contrast, yearly waiting list registrations, removals, and transplants increased among HCV^- individuals with ESLD, going from 5,191 to 7,804 average yearly listings, and from 5,163 to 7,776 average yearly removals and transplants. The most common outcome of the wait-listing process is a transplant from a deceased donor, followed by removal from the waiting list due to condition deterioration or death. For both HCV^+ and HCV^- registrants, the probability of removal due to condition deterioration or death fell in the period following DAA availability, while removal due to condition improvement increased. MELD scores indicate that, on

[7] Using this approach, 1,804 additional registrants (roughly 120 per year) can be flagged as HCV^+ relative to the 93,547 registrants (roughly 6,236 per year) who are identified as HCV^+ or HCV^- using only their diagnosis code.

[8] For example, our coefficient estimate of the effect of DAA availability on transplants to HCV^- recipients is 0.31 log points using inferred HCV status versus 0.37 log points when using actual HCV antibody status.

average, HCV^- registrants face a higher mortality risk than HCV^+ registrants. Due in part to the lower average MELD score for HCV^+ registrants, the time from listing to transplant is longer for those with HCV. The descriptive statistics indicate an increase in time to transplant in the DAA era for HCV^+ registrants and a decrease for HCV^- registrants. The majority of waiting list registrants are privately insured, between the ages of 40 and 64, and live in the South census region.

3.2 Trends in Equilibrium Transplants and Liver Demand

Figure 1 shows the equilibrium number of liver transplants over our sample period, both overall and by HCV status. We see a clear trend break following the introduction of DAAs, as the total number of liver transplants increased from 6,190 in 2014 to 8,330 in 2019. This total increase in transplants reflects both a significant reduction in transplants to HCV^+ individuals (solid line) and a significant increase in transplants to HCV^- individuals (long-dashed line). To quantify changes in raw trends, we estimate a series of comparative interrupted time series (CITS) models. CITS is a more general form of the difference-in-differences design where each group is compared to its own baseline trend rather than to a counterfactual generated by an untreated group, and is appropriate in this case because, consistent with our behavioral model above, both HCV^+ and HCV^- waiting list registrants are potentially affected by the development of DAAs. We stress that this exercise is meant to be descriptive in nature — we do not interpret CITS estimates as causal effects, but they serve as useful benchmarks to which we will compare difference-in-differences estimates in later sections. A description of the CITS specification, as well as the full set of CITS results, can be found in Appendix Section 1 and Appendix Table 1.[9] From 2014 to 2019, the number of HCV^- liver transplant recipients increased by an average of 53.6% relative to their baseline trend, while the number of HCV^+ individuals receiving a transplant decreased by an average of 55.7%. Before 2014, approximately 30% of HCV^+ and HCV^- waiting list registrants received a liver transplant each year, and the trends in this outcome were flat for both groups; by 2019, the share of HCV^- registrants who exited the waiting list because they received a transplant stood at nearly 65%.[10]

Conceptually, changes in equilibrium transplants shown in Figure 1 reflect both changes in the demand and supply of livers. In Section 4.1.3, we return to the issue of how DAAs may have changed the supply of livers, but our primary statistical and econometric exercises focus on demand-side effects. To study the role of these effects on equilibrium levels of transplants, we begin by documenting trends

[9] When interpreting the magnitudes of the changes implied by the coefficient estimates from logged outcome models, we use the following calculation: $\%\Delta = 100 \times (e^{estimate} - 1)$.

[10] We present trends in transplant rates in Appendix Figure 2.

in waiting list additions and removals. Figure 2a presents trends in the number of liver transplant waiting list registrants, both overall and by HCV status. Between 2005 and 2012, both the size and HCV composition of the waiting list were relatively flat and stable. From 2013 to 2019, the total waiting list count fell from 16,738 to 13,911 registrants, and the composition of the waiting list shifted toward HCV^- registrants. Changes in waiting list size could be driven by the changes in transplant volume documented in Figure 1, but they could also result from changes in the flow of patients to the list. Indeed, because Figure 2a shows a decline in the size of the list, our model predicts that marginal ESLD patients will be induced to join the list. Figure 2b shows that following the introduction of DAAs, waiting list additions for HCV^+ registrants sharply declined, while additions for HCV^- registrants increased. The estimates from our CITS models indicate an average increase in waiting list additions of 22.6% from 2014 to 2019 for HCV^- registrants and an average decrease of 51.4% for HCV^+ registrants relative to each group's baseline mean.

In addition to changes in transplants, the change in the health composition of the waiting list is also important because it potentially affects the value of the average transplant in terms of graft survival. To examine changes in the health composition of the waiting list, Figure 3a shows the average last MELD score prior to transplant for both HCV^- and HCV^+ waiting list registrants. Average MELD scores at transplant were rising (i.e., worsening health) for both HCV^+ and HCV^- registrants between 2005 and 2013. HCV^+ registrants saw steep declines in average MELD scores at transplant coinciding with the introduction of DAAs, while the growth rate in average MELD score at transplant for HCV^- registrants fell at a slower rate. Evidence in Figure 3a could reflect a selection of healthier patients on the waiting list, or it could reflect shorter waiting times from listing to transplant. In Figure 3b, we present the mean initial MELD score upon listing for both HCV^- and HCV^+ waiting list registrants. The mean initial MELD score for HCV^- registrants rises slightly through the introduction of DAAs, whereas it falls from roughly 17 to 15 for HCV^+ patients. For both transplant and listing, we present CITS estimates of changes in MELD scores associated with the introduction of DAAs in Appendix Table 2. These results are consistent with health improvements for both HCV^+ and HCV^- patients at the time of transplant and for HCV^+ patients at the time of listing.[11]

[11] We also track trends in waiting list attrition due to condition deterioration/death and condition improvement before and after the introduction of DAAs. The likelihood of leaving the waiting list because of deteriorated condition or death was increasing for both groups through 2013 before declining once DAAs became available (Appendix Figure 1a and Appendix Table 3). HCV^- registrants were consistently more likely to leave the waiting list due to condition improvement compared to HCV^+ registrants in the pre-DAA period, but this relationship reversed shortly after the introduction of DAAs (Appendix Figure 1b and Appendix Table 3).

There are several key takeaways from the patterns we observe in transplant, wait-listing behaviors, and the health composition of liver waiting list registrants. We document an increase in the number of liver transplants following the introduction of DAAs that is driven entirely by HCV^- recipients. We also see significant reductions in both the number of HCV^+ waiting list registrants and transplants to HCV^+ recipients. These patterns highlight the extent of the positive externalities of DAA development that have accrued to HCV^- individuals with ESLD. Namely, reduced demand for livers from HCV^+ individuals has resulted in greater organ availability for HCV^- individuals. Therefore, we conclude that the post-DAA growth in HCV^- liver waiting list registrants is primarily a function of marginal candidates entering the waiting list (i.e., individuals who likely would not have wait-listed in the absence of DAA-induced changes to the value of listing). This interpretation is supported by higher post-DAA MELD scores at the time of listing for HCV^- registrants and by prior research which has found that fewer than half of those who met the clinical guidelines to join the liver transplant waiting list actually did prior to DAAs (Jesse et al., 2019; Goldberg et al., 2016; Bryce et al., 2010, 2009). Further, HCV^- waiting list registrants were more likely to suffer from ALD in the post-DAA period and those with ALD comprised the bulk of new waiting list additions (see CITS evidence by diagnosis category in Appendix Table 4). Evidence indicates that physicians are less likely to refer ALD patients to the waiting list relative to other diagnosis categories and that pre-DAA rates of liver transplant wait-listing among those with ALD were as low as 5% (Leong & Im, 2012). Finally, lower average MELD scores for HCV^- recipients at the time of transplant, likely due to shorter times from wait-listing to transplant (see Appendix Figure 7 and Appendix Table 5), have implications for graft survival and the benefits associated with transplant. We return to this point later in our discussion of the value of the innovation-induced externalities generated by DAAs in Section 5.

4 Research Design: Comparing Trends in Livers and Kidneys

While trend estimates imply substantial gains to HCV^- individuals with ESLD associated with the timing of DAA introduction, the lack of a comparison group that is unaffected by the availability of DAAs could limit our ability to address potential sources of confounding. For example, a supply shock to the liver transplant waiting list concurrent with the introduction of DAAs is the increase in the availability of transplantable organs associated with the rising number of drug overdose deaths (see Appendix Figure 4). From 2014 to 2019, drug overdose deaths from synthetic opioids, including

fentanyl, increased by an average of 58% per year compared to an average increase of 12% per year between 2005 and 2013, leading to an estimated 25,000-plus additional organ transplants (Dickert-Conlin et al., In press). Similarly, the Affordable Care Act's Medicaid expansions, which 26 states and Washington D.C. adopted in 2014, led to increased organ waiting list registrations (Lemont, 2023). CITS models are unable to distinguish between concurrent shocks, and thus return the combined effect of DAAs and drug overdose deaths or health insurance gains on changes in transplant and waiting list registration.

To separately identify the impact of DAAs from concurrent shocks, we estimate a traditional difference-in-differences (DiD) design that compares equilibrium liver transplants and liver demand (i.e., waiting list additions) for both HCV^+ and HCV^- individuals to similar outcomes and behaviors for end-stage renal disease (ESRD) patients before and after the introduction of DAAs. To the extent that secular trends in the supply or demand for transplantable organs are reflected similarly among HCV^- liver waiting list registrants and those on the kidney waiting list, the DiD strategy will improve our ability to isolate the reallocation effects of DAAs on the listing behaviors and outcomes for HCV^- registrants and estimate the value of the innovation-induced externality. For example, Dickert-Conlin et al. (In press) shows that the opioid epidemic has led to a large increase in the supply of transplantable organs. However, since the magnitude of this supply shock was similar for livers and kidneys, our DiD models should difference out the influence of overdose deaths, allowing us to isolate the effect of DAAs. Similarly, Lemont (2023) shows that Medicaid expansion was associated with comparable increases in both liver and kidney waiting list registrations (34% for livers and 38% for kidneys) and transplants (40% for livers and 50% for kidneys) for Medicaid beneficiaries.[12]

Data on equilibrium kidney transplants and waiting list additions also come from SRTR, and Appendix Table 6 provides descriptive statistics for these data.[13] For a comparison of liver and kidney trends to produce credible causal estimates of the effect of DAA availability on transplants and listing behaviors for HCV^- individuals with ESLD, baseline differences in outcomes between liver and kidney transplant recipients and waiting list registrants must remain stable over time in the absence of DAAs. While this parallel trend assumption is not directly testable, we provide suggestive evidence that it holds by plotting trends in equilibrium kidney and liver transplants and waiting list

[12] In a subsample of states yet to expand Medicaid by 2019, estimates of DAA effects on transplants and wait-listing behavior were similar to those from our full sample and are available upon request.

[13] We exclude known HCV^+ kidney transplant waiting list registrants based on optionally provided diagnosis text from our control group in all analyses, which amounts to only 0.13% of all kidney candidates from 2005 to 2019. For reference, HCV^+ kidney transplant recipients account for fewer than 5% of all recipients in our data based on antibody tests at the time of transplant. Because five kidney DSAs do not have a liver program, our sample includes 50 modified DSA identifiers for kidneys and 45 modified DSA identifiers for livers.

inflows in Figure 4. Because of the large level differences between liver and kidney transplants and waiting list registrations, we plot log trends in Figure 4 and use log outcomes in our DiD regression models. Trends in kidney transplants (Figure 4a) and waiting list additions (Figure 4b) track closely with trends in liver transplant and waiting list additions through 2013, providing no indication of a violation of the parallel trends assumption.

We estimate the following DiD specification separately for HCV^+ and HCV^- liver transplant recipients and waiting list registrants using kidney transplant recipients and waiting list registrants as controls:[14]

$$Y_{dlt} = \beta[\mathbb{1}(l = liver) \times DAA_t] + \gamma_{dl} + \eta_t + \epsilon_{dlt}, \tag{1}$$

where Y_{dlt} is the outcome for DSA d, organ $l \in \{liver, kidney\}$, in year t. The treatment effect of interest is β, which is the coefficient on the interaction between the indicator for liver (i.e., treated) or kidney (i.e., control) transplant recipient/waiting list registrant and DAA_t, the indicator for the post-DAA period (2014–2019). Finally, we include DSA-by-organ fixed effects γ_{dl}, year fixed effects η_t, and an idiosyncratic error term ϵ_{dlt} clustered at the DSA-by-organ level.

Table 2 contains our DiD estimates of the effects of DAA availability on liver transplants (columns 1 and 2) and liver transplant waiting list additions (column 3) for HCV^- individuals (Panel A) and HCV^+ individuals (Panel B). The estimates in columns 1 and 3 are from models where the dependent variables are measured in logs, while the estimate in column 2 is from a model where the dependent variable is defined as a fraction of the HCV-specific number of registrants on the waiting list (i.e., the transplant rate). Thus, estimates in column 2 effectively remove the influence of DAA-induced changes to waiting list inflows and outflows and provide an indication of how DAAs impacted transplants conditional on wait-listing.

Table 2, column 1 presents transplant estimates and underscores the substantial externality accruing to HCV^- individuals with ESLD seeking transplant as a result of DAA availability. Average annual liver transplants for HCV^- recipients increased by $100 \times (e^{0.3059} - 1) = 35.8\%$ relative to changes in kidney transplants from 2014 through 2019. Estimates in Panel B clearly show that the gains to HCV^- transplant recipients came from the reallocation of transplantable livers from HCV^+ individuals who no longer needed a transplant. We estimate that DAAs reduced average annual liver transplants for HCV^+ individuals by 39.1% relative to kidney transplants.

[14]We primarily report OLS estimates using logged outcomes throughout the paper. We also estimated Poisson regressions that generated virtually identical results that are available upon request.

Estimates of DAA-induced changes in HCV-specific transplant rates in Table 2, column 2 indicate that transplants to HCV^- recipients increased relative to the number of HCV^- waiting list registrants (16.0 percentage points, 31.6%). In other words, DAA-induced transplant gains to HCV^- recipients were (proportionally) larger than the net overall growth in waiting list additions, suggesting that HCV^- waiting list registrants were receiving more frequent and/or earlier liver offers. Consistent with this interpretation, we show in Appendix Figure 7 and Appendix Table 5 that the time to transplant for HCV^- patients declined by 16% following the introduction of DAAs. The transplant rate estimate for HCV^+ registrants in Panel B, column 2 is positive (5.8 percentage points, 11.4%) and, while not statistically significant at conventional levels, suggests that DAAs conferred modest benefits to HCV^+ individuals who remained on the waiting list. We interpret this finding as evidence that the large, estimated reduction in transplants to HCV^+ recipients in Panel B, column 1 was driven entirely by the reduction in transplant demand from HCV^+ individuals who were cured by DAA treatment.

Estimates of the effect of DAAs on liver transplant waiting list additions are presented in Table 2, column 3. DAAs increased HCV^- liver waiting list additions by an average of 36.8% relative to kidney waiting list additions from 2014 through 2019 and decreased HCV^+ liver waiting list additions by an average of 45.4%.[15]

We also estimate a time-disaggregated (i.e., event study) version of our DiD specification:

$$Y_{dlt} = \sum_{k=2005}^{2019} \beta_k [\mathbb{1}(l = liver) \times \mathbb{1}(t = k)] + \gamma_{dl} + \eta_t + \epsilon_{dlt}, \tag{2}$$

where the vector of the coefficient estimates, β_k, reflects the time-specific differences in outcomes between liver and kidney waiting list registrants and transplant recipients. We specify the baseline period as 2012 in our event study models so that we can detect any potential anticipatory effects occurring in 2013 as DAAs became available in December of that year. These estimates allow us to investigate whether there were any differential pre-intervention trends between liver and kidney transplant recipients and waiting list registrants as well as the dynamics of the treatment effects across the post-treatment periods.

Figure 5 presents event study estimates that correspond to the DiD transplant and wait-listing estimates in Table 2 (see Appendix Figure 3 for transplant rate event studies). Relative to kidney transplants and waiting list additions, Figure 5a shows a clear decline in liver transplants to HCV^+

[15] Our regression results are economically similar when we restrict our sample by dropping those patients observed to ever list for both a liver and a kidney.

recipients, and Figure 5b shows a clear decline in liver waiting list additions from HCV^+ individuals. In both cases, trends in the pre-DAA period were flat, with annual estimates growing monotonically over time from 2013/2014. Results are a mirror image for HCV^- individuals – both liver transplants (5c) and liver waiting list additions monotonically increase (Figure 5d), with little evidence of differential pre-trends. Our event study estimates imply that DAAs led to an additional 1,648 HCV^- people joining the liver transplant waiting list per year, on average, or 9,888 total HCV^- additions to the liver transplant waiting list from 2014 to 2019. On average, DAAs reduced HCV^+ liver transplant waiting list additions by 1,616 people each year for a total of 9,693 fewer HCV^+ additions to the liver transplant waiting list from 2014 to 2019.

Finally, we conduct a heterogeneity analysis that allows the effect of DAAs on transplants and wait-listing for HCV^- patients to vary by baseline DSA HCV prevalence. Technically, the regression specification is a triple differences strategy where we compare liver transplant recipients and waiting list registrants to kidney recipients/registrants and allow that comparison to vary by the baseline share of DSA transplant recipients testing positive for HCV. The intuition behind this approach is that the demand response to DAA availability from HCV^+ individuals with ESLD should be larger in areas with greater HCV prevalence, freeing more livers for transplant to HCV^- recipients listing in these areas. Table 3 presents these results for waiting list additions (Panel A) and log transplants (Panel B). Column 1 of Table 3, which we label the dose-response effect, shows clearly that both waiting list additions and transplants are increasing in the fraction of DSA transplant recipients with HCV. For every 10-percentage point increase in baseline transplant recipient HCV share, the effect of DAAs on HCV^- wait-listing and transplant increases by 13.7% and 13.1%, respectively. In Columns 2 and 3 of Table 3, we split our sample by baseline HCV rate and repeat our standard DiD analysis from Equation 1. Again, the evidence suggests a strong dose response; our estimates of the impact of DAAs on both HCV^- waiting list additions and transplants are significantly larger in the subsample of DSAs that are above the baseline HCV rate median.

4.1 Robustness

4.1.1 Concurrent Shocks

Our conceptual model suggests that the value of wait-listing for HCV^- individuals increases when the number of HCV^+ waiting list registrants falls, and so we expect to see increased HCV^-

wait-listing following the introduction of DAAs.[16] However, a competing explanation for the observed pattern in HCV^- wait-listing in Table 2 would be concurrent changes in the prevalence of non-HCV conditions leading to ESLD. To distinguish between these explanations, we first estimate changes in waiting list additions by leading non-HCV disease indicators for wait-listing including nonalcoholic steatohepatitis (NASH) and alcohol liver disease (ALD).[17] These estimates are included in Appendix Table 4 and indicate that HCV^- waiting list additions following DAAs are being driven by individuals with ALD. Second, we use data from the NHANES to track ALD prevalence rates among adults in the U.S. using established guidelines for identifying ALD (Younossie et al., 2011). Appendix Figure 5 plots the prevalence of ALD throughout our sample period, indicating a small uptick in 2015/2016 followed by a return to pre-DAA levels by 2017/2018.[18] So, while post-DAA additions to the liver transplant waiting list were predominantly driven by HCV^- registrants with ALD, this appears to be a compositional change that aligns with our discussion of DAA-induced wait-listing for "marginal" registrants in Section 3.2.

4.1.2 DAA Spillovers to Kidney Transplants

Another consideration of using characteristics of kidney transplant recipients and waiting list registrants to generate the counterfactual for our DiD models is that DAA effects may spill over to individuals with ESRD. This can happen in several ways. First, the availability of DAAs may increase the willingness of kidney transplant waiting list registrants to accept an HCV^+ organ. Second, individuals who are cured of HCV may become organ donors.[19] Third, those cured of HCV may become less likely to develop ESRD and join the kidney waiting list,[20] or if they already have ESRD, they may become healthy enough for a kidney transplant.

In Appendix Figure 6, we assess each of these potential spillover pathways through which DAAs could induce changes in the supply or demand for transplantable kidneys. Appendix Figure 6a shows

[16] The idea is that marginal HCV^- individuals are induced to join the waiting list due to the increased likelihood of a transplant associated with DAA availability and because of a reduced time from listing to transplant. Appendix Figure 7 plots trends in time from wait listing to transplant for HCV^- recipients and shows a steep decline following the introduction of DAAs. Estimates in Appendix Table 5 indicate that the time from wait-listing to liver transplant fell by 16.0%, on average, for HCV^- liver waiting list registrants compared to kidney waiting list registrants following the introduction of DAAs.

[17] An individual in our sample was considered to have NASH/ALD when NASH/ALD was listed as a primary diagnosis or when hepatocellular carcinoma was listed as a primary diagnosis with a secondary diagnosis of NASH/ALD.

[18] We cannot include NHANES data for 2019 in our ALD prevalence rate estimates as the 2019/2020 NHANES data collection was halted due to COVID-19.

[19] Using a simulation model and data from the United Kingdom, Jena et al. (2019) estimate that curing 240,000 cases of HCV and then implementing universal screening and treatment would lead to an additional 127 kidney transplants per year.

[20] This is because HCV potentially increases the risk for developing ESRD (Lee et al., 2014).

a clear increase in the willingness of both kidney and HCV^- liver transplant waiting list registrants to accept an HCV^+ organ. We take this as evidence of a similar demand response among kidney waiting list registrants to the availability of DAAs. Therefore, our DiD estimates will isolate the decreased demand for transplantable livers associated with DAAs for HCV^+ registrants and its effect on HCV^- individuals, excluding gains associated with increased willingness to accept an HCV^+ liver. As a result, our DiD analyses will represent lower bound estimates of DAA-induced externalities. Appendix Figure 6b examines whether DAAs affected the supply of kidneys available for transplant in the case where those newly cured of HCV became living kidney donors. Since HCV status is determined through an antibody test and antibodies remain even after achieving viral clearance, we can examine whether the number of living kidney donors with HCV antibodies increased following the availability of DAAs. The figure indicates a slight increase in donors with HCV antibodies from 2012 to 2013, just before DAA availability. However, the magnitude of this increase is quite small, representing approximately 20 additional living donors with HCV antibodies per year, or about 0.3% of all living donors. Appendix Figures 6c and 6d plot the log number of HCV^+ transplant recipients and the share of recipients who are HCV^+ for both livers and kidneys. If DAAs impacted demand for kidneys through improved health for those with ESRD, we would expect to see fewer HCV^+ kidney transplant recipients (similar to the effects for HCV^+ liver transplants). Instead, we see an uptick in the number of HCV^+ kidney transplant recipients in Appendix Figure 6c and no discernible change in the share of kidney transplant recipients who are HCV^+ from 2013 to 2019 in Appendix Figure 6d.

Finally, while the descriptive evidence in Appendix Figure 6a indicating an increased willingness to accept an HCV^+ liver is consistent with predictions from our conceptual model, the model developed in Howard (2002) also predicts that waiting list registrants will become more selective when demand from HCV^+ individuals falls and liver offers increase. We assess changing selectivity by estimating the effect of DAAs on livers discarded due to "poor quality" in Appendix Table 7.[21] Overall, the average annual number of livers discarded due to poor quality rose by 14.7% from 2014 through 2019 compared to kidneys (column 1) and the fraction of livers discarded increased by 2.4 percentage

[21] We define a discard as being due to "poor quality" based on disposition and discard codes in the SRTR deceased donor disposition file. One example is where authorization to recover an organ was not requested due to reason codes "Acute/Chronic Renal Failure" or "Donor Quality". Another example is where authorization was obtained but the organ was still not recovered due to reason codes such as "Poor Organ Function", "Infection", "Positive HIV", "Diseased Organ", and more. Finally, there are cases where the organ was recovered for transplant but discarded due to reason codes like "Too old on pump", "Vascular damage", "Donor medical history", "Warm ischemic time too long", "Poor organ function", "Infection", and so on. In constructing this indicator, we do not include cases where a recipient was not located, where the organ was refused by all programs, or other non-donor-quality codes such as "Other", "Surgical damage in OR", "No Local Recovery Team", "Medical Examiner Restricted", etc.

points (16%, column 2). Alternatively, estimates in column 3 of Appendix Table 7 show that there was no relative increase in the share of HCV^+ livers discarded due to poor quality following DAA availability. We interpret these results as suggestive evidence that transplant candidates became more selective after DAAs became available, but that HCV status was no longer viewed as a marker of poor organ quality.

4.1.3 Organ Supply Changes

To this point, we have focused our discussion on the demand-side effects of DAA availability, but equilibrium changes in transplants and waiting list additions could also be a function of changes in the supply of transplantable organs. Figure 6 plots the number of deceased donor livers and kidneys recovered for transplant separately by HCV status. Figure 6a shows a steep increase in HCV^+ livers and kidneys recovered for transplant beginning in 2014, which is likely driven by a combination of drug overdose deaths (which accrue disproportionately to HCV^+ individuals (Durand et al., 2018)) and an increased willingness among waiting list registrants to accept HCV^+ organs (see Appendix Figure 6a). Figure 6b shows much smaller relative increases in the supply of transplantable organs recovered from HCV^- donors beginning in 2014. More importantly for our identification strategy, the magnitudes of the increases in organ availability for both HCV^+ and HCV^- livers and kidneys are quite similar suggesting that estimates from our DiD models reflect demand-side changes in response to the introduction of DAAs.

4.1.4 Reconciling CITS and DiD Estimates

In Section 3.2, we discuss trends in liver transplants and waiting list inflows and outflows for those with and without HCV. To measure the magnitude of these trends compared to the baseline (i.e., pre-DAA) means, we use a CITS procedure, which is detailed in Appendix Section 1. We then present DiD estimates that assess the effect of DAAs on transplant and liver waiting list additions, using kidney transplant recipients and waiting list registrants as controls. We now compare the estimates generated by these two different techniques and briefly describe the relevance of this exercise to our preferred identification strategy.

Table 4 contains annual estimates of the effect of DAAs on transplants for HCV^- recipients from our CITS model (column 1) and our DiD model (column 2) relative to the 2005–2012 period. In every year, the CITS estimates are larger than the DiD estimates, likely due to unobserved confounders inflating the CITS estimates (e.g., drug overdose deaths, Medicaid expansion, increased willingness

to accept HCV^+ donor organs, etc.). Column 3 calculates the magnitude of the difference between the CITS and DiD estimates, and columns 4–6 contain CITS estimates of trends in transplant for all organs, livers, and kidneys, respectively.

Two key takeaways from Table 4 are worth noting. First, annual growth in liver and kidney transplants are quite similar over the post-DAA period. For example, liver transplants had increased by 42.7% (column 5) and kidney transplants by 39.9% (column 6) from 2012 to 2019, indicating that trends in the availability of livers and kidneys for transplant were similarly affected by supply changes and willingness to accept HCV^+ organs over this period. Second, the differences between our CITS and DiD estimates of DAA effects on transplants for HCV^- recipients in column 3 are nearly identical to the overall growth of organ transplants in column 4, suggesting that our DiD estimates capture the externality effect of a reallocation of livers from HCV^+ to HCV^- transplant recipients, removing the influence of confounders. Taken together, these findings provide additional support for our choice to use kidney transplant recipients and waiting list registrants to approximate the counterfactual in our DiD model.

5 Value of Externalities

Our DiD event study estimates from Table 4 indicate that from 2014 through 2019, DAAs were responsible for an additional 5,682 liver transplants to HCV^- recipients. Given the large concurrent reduction in HCV^+ individuals on the liver transplant waiting list, the evidence we present suggests that these transplant gains for HCV^- recipients did not crowd out transplants that would have otherwise gone to those who were HCV^+. Multiplying 5,682 transplants by 10.1 life-years[22] per liver transplant (Rana et al., 2015) equals 57,388 life-years, and assuming a 3% annual discount rate and a value of $150,000 per life-year, our DiD estimates imply that DAAs generated $7.52 billion, or $1.25 billion per year, in value to HCV^- transplant recipients between 2014 and 2019. For context, Chhatwal et al. (2015) estimate that providing DAAs for all HCV^+ individuals in 2015 at market prices would have cost roughly $65 billion. Recognizing that providing DAAs to all those who were HCV^+ would have generated further externalities, our estimated innovation-induced externality value accruing to HCV^- individuals with ESLD is roughly 11.5% of the total potential market for DAAs in 2015.

It is also worth reiterating that this externality estimate is likely to represent a lower bound for two

[22] Jena et al. (2016) assume a more conservative 7.2 years, but this estimate does not appear in the literature.

reasons. First, our DiD estimates do not capture additional transplants that arose due to the increased willingness to accept an HCV^+ organ once DAAs became available, since we see a similar increased willingness among those on the kidney transplant waiting list. Second, whether through improved time from listing to transplant or through health compositional changes in marginal registrants, we show evidence that HCV^- transplant recipients are in better health at the time of their transplant in the post-DAA era and this is not reflected in the estimates of post-transplant survival that we use in our value calculation. While a direct mapping between pre-transplant MELD score and post-transplant survival has yet to be established, evidence indicates that moving from a pre-transplant MELD score above 25 to a score below 25 – consistent with the pattern for HCV^- recipients following the introduction of DAAs (see Figure 3a) – is associated with up to a 30% improvement in 10-year post-transplant survival (Habib et al., 2006).

Relative to the simulation-based literature, our estimates of the value that DAAs conferred on HCV^- individuals with ESLD are large. For example, Jena et al. (2016) simulate an epidemiological model for 20 years starting in 2015 and conclude that DAAs would lead to an additional 7,321 HCV^- liver transplants, or 366 transplants per year. By contrast, using actual retrospective data, we estimate an additional 947 HCV^- transplants per year between 2014 and 2019, on average. The key conceptual difference is that our economic model suggests changes in listing behavior among HCV^- patients when the size of the waiting list changes. In the simulation model of Jena et al. (2016), the demand for organs from HCV^- individuals is assumed to increase linearly until 2025 and then remain flat, and this demand is not a function of the characteristics of the waiting list. Our point is that consistent with the notion that listing behavior is elastic with respect to expectations about transplant probabilities and outcomes (Dickert-Conlin et al., 2019; Agarwal et al., 2021), DAAs shrank the waiting list, which induced marginal HCV^- patients to list, and these marginal HCV^- individuals may have contributed significantly to the effect of DAAs on HCV^- transplants. For example, using kidney transplant waiting list additions as a counterfactual, our estimates imply that DAA availability resulted in an additional 9,888 HCV^- liver transplant waiting list registrants from 2014 and 2019, or 1,648 additions per year.

Accounting for the behavioral impact of DAAs on waiting list additions is important considering the implications of our findings for the size of the liver transplant waiting list. We estimate that, in the absence of DAAs, 6,397 HCV^- individuals with ESLD would have joined the liver transplant waiting list in 2019.[23] That same year, there were 6,182 liver transplants performed on HCV^-

[23]The actual number of HCV^- liver transplant waiting list adds in 2019 was 9,399.

recipients and, as Figure 1 indicates, this number was maintaining an upward trend in the post-DAA period. As a result, with no DAA-induced HCV^- wait-listing response, our estimates suggest that the development of DAAs would have effectively eliminated the liver transplant waiting list. Instead, the gap between the number of HCV^- waiting list adds and transplants to HCV^- recipients was actually larger in 2019 than in 2012 (the year prior to the development of DAAs).[24]

6 Conclusion

We study the externalities generated by technological innovation in the context of HCV and liver transplantation. Our primary finding reveals that the availability of DAAs, which were approved to treat HCV in late 2013, generated substantial benefits for individuals outside the market for HCV medical care: those with non-HCV-induced ESLD. Our economic model suggests that part of the externality effect is driven by endogenous HCV^- listing. Given the dramatic reduction in the size of the liver transplant waiting list, HCV^- individuals with ESLD who may have been either relatively healthy, perhaps attempting to forestall listing, or very sick, perhaps rationally not expecting to receive a transplant, chose to list. Notably, a significant fraction of these marginal listers received a transplant.

Although our estimates are conservative, as we may be under-counting HCV cases in kidney transplantation and there may be spillovers (on top of our controls and research design) of DAAs on the demand and supply of kidneys, they clearly highlight the importance of considering innovation-induced externalities when valuing technological advances. Additionally, it is likely we underestimate the number of DAA-induced HCV^- liver transplant waiting list adds, and our results show larger effects when HCV status is measured through antibody testing at the time of transplant rather than at listing.

In sum, we provide the first retrospective evidence on the effect of DAAs on liver transplant and wait-listing behaviors, and, by doing so, we contribute to a growing economics literature on the incentives generated by medical innovation. Our results are timely. In March of 2023, the Biden administration proposed funding that would expand access to DAAs, with the goal of eliminating HCV by 2034. Using a similar model to that in Jena et al. (2016), Chhatwal et al. (2023) simulated that from 2024 to 2034, increased DAA access will decrease U.S. HCV prevalence by 94% and prevent the need for 2,500 liver transplants. Our work suggests that these 2,500 spared transplants will generate

[24] There were 5,440 HCV^- waiting list adds in 2012 and 2,720 transplants to HCV^- recipients (difference = 2,720). There were 9,399 HCV^- waiting list adds in 2019 and 6,182 transplants to HCV^- recipients (difference = 3,217).

significant value for HCV^- patients in search of a liver.

References

Agarwal, Nikhil, Ashlagi, Itai, Somaini, Paulo, & Waldinger, Daniel. 2018. Dynamic Incentives in Wait List Mechanisms. AEA Papers and Proceedings, **108**(May), 341–47.

Agarwal, Nikhil, Hodgson, Charles, & Somaini, Paulo. 2020 (November). Choices and Outcomes in Assignment Mechanisms: The Allocation of Deceased Donor Kidneys. Working Paper 28064. National Bureau of Economic Research.

Agarwal, Nikhil, Ashlagi, Itai, Rees, Michael A., Somaini, Paulo, & Waldinger, Daniel. 2021. Equilibrium Allocations Under Alternative Waitlist Designs: Evidence From Deceased Donor Kidneys. Econometrica, **89**(1), 37–76.

ASPE. 2022. Trends in Prescription Drug Spending, 2016-2021. Issue Brief. Assistant Secretary for Planning and Evaluation Office of Science & Data Policy.

Auty, S.G., Griffith, K.N., Shafer, P.R., Gee, R.E., & Conti, R.M. 2022. Improving Access to High-Value, High-Cost Medicines: The Use of Subscription Models to Treat Hepatitis C Using Direct-Acting Antivirals in the United States. Journal of health politics, policy and law, **47**(6), 691–708.

Axelrod, D., Schnitzler, M., Alhamad, T., & et al. 2018. The impact of direct-acting antiviral agents on liver and kidney transplant costs and outcomes. American Journal of Transplantation, **18**(10), 2473–2482.

Baranov, V., Bennett, D., & Kohler, H. 2015. The indirect impact of antiretroviral therapy: Mortality risk, mental health, and HIV-negative labor supply. Journal of health economics, **44**, 195–211.

Bryce, C.L., Angus, D.C., Arnold, R.M., C., Chang., Farrell, M.H., Manzarbeitia, C., Marino, I.R., & Roberts, M.S. 2009. Sociodemographic Differences in Early Access to Liver Transplantation Services. American Journal of Transplantation, **9**(9), 2092–2101.

Bryce, C.L., Chang, C.H., Angus, D.C., Arnold, R.M., Farrell, M., & Roberts, M.S. 2010. The Effect of Race, Sex, and Insurance Status on Time-to-Listing Decisions for Liver Transplantation. Journal of Transplantation.

Burstow, N.J., Mohamed, Z., Gomaa, A.I., Sonderup, M.W., Cook, N.A., Waked, I., Spearmen,

C.W., , & Taylor-Robinson, S.D. 2017. Hepatitis C treatment: where are we now? Int J Gen Med, **10**, 39–52.

CDC. 2020. National progress report 2025 goal: Reduce reported rate of hepatitis C-related deaths by 20%. Policy Report. Centers for Disease Control & Prevention.

Chan, Tat Y., Hamilton, Barton H., & Papageorge, Nicholas W. 2015. Health, Risky Behaviour and the Value of Medical Innovation for Infectious Disease. The Review of Economic Studies, **83**(4), 1465–1510.

Chernew, M.E., & Newhouse, J.P. 2011. Health care spending growth. Chap. 1, pages 1–43 of: Pauly, M.V., Mcguire, T.G., & Barros, P.P. (eds), Handbook of Health Economics, vol. 2. Amsterdam, North Holland: Elsevier.

Chhatwal, J., Wang, X., Ayer, T., Kabiri, M., Chung, R.T., Hur, C., Donohue, J.M., Roberts, M.S., , & Kanwal, F. 2016. Hepatitis C disease burden in the United States in the era of oral direct-acting antivirals. Hepatology, **64**(5), 1442–1450.

Chhatwal, Jagpreet, Kanwal, Fasiha, Roberts, Mark S., & Dunn, Michael A. 2015. Cost-Effectiveness and Budget Impact of Hepatitis C Virus Treatment With Sofosbuvir and Ledipasvir in the United States. Annals of Internal Medicine, **162**(6), 397–406. PMID: 25775312.

Chhatwal, Jagpreet, He, Tianhua, Hur, Chin, & Lopez-Olivo, Maria A. 2017. Direct-Acting Antiviral Agents for Patients With Hepatitis C Virus Genotype 1 Infection Are Cost-Saving. Clinical Gastroenterology and Hepatology, **15**(6), 827–837.e8.

Chhatwal, Jagpreet, Aaron, Alec, Zhong, Huaiyang, Sood, Neeraj, Irvin, Risha, Alter, Harvey J, Zhuo, Yueran, Sharfstein, Joshua M, & Ward, John W. 2023 (April). Projected Health Benefits and Health Care Savings from the United States National Hepatitis C Elimination Initiative. Working Paper 31139. National Bureau of Economic Research.

Ciesek, S., & Wedemeyer, H. 2012. Immunosuppression, liver injury and post-transplant HCV recurrence. Journal of Viral Hepatitis, **19**(1), 1–8.

Cutler, David M, & McClellan, Mark. 2001. Is technological change in medicine worth it? Health affairs, **20**(5), 11–29.

Dageforde, L.A., Box, A., Feurer, I.D., & Cavanaugh, K.L. 2015. Understanding patient barriers to kidney transplant evaluation. Transplantation, **99**(7), 1463.

Dickert-Conlin, S., Elder, T.E., Lemont, B., & Teltser, K. In press. Opioids and Organs: How Overdoses Affect the Supply and Demand for Organ Transplants. American Journal of Health Economics.

Dickert-Conlin, Stacy, Elder, Todd, & Teltser, Keith. 2019. Allocating Scarce Organs: How a Change in Supply Affects Transplant Waiting Lists and Transplant Recipients. American Economic Journal: Applied Economics, **11**(4), 210–39.

Dow, W.H., Philipson, T.J., & Sala-i Martin, X. 1999. Longevity complementarities under competing risks. American Economic Review, **89**(5), 1358–1371.

Dranove, David, Garthwaite, Craig, Heard, Christopher, & Wu, Bingxiao. 2022. The economics of medical procedure innovation. Journal of Health Economics, **81**, 102549.

Dunn, A., Fernando, L., & Liebman, E. 2023. How Much Are Medical Innovtions Worth?: A Detailed Analysis Using Thousands of Cost-Effectiveness Studies. Working Paper.

Durand, C.M., Bowring, M.G., Thomas, A.G., Kucirka, L.M., Massie, A.B., Cameron, A., Desai, N.M., Sulkowski, M., & Segev, D.L. 2018. The drug overdose epidemic and deceased-donor transplantation in the United States: a national registry study. Annals of internal medicine, **168**(10), 702–711.

Erman, A., Wong, W.W., Feld, J.J., Grootendorst, P., , & Krahn, M.D. 2020. The health impact of delaying direct-acting antiviral treatment for chronic hepatitis C: A decision-analytic approach. Liver International, **40**(1), 51–59.

Fendrick, A.M., Chernew, M.E., Hirth, R.A., & Menon, D. 1996. Understanding the behavioral response to medical innovation. American Journal of Managed Care, **2**(7), 793–799.

Fernandez, J.M., Howard, D.H., & Stohr Kroese, L. 2013. The effect of cadaveric kidney donations on living kidney donations: An instrumental variables approach. Economic Inquiry, **51**(3), 1696–1714.

Fleurence, R.L., & Collins, F.S. 2023. A National Hepatitis C Elimination Program in the United States. JAMA, **329**(15), 1251–1252.

Goldberg, D.S., French, B., Sahota, G., Wallace, A.E., Lewis, J.D., & Halpern, S.D. 2016. Use of population-based data to demonstrate how waitlist-based metrics overestimate geographic disparities in access to liver transplant care. American Journal of Transplantation, **16**(10), 2903–2911.

Habib, Shahid, Berk, Brian, Chang, Chung-Chou H, Demetris, Anthony J, Fontes, Paulo, Dvorchik, Igor, Eghtesad, Bijan, Marcos, Amadeo, & Shakil, A Obaid. 2006. MELD and prediction of post–liver transplantation survival. Liver transplantation, **12**(3), 440–447.

Hall, R.E., & Jones, C.I. 2007. The value of life and the rise in health spending. The Quarterly Journal of Economics, **122**(1), 39–72.

Harding, J.L., Perez, A., Snow, K., Retzloff, S., Urbanski, M., White, M.S., & Patzer, R.E. 2021. Non-medical barriers in access to early steps of kidney transplantation in the United States–A scoping review. Transplantation Reviews, **35**(4), 100654.

He, T., Lopez-Olivo, M. A., Hur, C., & Chhatwal, J. 2017. Systematic review: cost-effectiveness of direct-acting antivirals for treatment of hepatitis C genotypes 2-6. Alimentary Pharmacology & Therapeutics, **46**(8), 711–721.

Henry, B. 2018. Drug pricing & challenges to hepatitis C treatment access. Journal of Health & Biomedical Law, **14**, 265.

Hernandez, I., Good, C.B., Cutler, D.M., Gellad, W.F., Parekh, N., & Shrank, W.H. 2019. The Contribution of New Product Entry Versus Existing Product Inflation in the Rising Costs of Drugs. Health Affairs, **38**(1), 76–83.

Howard, David H. 2002. Why do transplant surgeons turn down organs?: A model of the accept/reject decision. Journal of Health Economics, **21**(6), 957–969.

Hult, K.J., & Philipson, T.J. 2023. The value of medical innovation versus industry rewards. Value in Health, **26**(3), 320–327.

Hult, K.J., Jaffe, S., & Philipson, T.J. 2018. How does technological change affect quality-adjusted prices in health care? Systematic evidence from thousands of Innovations. American Journal of Health Economics, **4**(4), 433–453.

Jena, A.B., & Philipson, T.J. 2008. Cost-effectiveness analysis and innovation. Journal of health economics, **27**(5), 1224–1236.

Jena, A.B., Stevens, W., Sanchez Gonzalez, Y., Marx, S.E., Juday, T., Lakdawalla, D.N., & Philipson, T.J. 2016. The Wider Public Health Value of HCV Treatment Accrued by Liver Transplant Recipients. American Journal of Managed Care, **22**(sp6).

Jena, A.B., Snider, J.T., Espinosa, O.D., Ingram, A., Gonzalez, Y.S., & Lakdawalla, D. 2019. How Does Treating Chronic Hepatitis C Affect Individuals in Need of Organ Transplants in the United Kingdom? Value in Health, **22**(6), 669–676.

Jeon, Sung-Hee, & Pohl, R. Vincent. 2019. Medical innovation, education, and labor market outcomes of cancer patients. Journal of Health Economics, **68**, 102228.

Jesse, M.T., Abouljoud, M., Goldstein, E.D., Rebhan, N., Ho, C., Macaulay, T., Bebanic, M., Shkokani, L., Moonka, D., & Yoshida, A. 2019. Racial Disparities in Patient Selection for Liver Transplantation: An Ongoing Challenge. Clinical transplantation, **33**(11), e13714.

Kaestner, Robert, Darden, Michael, & Lakdawalla, Darius. 2014. Are investments in disease prevention complements? The case of statins and health behaviors. Journal of Health Economics, **36**, 151–163.

Kamal, S.M. 2008. Acute hepatitis C: A systematic review. American Journal of Gastroenterology, **103**(5), 1283–1297.

Koijen, Ralph S J, & Van Nieuwerburgh, Stijn. 2019. Combining Life and Health Insurance*. The Quarterly Journal of Economics, **135**(2), 913–958.

Kwong, A., Kim, W., Lake, J., Smith, M., Schladt, D.P., Skeans, M.A., Noreen, S.M., Foutz, J., Miller, E., Snyder, J.J., Israni, A.K., , & Kasiske, B.L. 2020. OPTN/SRTR 2018 Annual Data Report: Liver. American Journal of Transplantation, **20**(s1), 193–299.

Lee, J., Lin, M., Chang, J., Hung, C., Chang, J., Chen, H., Yu, M., & Hwang, S. 2014. Hepatitis C virus infection increases risk of developing end-stage renal disease using competing risk analysis. PloS one, **9**(6), e100790.

Lemont, B. 2023. The Effect of Distance on Use of Care: Evidence from Low-Income Organ Transplant Candidates. Working Paper.

Leong, Jennifer, & Im, Gene Y. 2012. Evaluation and Selection of the Patient with Alcoholic Liver

Disease for Liver Transplant. Clinics in Liver Disease, **16**(4), 851–863. A Practical Approach to the Spectrum of Alcoholic Liver Disease.

Levitsky, J., Formica, R., D., Bloom, & et al. 2017. The American society of transplantation consensus conference on the use of hepatitis C viremic donors in solid organ transplantation. American Journal of Transplantation, **17**(11), 2790–2802.

Maclean, J.C., Mallatt, J., Ruhm, C.J., & Simon, K. 2021. Economic Studies on the Opioid Crisis: A Review. NBER Working Paper.

Martin, Anne B, Hartman, Micah, Whittle, Lekha, Catlin, Aaron, et al. 2014. National Health Spending In 2012: Rate Of Health Spending Growth Remained Low For The Fourth Consecutive Year. Health Affairs, **33**(1), 67–77.

Moghtaderi, Ali, & Dor, Avi. 2021. Immunization and Moral Hazard: The HPV Vaccine and Uptake of Cancer Screening. Medical Care Research and Review, **78**(2), 125–137.

Murphy, K.M., & Topel, R.H. 2006. The Value of Health and Longevity. Journal of Political Economy, **114**(5), 871–904.

Newhouse, J.P. 1992. Medical Care Costs: How Much Welfare Loss? Journal of Economic Perspectives, **6**(3), 3–21.

Papageorge, Nicholas W. 2016. Why medical innovation is valuable: Health, human capital, and the labor market. Quantitative Economics, **7**(3), 671–725.

Peltzman, S. 2011. Offsetting behavior, medical breakthroughs, and breakdowns. Journal of Human Capital, **5**(3), 302–341.

Philipson, T. 2000. Economic epidemiology and infectious diseases. Chap. 33, pages 1761–1799 of: Culyer, A.J., & Newhouse, J.P. (eds), Handbook of Health Economics, vol. 1B. Amsterdam, North Holland: Elsevier.

Powell, David, Alpert, Abby, & Pacula, Rosalie L. 2019. A Transitioning Epidemic: How The Opioid Crisis Is Driving The Rise In Hepatitis C. Health Affairs, **38**(2), 287–294. PMID: 30715966.

Rana, Abbas, Gruessner, Angelika, Agopian, Vatche G., Khalpey, Zain, Riaz, Irbaz B., Kaplan, Bruce, Halazun, Karim J., Busuttil, Ronald W., & Gruessner, Rainer W. G. 2015. Survival Benefit of Solid-Organ Transplant in the United States. JAMA Surgery, **150**(3), 252–259.

Roshenthal, E.S., & Graham, C.S. 2016. Price and affordability of direct-acting antiviral regimens for hepatitis C virus in the United States. Infectious Agents and Cancer, **11**(1), 1–8.

Song, C.H., & Jeung-Whan, H. 2016. Patent Cliff and Strategic Switch: Exploring Strategic Decision Possibilities in the Pharmaceutical Industry. SpringPlus, **5**(1), 1–14.

Sweat, Kurt. 2023. Endogenous Priority in Centralized Matching Markets: The Design of the Heart Transplant Waitlist. Working Paper. Stanford University.

van der Gronde, T., Uyl-de Groot, C.A., & Pieters, T. 2017. Addressing the Challenge of High-Priced Prescription Drugs in the Era of Precision Medicine: A Systematic Review of Drug Life Cycles, Therapeutic Drug Markets, and Regulatory Frameworks. PloS one, **12**(8), e0182613.

Wahid, N.A., Rosenblatt, R., & Brown Jr, R.S. 2021. A review of the current state of liver transplantation disparities. Liver Transplantation, **27**(3), 434–443.

Wright, L.S. 2022. Transplant Programs: An Overview of the Scientific Registry of Transplant Recipients. Nephrology Nursing Journal, **49**(6), 505–508.

Younossie, Z.M., Stepanova, M., Afendy, M., Fang, Y., Younossi, Y., Mir, H., & Srishord, M. 2011. Changes in the Prevalence of the Most Common Causes of Chronic Liver Diseases in the United States from 1988 to 2008. Clinical gastroenterology and hepatology, **9**(6), 524–530.

Zhang, Juanjuan. 2010. The Sound of Silence: Observational Learning in the U.S. Kidney Market. Marketing Science, **29**(2), 315–335.

Zibbell, J.E., Asher, A.K., Patel, R.C., Kupronis, B., Iqbal, K., Ward, J.W., , & Holtzman, D. 2018. Increases in acute hepatitis C virus infection related to a growing opioid epidemic and associated injection drug use United States 2004 to 2014. American Journal of Public Health, **108**(2), 175–181.

Zoulim, F., Chevallier, M., Maynard, M., , & Trepo, C. 2003. Clinical consequences of hepatitis C virus infection. Rev Med Virol, **13**(1), 57–68.

Tables and Figures

Table 1: Liver Registrants' Summary Statistics, by HCV Status

	HCV^+ Liver Registrants			HCV^- Liver Registrants		
	2005-19	2005-13	2014-19	2005-19	2005-13	2014-19
Totals						
National # of Listings	49,499	35,068	14,431	93,542	46,719	46,823
National # of WL Removals & TXs	54,058	36,157	17,901	93,123	46,470	46,653
Waiting List Flows (Counts)						
Nat'l Yrly # of Listings	3,300	3,896	2,405	6,236	5,191	7,804
Nat'l Yrly # of WL Remov. & TXs	3,604	4,017	2,984	6,208	5,163	7,776
Waiting List Outcomes (Means)						
Too Sick / Died	0.257	0.269	0.235	0.226	0.240	0.213
Improved	0.048	0.032	0.079	0.067	0.066	0.069
Dec. Don. TX	0.511	0.511	0.511	0.535	0.510	0.559
Liv. Don. TX	0.014	0.015	0.014	0.027	0.024	0.031
Days to TX	316.7	302.1	346.1	228.1	241.5	215.9
Waiting List Characteristics (Means)						
Initial MELD	16.47	16.60	16.15	19.67	19.18	20.15
High School or Less	0.582	0.576	0.593	0.448	0.470	0.429
White Pct.	0.680	0.691	0.654	0.731	0.736	0.725
Primary Payer: Private	0.549	0.584	0.464	0.609	0.642	0.576
Primary Payer: Medicare	0.251	0.226	0.311	0.236	0.217	0.255
Primary Payer: Medicaid	0.200	0.190	0.225	0.155	0.141	0.170
Listing Age 18 to 39	0.022	0.024	0.019	0.135	0.139	0.131
Listing Age 40 to 64	0.873	0.906	0.792	0.694	0.713	0.675
Listing Age Over 64	0.105	0.070	0.189	0.171	0.148	0.194
South Census Region	0.372	0.359	0.405	0.379	0.361	0.397
NE Census Region	0.220	0.228	0.199	0.186	0.195	0.177
MW Census Region	0.170	0.170	0.170	0.231	0.236	0.226
West Census Region	0.238	0.243	0.226	0.204	0.208	0.201

Notes: Authors' calculations of fraction of liver registrants belonging to each characteristic or outcome group from SRTR data. Except for waiting list outcomes (too sick/died, improved, transplants, and days to transplant), which are calculated based on the timing of waiting list removal, all summary statistics are calculated based on when the registrants joined the waiting list. Those for whom HCV status cannot be inferred are excluded from the calculations in this table. This amounts to roughly 15% of liver registrants, or 24,847 of 167,888 total liver registrants who listed between 2005 to 2019. Higher MELD score reflects higher mortality risk.

Table 2: Liver vs. Kidney Waiting List Additions and Transplants

	Log Transplants (1)	Transplant Rate (2)	Log WL Additions (3)
Panel A: HCV^-			
Liver x DAA	0.3059***	0.1604***	0.3134***
	(0.0514)	(0.0407)	(0.0545)
Baseline Mean	61.27	0.507	115.36
Observations	1,425	1,425	1,425
Number of Clusters	95	95	95
Panel B: HCV^+			
Liver x DAA	-0.4965***	0.0576	-0.6044***
	(0.0578)	(0.0392)	(0.0601)
Baseline Mean	46.89	0.506	86.59
Observations	1,425	1,425	1,425
Number of Clusters	95	95	95

Notes: The first and third columns of coefficients represent log point changes per year, which can be transformed into percentages using the formula $100 \times (e^{\hat{\beta}} - 1)$. In column 2, the outcome is defined as the number of transplants divided by the organ-specific number of waiting list registrants. Baseline means reflect the pre-treatment period (2005–2013) DSA-year means for liver registrants only. In columns 1 and 3, baseline means reflect level counts rather than log counts. While there are 57 DSAs in the U.S., we use modified DSA identifiers (see footnote 13) due to changes in DSA existence and services over time, which yields 50 kidney-serving DSA and 45 liver-serving DSA identifiers. Standard errors are in parentheses and are clustered at the DSA-by-organ level. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Heterogeneity among HCV^- Individuals by Fraction of Transplant Recipients with HCV Antibodies

	Dose-Response	$\geq$ Median HCV^+ Rate	$<$ Median HCV^+ Rate
Panel A: Log Waiting List Additions			
Liver x DAA	-0.2709	0.3547***	0.2086**
	(0.2757)	(0.0635)	(0.0836)
Liver x DAA x Fraction HCV^+	1.2829**		
	(0.6069)		
Mean of DV (Level)	115.36	145.53	83.81
Panel B: Log Transplants			
Liver x DAA	-0.2478	0.3649***	0.2109***
	(0.2860)	(0.0694)	(0.0697)
Liver x DAA x Fraction HCV^+	1.2347*		
	(0.6584)		
Mean of DV (Level)	61.27	71.52	50.56
Observations	1,350	690	660
N of Clusters	90	46	44

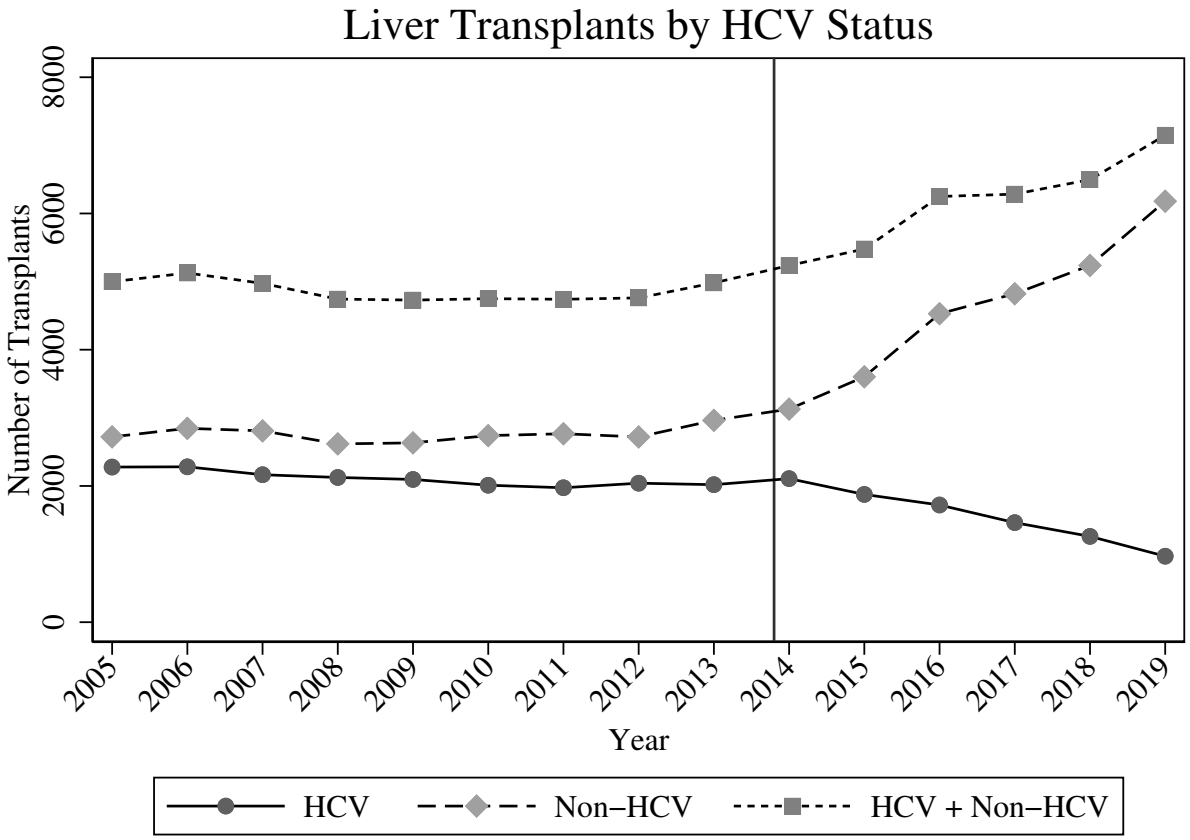
Notes: This table presents differences-in-differences heterogeneity estimates, comparing log HCV^- liver transplants and waiting list additions to log kidney transplants and waiting list additions, by DSAs' fraction of pre-treatment (2005-13) liver transplant recipients who tested positive for antibodies to HCV. The baseline means of the dependent variables reflect level counts (at the DSA-year level) rather than log counts during the pre-treatment period (2005-13) for liver registrants only. While there are 57 DSAs in the U.S., we use modified DSA identifiers (see footnote 13) due to changes in DSA existence and services over time, which yields 50 kidney-serving DSA and 45 liver-serving DSA identifiers. Standard errors are in parentheses, and clustered at the DSA-by-organ level. *** p<0.01, ** p<0.05, * p<0.1

Table 4: CITS vs. DiD Estimates of Transplants to HCV^- Registrants

	Log Transplants					
	HCV^- CITS	HCV^- DiD	***Difference***	All TX CITS	Liver TX CITS	Kidney TX CITS
	(1)	(2)	(3)	(4)	(5)	(6)
DAA x 2013	0.0960***	0.0667	***0.0293***	0.0241	0.0435	0.0159
	(0.0334)	(0.0435)		(0.0190)	(0.0288)	(0.0222)
DAA x 2014	0.1356***	0.0846*	***0.0510***	0.0587**	0.0844**	0.0417
	(0.0481)	(0.0499)		(0.0263)	(0.0381)	(0.0295)
DAA x 2015	0.2307***	0.1529***	***0.0778***	0.0895***	0.1055**	0.0715**
	(0.0618)	(0.0563)		(0.0312)	(0.0505)	(0.0339)
DAA x 2016	0.4750***	0.3391***	***0.1359***	0.1685***	0.2271***	0.1335***
	(0.0681)	(0.0581)		(0.0386)	(0.0620)	(0.0393)
DAA x 2017	0.5271***	0.3457***	***0.1814***	0.2132***	0.2620***	0.1822***
	(0.0873)	(0.0665)		(0.0409)	(0.0744)	(0.0410)
DAA x 2018	0.6035***	0.3666***	***0.2369***	0.2569***	0.2754***	0.2413***
	(0.0945)	(0.0642)		(0.0477)	(0.0843)	(0.0466)
DAA x 2019	0.7643***	0.4367***	***0.3276***	0.3494***	0.3553***	0.3356***
	(0.1074)	(0.0656)		(0.0508)	(0.0974)	(0.0486)
Observations	675	1,425		750	675	750
Number of Clusters	45	95		50	45	50

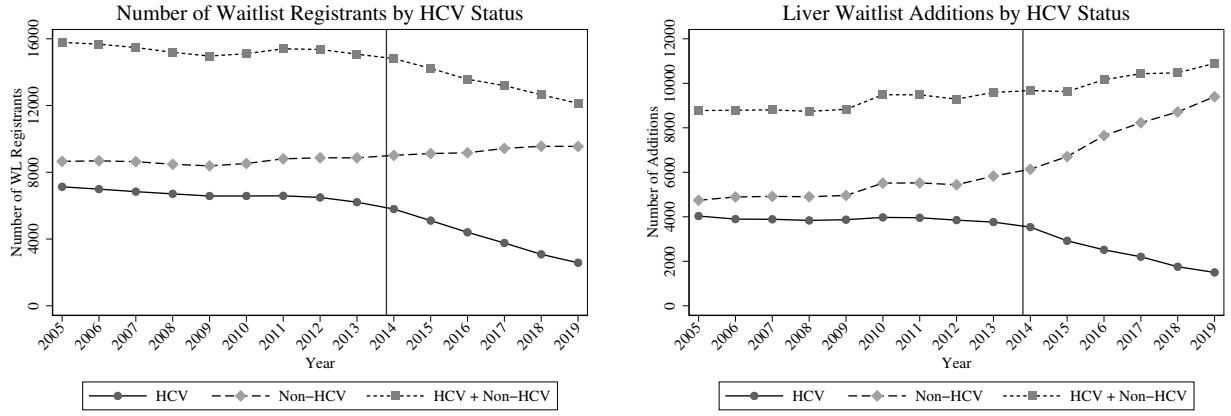
Notes: The outcome variables in columns 1 and 2 are log number of transplants received by HCV^- registrants, where the difference is column 1 presents time-disaggregated interrupted time-series estimates, while column 2 presents time-disaggregated DiD estimates comparing liver transplants to kidney transplants. Column 3 presents the difference between the column 1 and column 2 estimates for each post-treatment year. Columns 4-6 present time-disaggregated interrupted time-series estimates of overall transplant trends for all registrants (both HCV^- and HCV^+). Note that all coefficients in this table represent log point changes, which can be transformed into percentages using the formula $100 \times (e^{\hat{\beta}} - 1)$. While there are 57 DSAs in the U.S., we use modified DSA identifiers (see footnote 13) due to changes in DSA existence and services over time, which yields 50 kidney-serving DSA and 45 liver-serving DSA identifiers. Standard errors are in parentheses. They are clustered at the DSA-by-organ level when comparing livers to kidneys (column 2 only) and at the DSA level when estimating interrupted time-series models (all other columns). *** p<0.01, ** p<0.05, * p<0.1

Figure 1



Notes: Authors' calculations of yearly national counts using SRTR data.

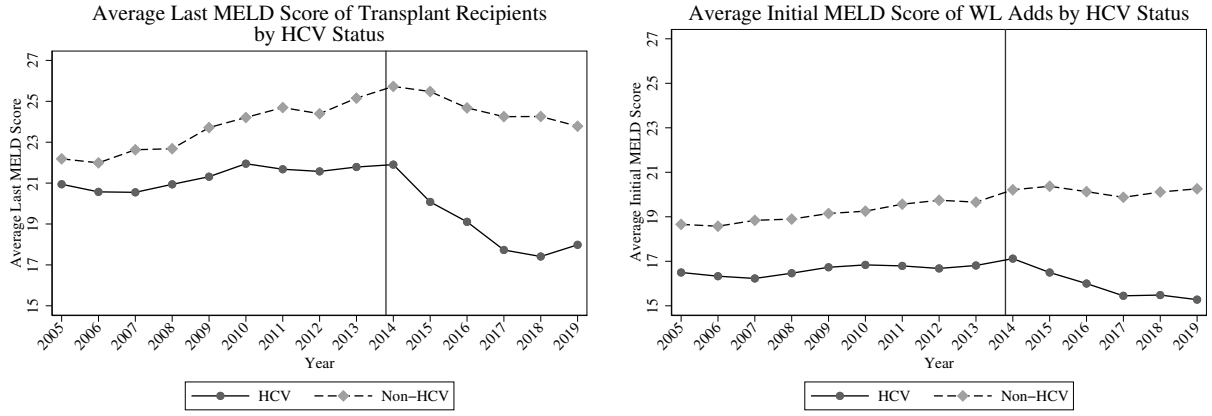
Figure 2: Liver Waiting List Levels and Inflows



(a) (b)

Notes: Authors' calculations of yearly national counts and rates using SRTR data.

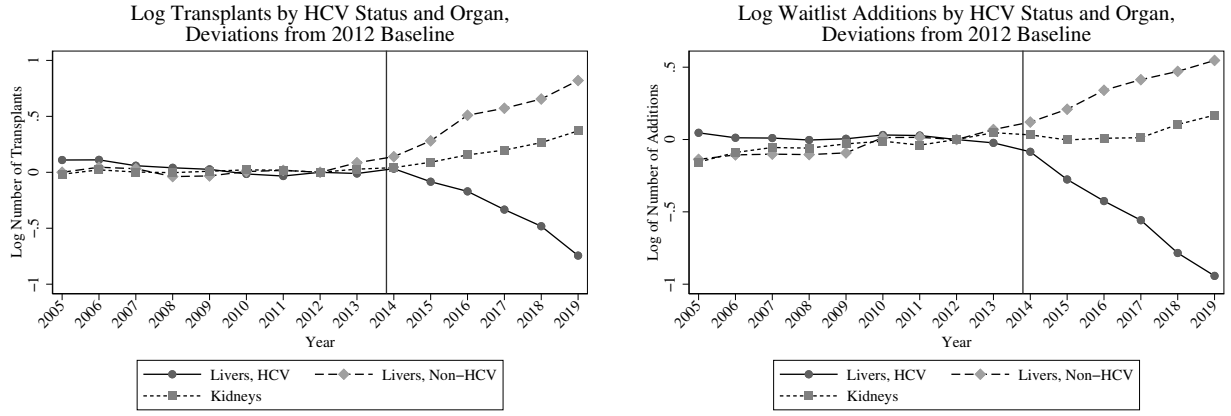
Figure 3: Change in Health Composition



(a) (b)

Notes: Authors' calculations of average MELD scores using SRTR data. Note that a higher MELD score reflects higher mortality risk. Roughly 20% of registrants have the same initial and last MELD score.

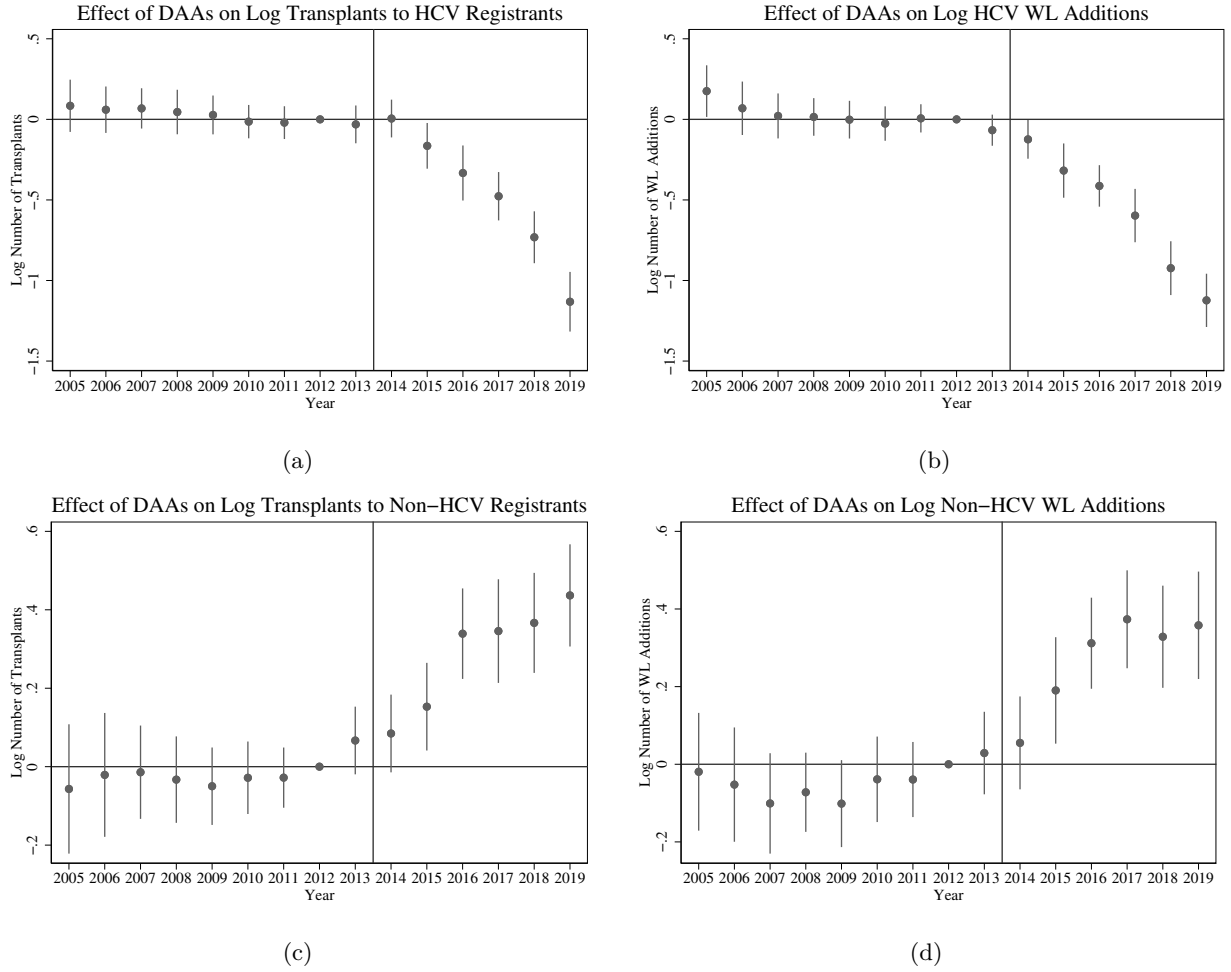
Figure 4: Liver vs. Kidney Waiting List Inflows and Outflows



(a) (b)

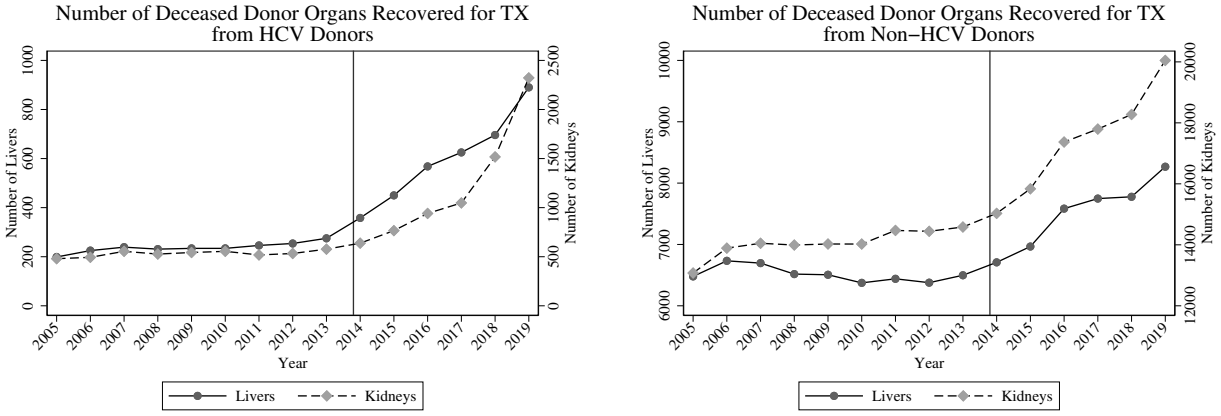
Notes: Authors' calculations of yearly national log counts using SRTR data. This figure adds the kidney registrant comparison group and recalculates the trends in terms of deviations from 2012. We exclude the 0.13% of kidney registrants who are known to have an HCV-related diagnosis using the optional diagnosis text field in the data.

Figure 5: Liver vs. Kidney Waiting List Additions and Transplants, Log Counts



Notes: Each panel presents time-disaggregated DiD estimates, comparing HCV-specific liver waiting list transplants and waiting list additions to kidney transplants and waiting list additions. The outcomes in each are log counts, implying that the coefficients can be transformed into percentage changes relative to the omitted baseline period (2012) using the formula $100 \times (e^{\hat{\beta}_k} - 1)$. The bars around each coefficient reflect the 95% confidence interval using standard errors clustered at the DSA-by-organ level.

Figure 6: Supply of HCV^+ and HCV^- Donor Organs



(a) (b)

Notes: Authors' calculations of yearly national counts using SRTR data. Includes all livers (left-scale) and kidneys (right-scale) recovered for transplant, including those that are subsequently discarded. For reference, the 2005-2013 average number of HCV^- kidneys recovered is 14,062; the corresponding average for livers is 6,513. The 2005-2013 average number of HCV^+ kidneys recovered is 531; the corresponding average for livers is 237.

Externalities from Medical Innovation: Evidence from Organ Transplantation
Online Appendix

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July 15, 2024

1 Comparative Interrupted Time Series

Our CITS model is specified as follows:

$$\begin{aligned} Y_{dHt} = \beta_1 t + \beta_2(H \times t) + \beta_3 DAA_t + \beta_4(H \times DAA_t) + \\ \beta_5(DAA_t \times t) + \beta_6(H \times DAA_t \times t) + \gamma_{dH} + \epsilon_{dHt} \end{aligned} \tag{1}$$

where d indexes donor service area (DSA),[1] H indexes HCV status, and t indexes year. The first regressor, t, is a linear time trend, such that β_1 measures the slope of the pre-DAA trend for HCV^- registrants and $\beta_1 + \beta 2$ measures the slope of the pre-DAA trend for HCV^+ registrants. DAA_t is an indicator for the post-DAA period (i.e., 2014 through 2019). Thus, β_3 reflects the level change in HCV^- registrants' outcomes associated with the introduction of DAAs relative to their baseline level, while $\beta_3 + \beta_4$ reflects this level change for HCV^+ registrants. Finally, β_5 measures the post-DAA change in slope relative to the pre-DAA slope β_1 for HCV^- registrants, while $\beta_5 + \beta_6$ captures this slope change for HCV^+ registrants. Finally, we include DSA-HCV fixed effects γ_{dH} to address potential unobserved confounders across HCV status and donation service areas, and an idiosyncratic error term ϵ_{dHt} clustered at the DSA-HCV level.

[1] Note that we use modified DSA identifers throughout our analyses due to changes over time in the existence and services of certain DSAs. First, we combine the Sierra Donor Services DSA into the Donor Network West DSA in California, as Sierra Donor Services ended their liver program in 2008/2009 and was geographically entirely surrounded by Donor Network West. Second, the Mississippi Organ Recovery Agency started up in 2013, so we combine that DSA with their pre-existing contiguous DSAs in Tennessee and north Mississippi, Louisiana, and Alabama. Third, because Lifelink of Southwest Florida ended in 2004, OurLegacy in Florida started in 2007, and Lifelink Puerto Rico started in 2012, we combine all Florida and Puerto Rico DSAs into one DSA unit. It is also important to note that 5 DSAs do not have a liver program. Thus, we end up with 50 modified DSA identifiers for kidneys and 45 modified DSA identifiers for livers.

Appendix Table 1: Comparative Interrupted Time-Series, Liver Waiting List Additions and Transplants

	Log Transplants	Transplant Rate	Log WL Additions
Years Since DAA	0.1169***	0.0808***	0.0569***
	(0.0154)	(0.0134)	(0.0142)
$HCV^+\times$ Years Since DAA	-0.2604***	-0.0688***	-0.2276***
	(0.0252)	(0.0179)	(0.0224)
DAA	-0.0116	-0.0195	-0.0144
	(0.0376)	(0.0364)	(0.0411)
$HCV^+\times$ DAA	0.2856***	0.0980*	0.0979
	(0.0714)	(0.0559)	(0.0709)
Pre-DAA Trend	0.0097	-0.0166*	0.0300***
	(0.0095)	(0.0091)	(0.0083)
$HCV^+\times$ Pre-DAA Trend	-0.0235*	0.0053	-0.0292**
	(0.0129)	(0.0115)	(0.0122)
HCV^- Mean of DV (Level)	61.27	0.507	115.36
HCV^+ Mean of DV (Level)	46.89	0.506	86.59
Observations	1,350	1,350	1,350
N of Clusters	90	90	90

Notes: The outcome variable in column 1 is the log number of transplants per DSA-year. In column 3, the outcome variable is defined as the log number of waiting list additions. The estimates in columns 1 and 3 can be transformed into percentages using the formula $100 \times (e^{\hat{\beta}} - 1)$. In column 2, the outcome is defined as the number of transplants divided by the HCV-specific number of waiting list registrants. Dependent variable means (at the DSA-year level) are reported in the two rows immediately following the coefficients, and reflect the pre-treatment period (2005-13) means for liver registrants. In columns 1 and 3, the means are of level counts rather than log counts. While there are 57 DSAs in the U.S., we use modified DSA identifiers (see footnote 1) due to changes in DSA existence and services over time, which yields 50 kidney-serving DSA and 45 liver-serving DSA identifiers. Standard errors are in parentheses, and clustered at the DSA level. *** p<0.01, ** p<0.05, * p<0.1

2 Health Composition

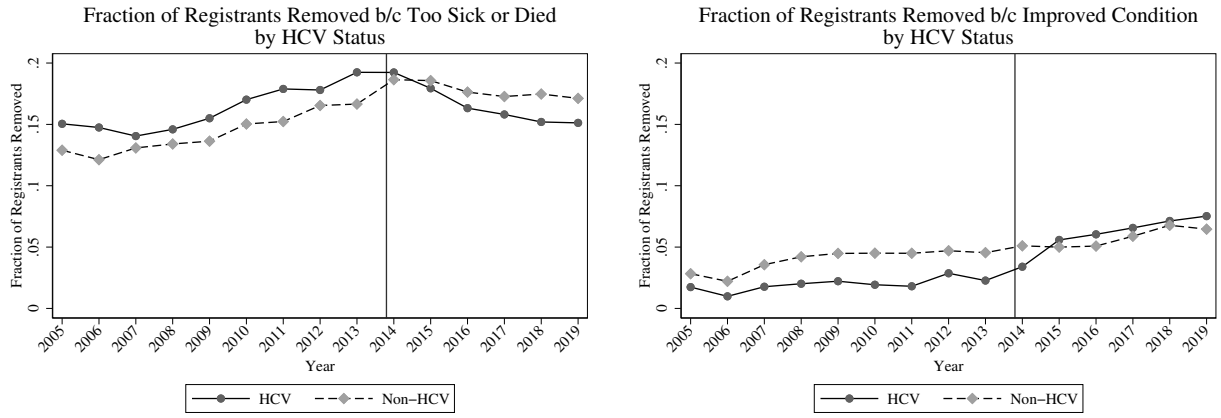
Appendix Table 2: CITS, Health of Liver Waiting List Registrants and Transplant Recipients

	Initial MELD at Listing	Final MELD before Transplant
Time Since DAA	-0.2198***	-0.8480***
	(0.0729)	(0.0971)
$HCV^+ \times$ Time Since DAA	-0.0364	0.0298
	(0.1233)	(0.1846)
DAA	0.5182**	0.9127***
	(0.2590)	(0.3411)
$HCV^+ \times$ DAA	-0.6301	-1.3716**
	(0.4281)	(0.6002)
Pre-DAA Trend	0.1614***	0.4257***
	(0.0384)	(0.0505)
$HCV^+ \times$ Pre-DAA Trend	-0.0998*	-0.2329***
	(0.0507)	(0.0704)
HCV^- Mean of DV	19.22	23.42
HCV^+ Mean of DV	16.82	21.03
Observations	1,350	1,350
R-squared	0.5800	0.5763
N of Clusters	90	90

Notes: The outcome variable in column 1 is the average MELD score among new waiting list additions by DSA-year. The outcome variable in column 2 is the average last MELD score among individuals receiving a transplant. A higher MELD score indicates a shorter life expectancy in the absence of a liver transplant, and thus confers higher priority on the waiting list. Dependent variable means (at the DSA-year level) are reported in the two rows immediately following the coefficients, and reflect the pre-treatment period (2005-13) means for liver registrants. While there are 57 DSAs in the U.S., we use modified DSA identifiers (see footnote 1) due to changes in DSA existence and services over time, which yields 50 kidney-serving DSA and 45 liver-serving DSA identifiers. Standard errors are in parentheses, and clustered at the DSA level. *** p<0.01, ** p<0.05, * p<0.1

3 Waiting List Attrition

Appendix Figure 1: Liver Waiting List Outflows



(a) (b)

Notes: Authors' calculations of yearly national rates using SRTR data.

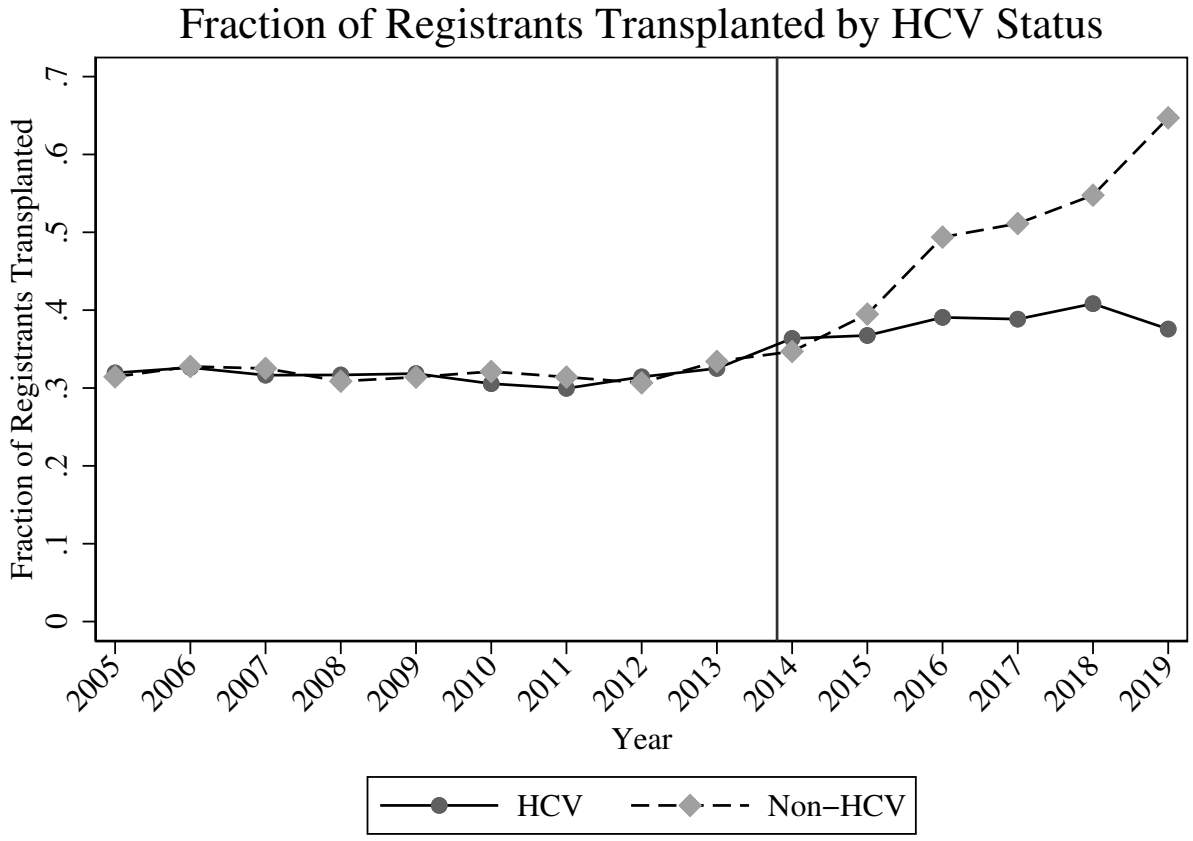
Appendix Table 3: CITS, Liver Transplant Waiting List Outflows

	Log Outcomes		Rates	
	Too Sick / Died	Improved	Too Sick / Died	Improved
Years Since DAA	-0.0470***	-0.0057	-0.0064**	-0.0018
	(0.0168)	(0.0352)	(0.0028)	(0.0035)
HCV^+ x Years Since DAA	-0.1766***	-0.0378	-0.0041	0.0087
	(0.0264)	(0.0499)	(0.0048)	(0.0053)
DAA	0.1176**	-0.0425	0.0258***	0.0014
	(0.0469)	(0.0875)	(0.0097)	(0.0087)
HCV^+ x DAA	-0.0686	0.3017**	-0.0378**	0.0039
	(0.0837)	(0.1324)	(0.0179)	(0.0141)
Pre-DAA Trend	0.0523***	0.0743***	0.0042**	0.0033**
	(0.0096)	(0.0179)	(0.0017)	(0.0014)
HCV^+ x Pre-DAA Trend	-0.0165	-0.0258	0.0014	-0.0008
	(0.0152)	(0.0241)	(0.0027)	(0.0019)
HCV^- Mean of DV (Level)	27.52	7.60	0.161	0.046
HCV^+ Mean of DV (Level)	23.99	2.88	0.181	0.026
Observations	1,350	1,350	1,350	1,350
N of Clusters	90	90	90	90

Notes: Notes: The outcome variables in columns 1 and 2 are the log number of waiting list removals due to condition deterioration/death and condition improvement per DSA-year. The estimates in columns 1 and 2 can be transformed into percentages using the formula $100 \times (e^{\hat{\beta}} - 1)$. In columns 3 and 4, the outcomes are defined as the number of removals divided by the HCV-specific number of waiting list registrants. Dependent variable means (at the DSA-year level) are reported in the two rows immediately following the coefficients, and reflect the pre-treatment period (2005-13) means for liver registrants. In columns 1 and 2, the means are of level counts rather than log counts. While there are 57 DSAs in the U.S., we use modified DSA identifiers (see footnote 1) due to changes in DSA existence and services over time, which yields 50 kidney-serving DSA and 45 liver-serving DSA identifiers. Standard errors are in parentheses, and clustered at the DSA level. *** p<0.01, ** p<0.05, * p<0.1

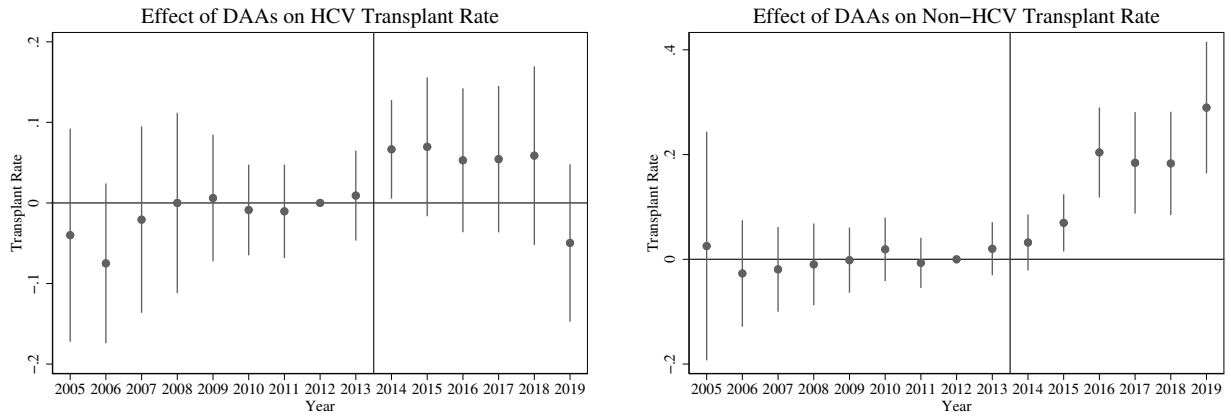
4 Transplant Rates

Appendix Figure 2



Notes: Authors' calculations of yearly national fractions using SRTR data.

Appendix Figure 3: Liver vs. Kidney Transplants



(a) (b)

Notes: Each subfigure presents time-disaggregated differences-in-differences estimates, comparing HCV^+ and HCV^- transplants to kidney waiting list additions and transplants. The outcome is defined as transplants divided by number of waiting list registrants. For kidneys, this rate reflects transplants divided by number of kidney registrants. For livers, this rate reflects transplants to HCV^+ registrants divided by number of HCV^+ liver registrants in subfigure (a), and transplants to HCV^- registrants divided by number of HCV^- liver registrants in subfigure (b). The bars around each coefficient reflect the 95% confidence interval using standard errors that are clustered at the DSA-by-organ level.

5 Dose-Response Regressions

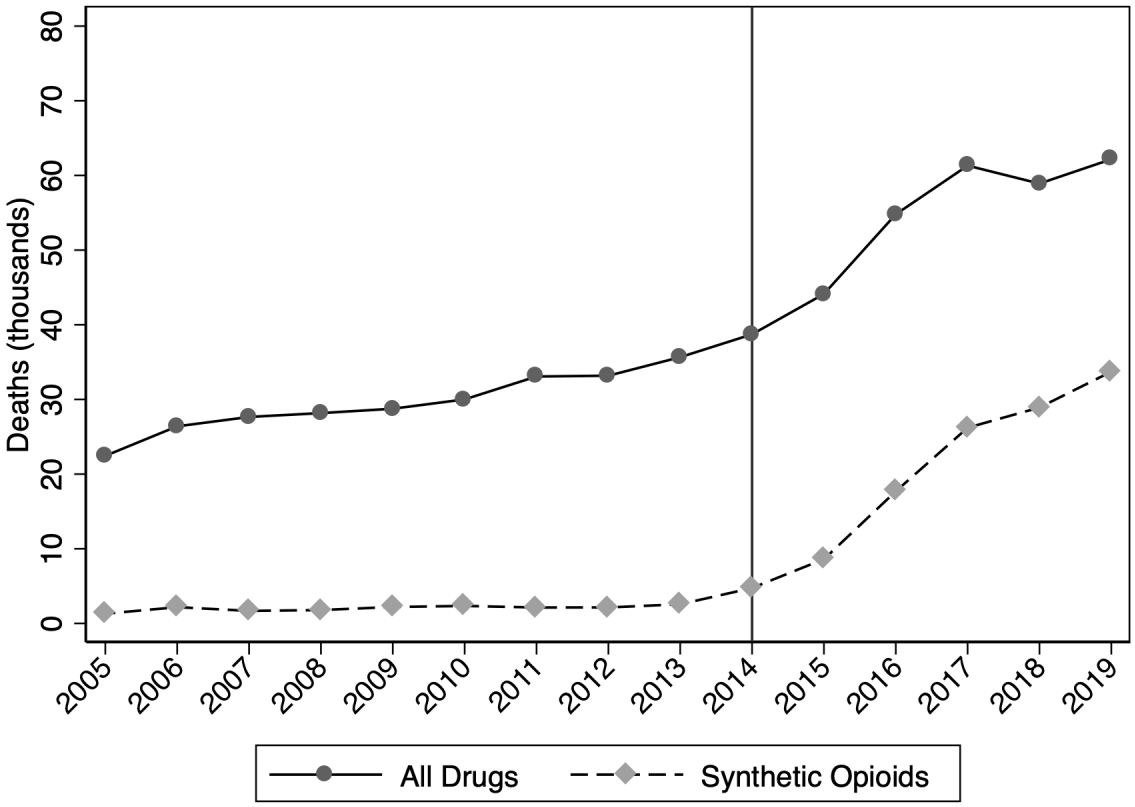
To build further understanding on our results in Table 2 of the main paper, we estimate regressions in which we allow the effects of DAAs to vary by the baseline HCV^+ rate in a DSA. Beacuse our hypothesized mechanism is that DAAs affect HCV^- listing behavior and transplant outcomes through reduced HCV^+ liver demand, we should expect to see larger effects of DAAs in areas with greater HCV prevalence. The regression we estimate is:

$$Y_{dlt} = \beta[\mathbb{1}(l = liver) \times DAA_t] + \tau[\mathbb{1}(l = liver) \times DAA_t]F_d + \gamma_{dl} + \eta_t + \epsilon_{dlt}, \tag{2}$$

where F_d is the pre-DAA mean prevalence of HCV in DSA d. Results are presented in Table 3 of the main paper.

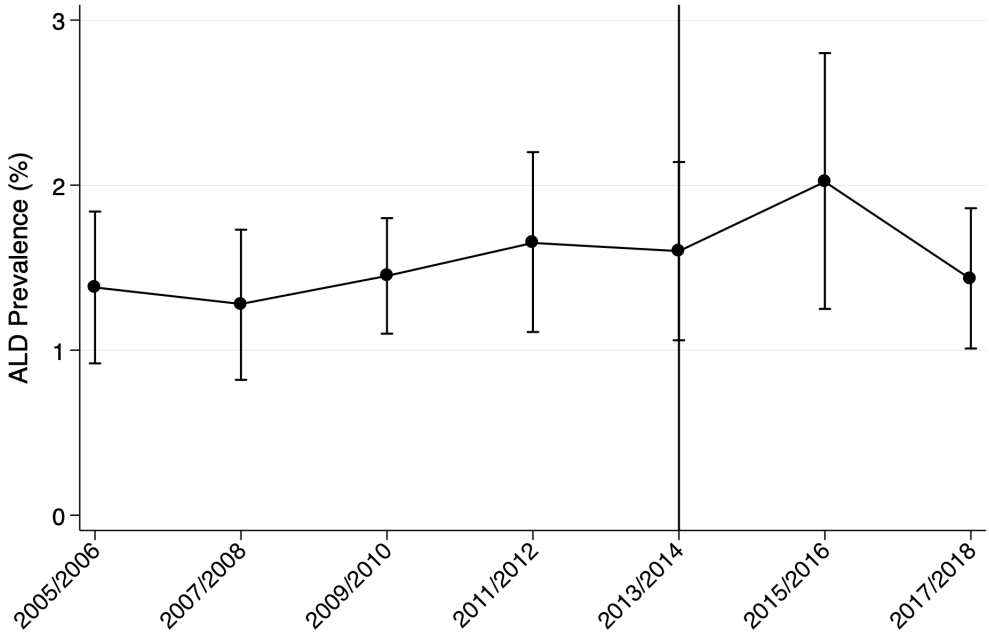
6 Concurrent Shocks

Appendix Figure 4: Drug Overdose Deaths by Year



Notes: Figure includes deaths deemed "prevantable or accidental". Synthetic opioids category is "synthetic opioids other than methadone" and includes fentanyl. Source: National Safety Council analysis of National Center for Health Statistics Mortality Data.

Appendix Figure 5: Alcoholic Liver Disease Prevalence by Year



Notes: Alcoholic liver disease is based on the following criteria: 1) average daily alcohol consumption of more than 10 grams for females and more than 20 grams for males and 2) alanine transaminase level or aspartate aminotransferase level greater than 31 U/L in females and an alanine transaminase level greater than 40 U/L or aspartate aminotransferase level greater than 37 U/L in males. Those with Hepatitis B or C infections were excluded. Source: National Health and Nutrition Examination Survey.

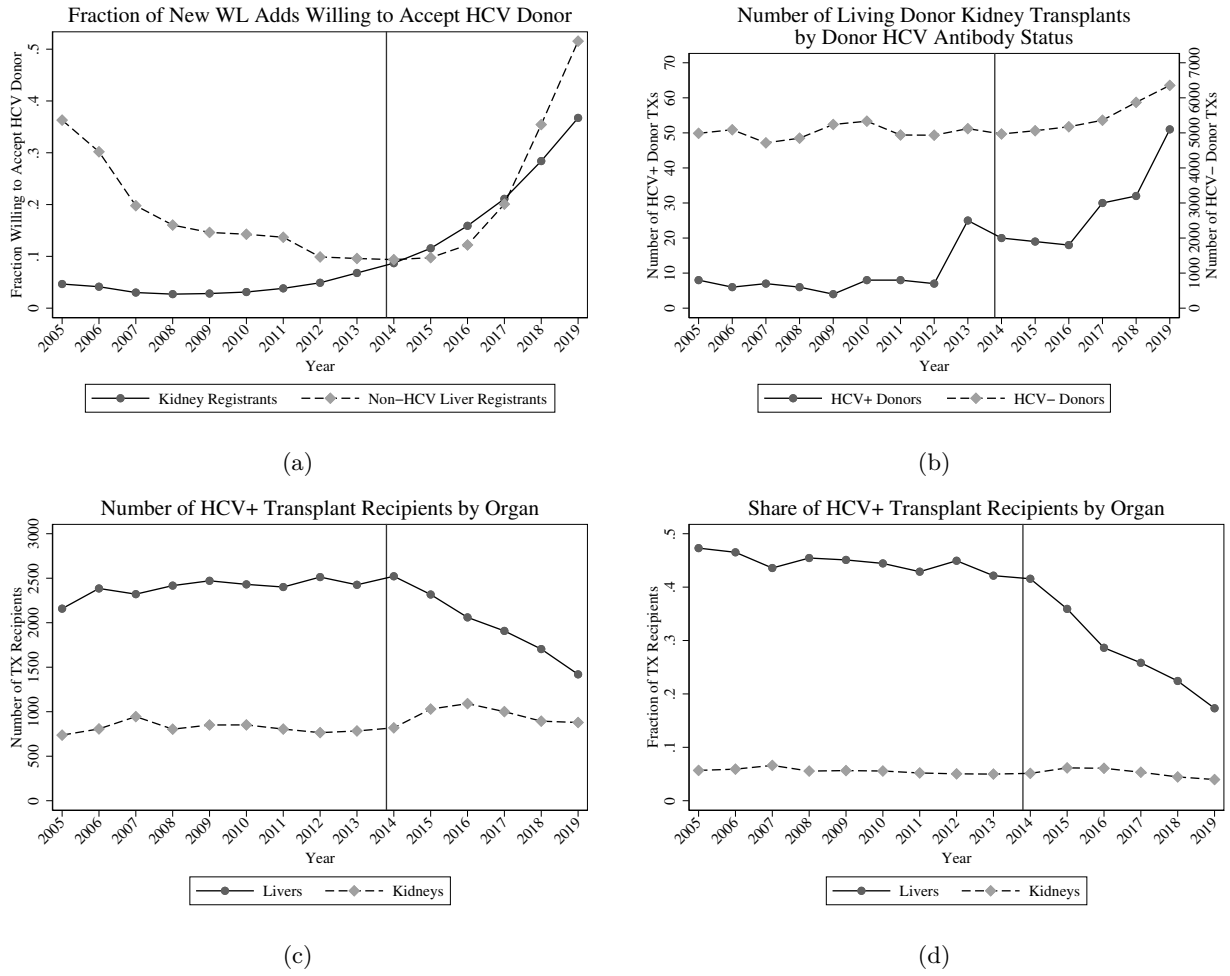
Appendix Table 4: CITS, HCV^- Liver Waiting List Additions by Diagnosis Category

	Log HCV^- WL Adds
Time Since DAA	0.0235
	(0.0146)
Time Since DAA x NASH	-0.0161
	(0.0157)
Time Since DAA x ALD	0.0679***
	(0.0142)
DAA	-0.0205
	(0.0391)
DAA x NASH	0.0326
	(0.0498)
DAA x ALD	0.0527
	(0.0573)
Year	-0.0030
	(0.0080)
Year x NASH	0.0992***
	(0.0089)
Year x ALD	0.0447***
	(0.0081)
Observations	2,025
R-squared	0.8825
N of Clusters	45

Notes: Includes DSA-by-Diagnosis FEs to mimic subsample analyses. Standard errors are in parentheses, and clustered at the DSA level. *** p<0.01, ** p<0.05, * p<0.1

7 Potential Spillovers

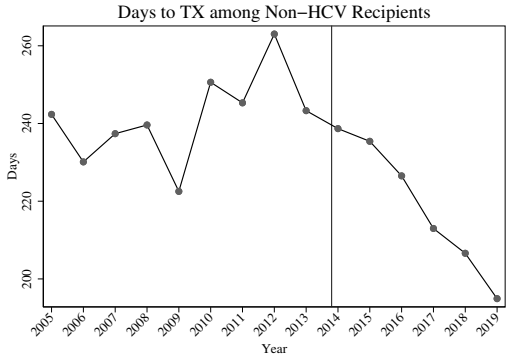
Appendix Figure 6: Potential Supply- and Demand-Side Spillovers to Kidney Context



Notes: Authors' calculations of yearly national counts and fractions using SRTR data. In panel (a), we exclude kidney registrants who are known to have an HCV-related diagnosis using the optional diagnosis text field in the data. This is a very small fraction of kidney candidates: only 0.13% of registrants from 2005 to 2019. Panels (c) and (d) use known HCV antibody test results at the time of transplant to identify HCV^+ transplant recipients. These results are conditional on receiving a transplant.

8 Further Evidence

Appendix Figure 7: Time from Wait-Listing to Transplant for HCV^- Liver Transplant Recipients



Notes: Authors' calculations of yearly national averages using SRTR data, measured as the difference between date of transplant and date of waiting list registration. In less than 0.2% of transplants, this equals zero. A value of zero can reflect either a true same-day transplant, or a case where a living liver donor recipient did not first join the deceased donor waiting list.

Appendix Table 5: Liver vs. Kidney Time from Wait-Listing to Transplant by HCV Status

	Log Days to TX	TX Faster Than 2005-12 Median
Panel A: HCV^-		
Liver x DAA	-0.1749***	0.0383**
	(0.0543)	(0.0155)
	[245.57]	[0.315]
Panel B: HCV^+		
Liver x DAA	-0.0057	-0.0303**
	(0.0505)	(0.0151)
	[295.04]	[0.266]
Observations	1,425	1,425
N of Clusters	95	95

Notes: Difference-in-differences estimates from Equation 1 of the main text. The dependent variable in the first column equals the log of 1 plus the number of days elapsed from waiting list registration to transplant. For those who got a transplant the same day or did not register on the waiting list before receiving a transplant, days elapsed equals zero. The second dependent variable is a binary indicator for whether the candidate received a transplant more quickly than the median days to transplant during the 2005-12 sample period. Dependent variable means (at the DSA-year level) are in brackets, and reflect the pre-treatment period (2005-13) means for liver registrants only. In column 1, the means reflect level number of days rather than log number of days. While there are 57 DSAs in the U.S., we use modified DSA identifiers (see footnote 1) due to changes in DSA existence and services over time, which yields 50 kidney-serving DSA and 45 liver-serving DSA identifiers. Standard errors are in parentheses, and clustered at the DSA-by-organ level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix Table 6: Liver and Kidney Waiting List Registrant Summary Statistics

	Liver Registrants				Kidney Registrants			
	2005-19		2005-13	2014-19	2005-19		2005-13	2014-19
	Mean	SD	Mean	Mean	Mean	SD	Mean	Mean
HCV-Related Diagnosis	0.295	0.456	0.365	0.201				
Can't Infer HCV Status	0.148	0.355	0.148	0.148				
Initial MELD	18.00	9.01	17.71	18.38				
Too Sick / Died	0.233	0.422	0.246	0.216	0.235	0.424	0.234	0.237
Improved	0.059	0.235	0.051	0.068	0.005	0.070	0.005	0.005
Dec. Don. TX	0.537	0.499	0.524	0.554	0.349	0.477	0.347	0.350
Liv. Don. TX	0.022	0.145	0.019	0.025	0.175	0.380	0.195	0.151
Days to TX	252.3	482.5	252.3	252.2	698.5	749.8	659.6	747.0
High School or Less	0.494	0.500	0.514	0.471	0.471	0.499	0.502	0.430
White Pct.	0.704	0.457	0.709	0.697	0.455	0.498	0.472	0.432
Primary Payer: Private	0.586	0.493	0.618	0.544	0.449	0.497	0.455	0.441
Primary Payer: Medicare	0.246	0.431	0.223	0.276	0.473	0.499	0.474	0.473
Primary Payer: Medicaid	0.168	0.374	0.159	0.180	0.078	0.267	0.071	0.086
Listing Age 18 to 39	0.095	0.293	0.091	0.100	0.189	0.392	0.197	0.179
Listing Age 40 to 64	0.749	0.434	0.789	0.694	0.634	0.482	0.642	0.624
Listing Age Over 64	0.156	0.363	0.119	0.206	0.177	0.381	0.162	0.197
South Census Region	0.373	0.483	0.355	0.396	0.376	0.484	0.360	0.399
NE Census Region	0.207	0.405	0.220	0.189	0.208	0.406	0.216	0.198
MW Census Region	0.207	0.405	0.207	0.206	0.197	0.398	0.205	0.187
West Census Region	0.213	0.410	0.217	0.209	0.218	0.413	0.220	0.216

Notes: Except for transplant/waiting list outcomes (too sick/died, improved, transplants, and days to transplant), which are calculated based on transplant timing and waiting list removal timing, all summary statistics are calculated based on when the candidates joined the waiting list.

Appendix Table 7: Livers Discarded Due to Poor Quality

	Log #	#/All Organs	#HCV/All HCV
Liver x DAA	0.1374**	0.0243***	-0.0353
	(0.0686)	(0.0081)	(0.0237)
Baseline Mean	24.96	0.152	0.377
Observations	1,500	1,500	1,414
N of Clusters	100	100	100

Notes: Difference-in-differences estimates from Equation 1 of the main text. The outcome variable in column 1 is the log number of livers that were discarded due to reasons related to poor quality per DSA-year (see footnote 21 in the main text for the definition of "poor quality"). Baseline means reflect the pre-treatment period (2005–2013) means for liver registrants only. In column 1, the mean reflects the DSA-year level count rather than log count. While there are 57 DSAs in the U.S., we use modified DSA identifiers (see footnote 1) due to changes in DSA existence and services over time, which yields 50 kidney-recovering and 50 liver-recovering DSA identifiers. Note that, even though there are only 45 modified DSAs with liver transplant programs in our data, organ procurement organizations across all 50 modified DSAs recover and allocate livers from deceased donors, which explains the slightly larger number of clusters and observations here relative to Tables 2-4. Standard errors are in parentheses and are clustered at the DSA-by-organ level. *** p<0.01, ** p<0.05, * p<0.1