Medicaid expansion and the mechanics of increased access to organ transplantation*

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The paper with Appendix is available at `www.saramachado.org/research`

Abstract

We estimate the effect of Medicaid expansion on organ transplantation. Using an outcome regression Callaway & Sant'Anna staggered differences-in-differences estimator and the universe of solid organ transplant candidates, between 2010 and 2018, we harness transplant candidates' full clinical journey to measure the impact of Medicaid expansion along four dimensions: coverage, access to care, change in payer mix, and organ allocation efficiency. In this nationwide all-payer data, our results show increased Medicaid coverage and changes in the payer mix, with Medicaid gaining relevance in relation to other public and private sources of payment. However, the effects are not immediate and we find limited evidence of increased access to organ failure care ahead of wait listing, within Medicaid. Finally, the findings are consistent with efficient organ allocation policies, with expanded coverage turning into increased access to transplants. Broader Medicaid coverage amplified the effect of the new kidney allocation system, which aimed to reduce transplant disparities.

Keywords: Medicaid expansion; Crowding out; Organ transplants; Staggered differences-in-differences
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1 Introduction

Medicaid expansion is a widely studied health policy reform. In the context of the Affordable Care Act, eligibility rules were simplified and now include all adults with household income below 138% of the federal income poverty line.[1] It was left to the states to decide whether or not to adopt this policy change. As it turns out, whether and when states implemented it is highly related to the Conservative or Democrat political ideology prevailing.(16) This exogenous variation in the decision to implement Medicaid expansion has been widely used by researchers to identify causal effects of providing health insurance, using quasi-experimental staggered difference-in-differences designs.

In this paper we combine nationwide data on transplant candidates with state-level population and Medicaid coverage data to examine the effects of Medicaid Expansion on solid organ transplantation. Our empirical strategy uses a reduced form approach to estimate the effect of Medicaid expansion on state-level patient listing behavior. We compute the average treatment effect on the treated states (ATT), using Callaway & Sant'Anna (2) outcome regression differences-in-differences estimator.

Our results are of high societal relevance due to the high need high cost nature of transplantation care, which ranks among the most live-saving interventions available. In fact, the details of transplantation pathways are also at the core of our main contribution, allowing us to explore the mechanism by which an expansion in Medicaid eligibility translates into health care coverage, access to care, and patient treatment decisions. Our research design conceptualizes a set of outcomes along the patient journey, to quantify the multidimensional relationship between health insurance and health care utilization.

We contribute to the literature about Medicaid expansion, which established early on its effects on increased coverage, confirming that the changes in eligibility criteria had effectively led to the enrollment of new Medicaid beneficiaries. For example, (13) estimated a 15.6 p.p average increase in rates of Medicaid coverage, using a simple differences-in-differences design. There is further evidence of large and heterogeneous increases in coverage based on age, education, and marital status, among others.(4; 9) Later papers studied the effects of Medicaid expansion in increasing access and utilization of several types of health care, including prescription drug use (6), preventive care (18), and opioid use disorder treatment (12), among others. More recently, the literature went on to study Medicaid expansion impact on health outcomes (11) and supply side effects, including clinicians' change in payer mix and labor supply (14).

The way evidence about Medicaid expansion evolved overtime is somehow illustrative of the nuances

[1] There are some exceptions to the 138% threshold, see (15). Before Medicaid expansion, or for states that have not implemented it, eligibility criteria is based in several dimensions such as income, household size, disability, family status, among others, and vary across states.

around the link between health insurance, demand for health care, and healthcare utilization. The topic has been widely studied since early results of the RAND Heath Insurance Experiment (10), but to the best of our knowledge the literature is remiss in what concerns transplantation. There are two main reasons why the transplantation market is a relevant setting to study such an expansion in health insurance. First, deceased donor organ allocation is centralized and covers the entire country, regardless of the payer. In practice, the resulting waiting list is an all-payer registry of the entire demand for a specific type of health care procedure. While there are some state level all-payer databases, the depth of the national coverage of these data enables in-depth analysis of the mechanisms triggered by Medicaid expansion which are extremely challenging with other data sources. Second, organ allocation mechanisms and the waiting list itself were created to bypass the supply-side restrictions due to the limited availability of donor organs. While these supply-side constraints might seem extreme, recent health crisis such as the COVID-19 pandemic brought to our attention several other shortages limiting health care provision. From limited supply of ICU beds during the worst waves of the pandemic to the shortages of health and social care workforce persisting beyond it, health care supply capacity constraints are frequent bottlenecks associated with equity and efficiency concerns. Our paper provides evidence on how these bottlenecks, along market solutions such as allocation mechanisms, might limit or enhance the ability of expanded coverage in enabling access to health care.

Besides the insights offered to other health care settings, our findings are relevant to inform policy-making on the nuances behind effectively increasing access to transplantation care, which has considerable impacts on health systems' budgets. On the on hand, the vast majority of these patients suffer from organ failure or end-stage organ disease and require intensive health services support.[2] On the other hand, there are high costs associated with each step of the transplantation process. First, it is costly to be added to the waiting list due to the investigations needed. Second, managing a patient on the waiting list is also costly, as these are patients with end-stage organ failure, often with recurrent re-admissions. Third, the cost of transplant itself, which is one of the most expensive procedures. And finally, there are also post-transplant costs, of which immunosuppressant medication is a key component. Even though, a successful transplant not only leads to massive quality of life improvements but it also reduces health care utilization. It is therefore essential to understand if the effects of Medicaid expansion reported for other domains are effectively replicated in this high need high cost patients.

[2]Heart failure patients, for example, have recurring hospitalizations and a high burden of pharmaceutical treatment and/or mechanical circulatory support. End stage renal disease patients waiting for a transplant will most likely have to be in dialysis 3 to 4 times per week. Without a transplant, their life expectancy is greatly reduced.

The paper is organized as follows: in Section 2 we outline our conceptual framework and present the outcomes of interest; Section 3 describes our empirical strategy and estimation methods; the data analysis and estimation results are shown in Section 4; and Section 5 concludes.

2 Conceptual Framework

2.1 Pathway to transplantation

An organ transplant is the culmination of a long process, which typically includes some chronic disease onset leading to organ failure.[3] The transplantation phase of a patient's clinical journey starts with either the diagnosis of a chronic disease that is known to lead to organ failure or with acute organ failure.[4] At that stage, the patient is informed of her options, which may include some form of organ replacement therapy but often identify an organ transplant as the standard of care. For example, for patients with chronic kidney disease evolving into end-stage renal failure, dialysis is a long standing renal replacement therapy, but the sooner the patient receives a renal transplant the better the health outcomes.[5] For some organs it is common to search for a living donor, particularly for kidneys but also for livers, to a lesser extent. However, most organ donors are deceased organ donors (henceforth, donors), which are the focus of this paper and whose search process is highly regulated.[6]

Access to donor organs is restricted to patients who are enrolled in the United Network for Organ Sharing (UNOS) waiting list. A patient must first be referred to a transplant center, whose transplant board then decides whether or not they are a suitable transplant candidate. A patient may be deemed unsuitable for transplantation due to reasons directly related to their organ's condition, e.g. they are already too sick to transplant, but also due to other clinical risk factors, e.g. obesity or inability to quit smoking. Moreover, they may be excluded from the list due to socioeconomic factors, such as the lack of support in the community, e.g. if they do not have a caregiver able to be off work for at least 2

[3]For simplicity, we refer to solid organs, specifically kidney, liver, lungs, and heart, whenever organs are mentioned throughout the paper. Our analysis focuses on these four organs, which represent almost 97% of the 63,631 new transplant candidates, measured by the number of waiting list additions, in 2018.

[4]Organ failure is the result of either chronic disease or some acute condition. Chronic kidney disease, for example, is the most frequent precursor of kidney failure, or end-stage renal disease. Cirrhosis of the liver often leads to liver failure, and chronic obstructive pulmonary disease, for example, leads to respiratory failure. A number of heart conditions, either chronic or acute onset, can lead to heart failure.

[5]Recent developments in mechanical circulatory support have enabled patients with heart failure to use a number of devices as either bridge to transplant or destination therapy, when the patient is not a viable transplant candidate.

[6]We focus on deceased donor organ transplantation and for simplicity refer to deceased donors as donors and deceased donor organ transplants as organ transplants. Living donation is restricted to a subset of kidney donation (2017: 29%, 5,811 out of 19,849 kidney transplant recipients) and a small fraction of liver transplants (2017: 4.7%, 367 out of 8,082 liver transplant recipients) and follows separate paths. Listing and organ allocation policies only apply to deceased donation.

weeks post transplant, or lack of financial means to cover the out of pocket costs (i.e. underinsurance[7]) of both the transplant procedure itself and the post-operative long term care, which includes life-long immunosuppressant medication. Needless to say, for most people lack of health insurance coverage would make it virtually impossible to reach this stage of the process, much less being able to support themselves financially throughout the transplant procedure. Ultimately, the decision of whether or not to add a patient to the waiting list is based on subjective criteria and can vary across transplant centers.

Transplant candidates, defined as patients on an organ-specific waiting list, are then matched with organ donors through organ allocation algorithms.[8] The waiting process can lead to numerous out of pocket expenses, including relocation, caregiver absence from work, and of course potentially hospitalizations due to illness severity. The allocation mechanisms centralize decision-making and use geographic and clinical criteria to optimize the longevity of donated organs. They are designed to be objective criteria. Once a donor is identified, the organ is matched with the transplant candidates. The algorithm produces a ranking of patients, who are offered the organ match sequentially. If the first, or most suitable, match rejects the offer, the second patient receives the offer, and so on. If and when a transplant candidate is successfully matched and the transplant procedure is successful, the following stage of the transplantation journey ensues, where the transplant recipient stays on a lifelong course of immunosuppressants in order to avoid or delay graft rejection. They will, however, for the most part, be able to live a life free from the restrictions caused by their organ failure pre-transplant. At this stage, behavioural risk factors and continued medical care are key to ensure the longevity of the transplanted organ and avoid graft failure.

2.2 Outcomes

We define four outcomes of interest, each related to a different margin that may be affected by Medicaid expansion: coverage, access to care, payer mix, and organ allocation efficiency. Each of these outcomes hinges on a different stage along organ transplant patients' clinical journey. These metrics are all anchored by the number of new transplant candidates with Medicaid listed as their primary source of payment (henceforth Medicaid waiting list additions, or Medicaid WLA). Each outcome is a ratio in which medicaid

[7] An interesting case are patients with end-stage renal disease, who automatically qualify for Medicare, without waiting period, but even that does not necessarily mean they would have the financial ability for the whole transplant process. None of the other organs benefit from streamlined Medicare benefits.

[8] There is a wide variety of organ-specific allocation algorithms, but they have a set of common elements, which include the primacy of severity of illness and aiming for an equitable allocation of organs. According to the Organ Procurement and Transplantation Network's "Final Rule for Organ Transplantation" (**(year?)**), organ allocation should be both efficient and equitable, aiming to maximize transplant recipient survival and thus longevity of donated organs, while taking into account group-specific needs. For example, exemptions are built in for highly sensitized kidney transplant candidates, who have more stringent deceased donor matching criteria.

waiting list additions are either the numerator (outcome 1, 2 and 3, with different denominators) or the denominator (outcome 4). Figure 1 outlines three main stages in the patient clinical journey, how patients transition between them and how to quantify the four outcomes.

Coverage The first outcome we study is coverage, a key and initial requirement to start the pathway towards organ transplantation. We hypothesize that increased coverage is a direct consequence of Medicaid expansion, as more citizens become eligible for Medicaid under the new criteria and mode of enrolment.

The first outcome is, for state s and time t,

$$\omega_{st}^1 = \frac{\text{Medicaid waiting list additions}_{st}}{\text{Population}_{st}}.$$

An increase in ω_{st}^1 is in line with our hypothesis and can be interpreted as the effect of increased Medicaid coverage, taking into account population size differences across states. Ultimately, coverage can be considered as our anchor/baseline outcome: it capture patients that are now able to join the waiting list because of being Medicaid beneficiaries but would not be considered for transplantation with Medicaid as their payer before its expansion. However, simply looking at ω_{st}^1 does not tell us enough about the mechanisms behind increased coverage with Medicaid expansion. For that we need additional outcomes.

Access to care At the first sight, the mechanism behind the effects on increased coverage seem to be simple and relate to affordability of the transplantation procedure itself. A closer look to the patient journey reveals that increased coverage can lead to wait listing through several channels. We use our second outcome, access to care, to disentangle two channels. Suppose we observe a higher number of waiting list additions, per capita, in expansion states. On the one hand, these additional transplant candidates may be patients with known organ failure who could not afford to be added to the waiting list without Medicaid expansion. On the other hand, these may be patients whose organ failure was now detected or referred to transplantation due to better access to health care with Medicaid expansion.

The second outcome is, for state s and time t,

$$\omega_{st}^2 = \frac{\text{Medicaid waiting list additions}_{st}}{\text{Medicaid beneficiaries}_{st}}.$$

This outcome separates two channels: more transplant candidates due to the passing through of newly covered patients, now able to afford the out-of-pocket costs of the transplant procedure, or more transplant candidates due to an increase in access to organ failure care among Medicaid beneficiaries, bringing them

to the waiting list. The exact interpretation of ω^2_{st} requires us to consider the severity of the patient population insured by Medicaid in each moment in time, and how it changes with Medicaid expansion. On the one hand, at similar patient population severity before and after expansion, an increase in ω^2_{st} suggests that patients were more likely to be wait-listed due to additional health care, either through timely organ failure diagnosis or care making them clinically eligible for transplantation.[9]. On the other hand, if overall patient severity increases (i.e. citizens insured after Medicaid expansion are on average sicker than before) additional wait-listings might just reflect higher need amongst newly covered patients. Nonetheless, the results can still be interpreted as increased access to care after expansion: while the average Medicaid patient after expansion would not receive more care than before expansion, the overall expenditure with care ahead of wait-listing would increase, due to increased volume of patients. Last, if ω^2_{st} decreases, then we have a higher number of beneficiaries but less additions to the waiting list. This would either mean that there is less access to care after expansion, holding patient severity constant, or that beneficiaries newly added to Medicaid are healthier, on average.

Payer mix It may also be the case that the additional Medicaid transplant candidates are merely the result of substitution of health care coverage, if patients listed after expansion via Medicaid would have been otherwise listed through Medicare or private insurers. While we cannot directly examine these crowding out effects, we can measure the change in the payer mix, e.g. how the three main types of payers (Medicaid, Medicare and private insurance) contribute to the financing of transplantation care.

The third outcome, for state s and time t, is then

$$\omega^3_{st} = \frac{\text{Medicaid waiting list additions}_{st}}{\text{Total waiting list additions}_{st}}.$$

If ω^3 is larger than one, Medicaid waiting list additions are increasing at a higher rate than other payers, which is our main hypothesis. Alternatively, but less likely, Medicare and private insurers wait-listing can also increase, either at a similar ($\omega^3 = 1$) or even higher rate ($\omega^3 < 1$). Additional conclusions arise from combining the first and the third outcomes. The combination of a positive ω^1 with ω^3 approaching one would suggest increased overall insurance coverage for expansion states, coming from both Medicaid, Medicare, and private insurers.[10]

[9] In the long run increased access to care might also slow down patient clinical deterioration towards organ failure, and hence postpone the need of a transplant. The timing of the interventions needed for such a change in the clinical journey make this unlikely to be the case in the first years after Medicaid expansion and thus not a factor in our analysis

[10] Other combinations of these outcomes are suggestive of payer crowding out, which we cannot investigate further with the existing data.

Organ allocation efficiency Efficient organ allocation would imply that, once on the waiting list, receiving an organ donor match offer would be independent of the payer, as the allocation algorithm does not include financial coverage. With the last outcome we investigate if a potential increase in Medicaid waiting list additions has led to a proportional increase in Medicaid transplant recipients. Hence, the fourth outcome is, for state s and time t,

$$\omega^4_{st} = \frac{\text{Medicaid transplants}_{st}}{\text{Medicaid waiting list additions}_{st}}.$$

Similarly to ω^2, the interpretation of ω^4' results depend on any effects on Medicaid's patient population severity.[11]. If severity is unchanged, $\omega^4 = 1$ indicates similar efficiency of organ allocation after Medicaid expansion. Therefore, access to the waiting list would have translated into access to the life-saving therapy, independent of the availability of deceased donor organs. On the contrary, ω^4 larger or smaller than one would be suggestive of positive or negative discrimination of Medicaid patients in organ matching, relative to other payers. While positive discrimination would be favourable to Medicaid beneficiaries, this would be controversial for the transplantation system as a whole. The interpretation of ω^4 increases in complexity if the patient population severity changes with Medicaid expansion. If this is the case, ω^4 larger or smaller than one might be associated with an increase in the transplantation system's efficiency. For example, a larger proportion of Medicaid transplant recipients after expansion ($\omega^4 > 1$) could be due to either higher patient severity or a higher likelihood of donor matching due to sociodemographic and clinical characteristics of this new group of beneficiaries.

3 Empirical strategy

In this section we describe the details of our differences-in-differences research design. We use the roll out of Medicaid expansion, staggered across states, to estimate the causal effect of the policy change, measured by the average treatment on the treated. For the main analysis, we use an outcome regression specification of the Callaway and Sant'Anna (CS, (3)) differences-in-differences model and estimator.

[11] Changes in the severity of Medicaid waiting list patients are examined in section 4.1.

3.1 Estimating Average Treatment on the Treated

The CS approach directly estimates the causal parameter of interest. In our case, the average treatment on the treated is defined as, for treatment group g and time t,

$$ATT(g,t) = \mathbf{E}[\omega_t^i(g) - \omega_t^i(0)|G_g = 1] \qquad i = 1, ..., 4 \tag{1}$$

which is defined for each quarter t and each treatment group g. The value $\omega_t^i(0)$ is the untreated potential outcome. Notice that g is a timing variable. States that expanded Medicaid on the same quarter $t = g$ belong to the same treatment group.

We define our control group as a never treated group, which is the set of states that chose not to expand Medicaid eligibility according to the Affordable Care Act criteria, between 2010 and 2018. We refer to the states that ever expanded Medicaid between 2014 and 2018 as Medicaid expansion states. Within those, each treatment group g is defined as the set of states that expanded Medicaid at the same time, or, in our case, in the same quarter. Figure 2 shows state composition of each of the 5 treatment groups. The largest group is the first, which expanded Medicaid in the first quarter of 2014, with 25 out of the 32 Medicaid expansion states. Our outcome variables ω^i are the four outcomes defined in Section 2.

For each ω^i, we can rewrite the causal parameters of interest as

$$ATT(g,t) = \mathbf{E}\left[\omega_t^i - \omega_{g-1}^i|G = g\right] - \mathbf{E}\left[\omega_t^i - \omega_{g-1}^i|C = 1\right] \qquad i = 1, ..., 4, \tag{2}$$

which measures the average difference-in-differences between ω^i in treatment group g and in control group C, compared to the pre-treatement values based on treatment timing $g - 1$.[12]

Estimation method: Outcome regression We model the ATT based on an outcome regression, with the following assumptions (i) zero anticipation periods[13], using the full path of experienced outcomes, both before and after Medicaid expansion; (ii) unconditional parallel trends; and (iii) with never treated states as control group, i.e., the states that did not expand Medicaid during the study period. As such, the ATT can be defined as

$$ATT^i(g,t) = \mathbf{E}\left[\omega_t^i - \omega_{g-1}^i - m_{g,t}^i\right] \qquad i = 1, ..., 4, \tag{3}$$

[12] General identification conditions are (un)conditional parallel trends based on never treated states, limited treatment anticipation, irreversibility of treatment, and random sampling across treatment groups, i.e. there is no relationship between treatment allocation and potential outcomes.

[13] $ATT(g,t) = 0$ for all pre-treatment periods

where $m^i_{g,t}$ is the difference $\mathbf{E} = \left[\omega^i_t - \omega^i_{g-1} | C = 1\right]$, i.e. restricted to never treated units.

Identification In Medicaid expansion, there is no treatment anticipation, as individuals can only become eligible for Medicaid coverage after the expansion itself, which will likely lead to a delayed effect on waiting list additions. Although reversibility of treatment was at stake during the past years, it never actually happened, and Medicaid expansion is, so far, an irreversible treatment. We revisit the parallel trends assumption in Section 4.3.[14]

Summarizing treatment effects Following (3), we define three aggregate treatment effect measures as a weighted average of time-group-specific $ATT^i(g,t)$, generally defined as

$$\theta = \sum_{g \in G} \sum_{t=2}^{\tau} w(g,t) ATT^i(g,t) \tag{4}$$

where $w(g,t)$ is a weighting function. For each ω^i, we estimate 1) the treatment effect across groups and all post-treatment periods

$$\theta^i_1(g) = \frac{1}{\tau - g + 1} \sum_{t=2}^{\tau} \mathbb{1}\{g \leq t\} ATT^i(g,t) \qquad i = 1, ..., 4$$

, which weighs each $ATT^i(g,t)$ across all post-treatment periods and all states with $G = g$.

$$\theta^i_2(g) = \sum_{g=2}^{\tau} \theta^i_1 P(G = g) \qquad i = 1, ..., 4$$

, which measures the overall effect of ever expanding Medicaid, and 3) balanced dynamic treatment effects,

$$\theta^i_3(e, e') = \sum_{g=2}^{\tau} \mathbb{1}\{g + e \leq e'\} ATT^i(g, g+e) P(G = g | G + e \leq e') \qquad i = 1, ..., 4$$

across all groups observed for $e' = 12$ post-treatment quarters, starting in January 2014. Time since treatment is given by $e = t - g$. Similarly to the other aggregate measures, the weight combines both time since treatment and the probability of the unit having been treated at a particular g.

Estimation and inference We use the did R package to perform the estimation. Given the restricted number of states in each $G = g$ other than $G = 1$, the first quarter of 2014, we estimate bootstrap point

[14] The assumption is a standard parallel trends assumption, which requires control and treated units would follow similar paths in the absence of the intervention, defined by $\mathbf{E}\left[\omega^i_t(0) - \omega^i_{t-1}(0) | G = 1\right] = \mathbf{E}\left[\omega^i_t(0) - \omega^i_{t-1}(0) | C = 1\right], i = 1, ...4$.

wise confidence intervals, with 2000 repetitions.

Alternative estimator In Appendix A, we describe the empirical strategy and provide a parallel analysis standard two-way fixed effects specification restricting the analysis to the first set of expansion states, in the first quarter of 2014. According to Bacon decomposition (7), also provided, this is the treatment group driving the treatment effect. In Appendix B we show dynamic treatment effects estimates using a standard event study specification.

3.2 The data

Our main data source is the restricted-use UNOS patient-level registry, from the Organ Procurement and Transplantation Network. This dataset includes patient-level information for the universe of organ donors and transplant candidates, including the dates of wait-listing and transplant, clinical assessments done ahead of each one of these phases, information of the transplantation payer, among others. For each of the organs studied we extract from UNOS dataset information on waiting list additions, transplants, payer and transplant candidate/recipient home state, between 2010 and 2018.

We then link these data with four additional sources of data, at the state-level for each year studied. To estimate our outcomes of interest we obtain state-population from the WONDER database of the Center for Disease Control and Prevention (CDC), and the number of Medicaid enrollees from the Medicaid and CHIP State Health Facts. From the American Community Survey (17), we obtain information to control for state-level demographics in our models, including age (proportion below 18 and above 65), gender, race/ethnicity (White non hispanic, Black non hispanic, Hispanic, and other) and educational level of individuals (proportion with college education). Last, from the Global Burden of Disease we obtain estimates for the prevalence of diseases potentially leading to the need of a transplant, for each organ: chronic kidney disease, cardiovascular disease, liver disease, lung disease.[15]

4 Results

In this Section we first present evidence on the evolution of the transplant candidates' severity (Section 4.1). We then present the state-level ATT estimates of the causal effect of Medicaid expansion on each outcome ω^i.[16] First, Section 4.2 shows aggregate estimates, comparing all the states that expanded Medicaid between 2014 and 2018 with never treated states. It also provides results separately for the first group g

[15] Detailed information about the specific diagnosis that were considered for each disease group is available upon request.
[16] All ATT estimates were computed using the R package did (2).

to expand Medicaid, in the first quarter of 2014 (designated first expansion group from now on).[17] Section 4.3 shows dynamic treatment effects for the 2 years following Medicaid expansion, estimated based on a balanced sample exposed to 9 quarters of Medicaid expansion. In this Section we will revisit and verify the unconditional parallel trends assumption mentioned in Section 3.1, as the estimation of dynamic treatment effects provides a test for the parallel trends assumption. Last, Section 4.4 presents results stratified by organ - kidney, liver, heart, and lung. The four organs have independent waiting lists and organ allocation policies, even though there are some links between their markets, namely through common donation service areas and organ procurement organizations.

4.1 Patient severity

In Figure 4 we compare the distributions of three key patient characteristics - age, gender, and race/ethnicity - before and after Medicaid expansion for treated states (top panel). There is barely any change in the density of age at listing and gender with the reform. We observe a slight increase in the relative proportion of Hispanic and Other transplant candidates, whereas the opposite happens for White and especially African American patients. We do also analyze the distributions of organ-specific metrics of patient severity at admission. For all the organs except heart highest scores are associated with highest severity of disease, and greatest urgency for transplantation. Bottom panel of Figure 4 suggests a small increase in patient severity for both heart and kidney candidates, while a larger shift is observed in the distributions of MELD[18] and LAS[19] scores, respectively for liver and lungs transplant candidates. Overall, evidence is suggestive of a deterioration in the severity of Medicaid wait listing additions for all the four organs, after expansion. These differences are unlikely to be driven by a selection on transplant candidates demographic characteristics, in which data suggests a very limited change after Medicaid expansion.

4.2 Aggregate Treatment Effects

There were a total of 284,112 kidney, 97,582 liver, 30,232 heart, and 22,246 lung new transplant candidates added to the waiting list between 2010 and 2018 (N=434,172). Of those, 63% (kidney), 64% (liver), 61% (heart), and 65% (lung) percent were added in Medicaid expansion states. In Table 1 we find ATT estimates

[17] Due to the small size of the remaining g, with less than 5 states each, we are unable to provide separate estimates for those groups.

[18] Model for End-stage Liver Disease, which measures the severity of chronic liver disease. It was adopted in 2002 in response to the Final Rule for Organ Allocation's (1) requirements improved allocation metrics that would target existing disparities in access to deceased donor organs. For more details, see, for example, (20).

[19] The LAS was adopted in 2005. It measures patient severity and expected post-transplant survival. Together with blood type and distance between donor and recipient hospitals, it is used in the allocation of deceased donor lungs. For more information, see `https://optn.transplant.hrsa.gov/resources/allocation-calculators/las-calculator/learn-about-las/`

for each outcome ω^i. For coverage (ω^1) the estimate of the aggregate effect on waiting list additions per 100,000 population is 0.145 (SE: 0.050), 38% of the its pre-treatment mean. The full 95% confidence interval is above zero. The first expansion group has a similar effect (0.151), but in this case the confidence interval's lower bound is slightly below zero (-0.007). The ATT on the outcome related to payer mix (ω^3) is over 34% of the pre-treatment mean (estimate: 2.946, SE: 1.180). In other words, Medicaid expansion states have an over 34% higher proportion of Medicaid patients amongst their new transplant candidates, after expansion. The estimated effect is proportionately smaller for access to care (ω^2, 9.8%) and organ allocation efficiency (ω^4, 7.3%), with wide confidence intervals around zero. Together, these findings are indicative of a strong coverage expansion in transplant care, via ω^1, accompanied by a change in the payer mix, via ω^1.

4.3 Dynamic Treatment Effects

In this section we analyse temporal variation in the four outcomes, first showing the evolution of the distribution of each of the outcomes and then providing dynamic treatment effects estimates. We will discuss the results of the CS estimator, which uses all pairwise comparisons of group means at each quarter to compute group-time ATT. We chose to compute the aggregated dynamic treatment effects based on a common post-treatment exposure time, 9 quarters. The estimation of dynamic treatment effects using the (2) R package enables us to directly test the unconditional parallel trends assumption, which are also confirmed by the data in Figure 3.[20]

Outcomes over time by treatment status We first look at the evolution of the mean and 95% CI of each outcome, separated according to whether or not they ever expanded Medicaid (Figure 3). We can observe a diverging pattern between mean outcomes between never treated and treated in $\omega^1 - \omega^3$. Until 2014, they exhibit parallel paths. From then on, outcomes from states that expanded Medicaid at some point in our study period steadily increase. In ω^3, for example, the mean percentage of Medicaid waiting least additions rises from 10 in 2014:Q1 to 14 from 2015:Q1, a 40% increase. There is a noticeable spike in 2015:Q1 in ω^1 and ω^2. This is due to the new kidney allocation system (KAS), implemented in December 2014, which enabled a large group of pending transplant candidates to be added to the waiting list at that point. In Section 4.4 we will analyse the heterogeneous treatment effect across organs. Interestingly, we

[20]For more information, see `https://cran.r-project.org/web/packages/did/vignettes/pre-testing.html`. In Appendix B.1 we provide further analysis confirming these results using event studies. As pointed out in (19) if there is selective or non-random treatment timing these estimates can be misleading. In this paper, this problem is minimized, as there is virtually no direct link between transplantation behavior and states choosing whether or not to expand Medicaid eligibility.

observe no KAP effect on ω^3 and ω^4, which means that the effect was evenly distributed across payers. In fact, we don't observe any systematic change in ω^4 overall or per organ in the period studied. This suggests that whatever changes are happening upstream, they do not seem to affect the ratio between the flow of new Medicaid transplant candidates and new Medicaid transplant recipients.

Dynamic treatment effects estimates The dynamic ATT estimates, based on the number of quarters since the adoption of Medicaid expansion, can be found in Figure S1, depicting one w^i per quadrant. We can see a common pre-treatment path across all outcomes, based on the 12 quarters pre-medicaid expansion. The estimates are large in line with the path observed in Figure 3, ascertaining the relevance of the first treatment group since for these states calendar time and time since event are the same. The results are indicative of a delayed response to Medicaid expansion. It seems to be the case that the change is not immediate, rather the policy change takes at least 1 year to reach a somewhat constant higher level for ω^1 and ω^3. In particular, the change in payer mix not immediate, rather it steadily grows to 4 percentage points, in line with the previous estimate of a 40% increase. If there is also a higher steady state in ω^2, it is small in magnitude, compared to ω^1 and ω^3. We observe no systematic effect on ω^4, which is in line with the hypothesis of no effect of Medicaid expansion on access to donor organs above and beyond the effect from increased access to the waiting list. As such, it is reasonable to conclude that organ allocation policies are independent of upstream changes.

4.4 Heterogeneity across organ type

Estimated ATT The results are summarized in Table S1. The first thing to note is the differences in organ-specific magnitude of the effects on ω^1. The number of additional transplant candidates per capita is an order of magnitude higher for kidney and liver transplants. In fact, across all untreated periods for Medicaid expansion states, there were, on average across states, 0.186 kidney waiting list additions per 100,000 population. Over the same period, there were 0.338 heart and 0.134 lung waiting list additions per 1,000,000 population. Nevertheless, ω^1 ATT estimates are relatively similar across organs, albeit with wide confidence intervals for heart and lungs. In general, the estimates are imprecise, but of the same sign and with large relative magnitudes.

Kidney transplant candidates Kidney transplantation has some unique features amongst the solid organs being analyzed in this study, that might justify the largest magnitude of its results. On the one hand, there was the change in the Kidney Allocation Policy (KAP), which has, in practice, changed the overall

dynamic of governing waitlisting timing.[21] There may have been a bolus effect in the quarter immediately following the change in KAP. One the other hand, patients with end-stage renal disease are the only ones qualifying for Medicare, via disability insurance, immediately after diagnosis [22]. It is therefore all the more indicative of crowding out of Medicare as primary source of payment that we estimate a large ω^3 ATT specifically for kidney transplant candidates.

5 Conclusion and policy implications

Taken together, our findings are indicative of an effect of Medicaid expansion on increased coverage of transplant candidates. There was also a considerable change in payer mix towards a higher share of Medicaid transplant candidates, compared to Medicare and private insurance transplant candidates. These effects are anchored in kidney patients, which also account for the vast majority of transplant candidates and recipients. Limited statistical significance hinders our ability to extrapolate from some of our results, namely the evidence of an increase in access to care among Medicaid beneficiaries. Nonetheless the combination of estimated treatment effects with non parametric evidence on patient severity indicate that organ allocation policies are not systematically discriminating across payer sources, as measured by the relationship between waiting list additions and transplants. As such, it is conceivable that deceased donor organ allocation algorithms may be efficient.

Our results also indicate that Medicaid expansion may have had a multiplier effect on the new KAP, which was designed to increase equity in access to deceased donor kidney transplants. Moreover, there is evidence of a lagged uptake across all outcomes. We find that after one year of Medicaid expansion, states converge to a higher steady state.

Overall, we find increased patient severity, post Medicaid expansion, but no changes in age or gender distributions. There is a signal of racial differences, which deserves a deeper study. Our findings are compatible with the absence of ex post moral hazard among transplant candidates. By default, this is an extremely sick population, which in itself contributes to minimizing inefficient health care utilization of transplantation-related services. The new patients are slightly sicker in expansion states, when compared to states that never expanded Medicaid. We are, however, unable to observe any variable quantifying health care expenditure, rather focusing on being on the waiting list as a proxy for health care utilization.

[21] Specifically, end-stage renal disease patients undergoing dialysis can now count the time since they started dialysis towards their waiting list timing, which may impact waiting list timing decisions as the system is no longer merely based on a first come, first served patient ranking.

[22] None of the other organs qualifies for this waiver, so patients have to wait at least two years to be eligible for Medicare disability coverage

Tables and Figures

Figure 1: Transplantation pathway and outcomes

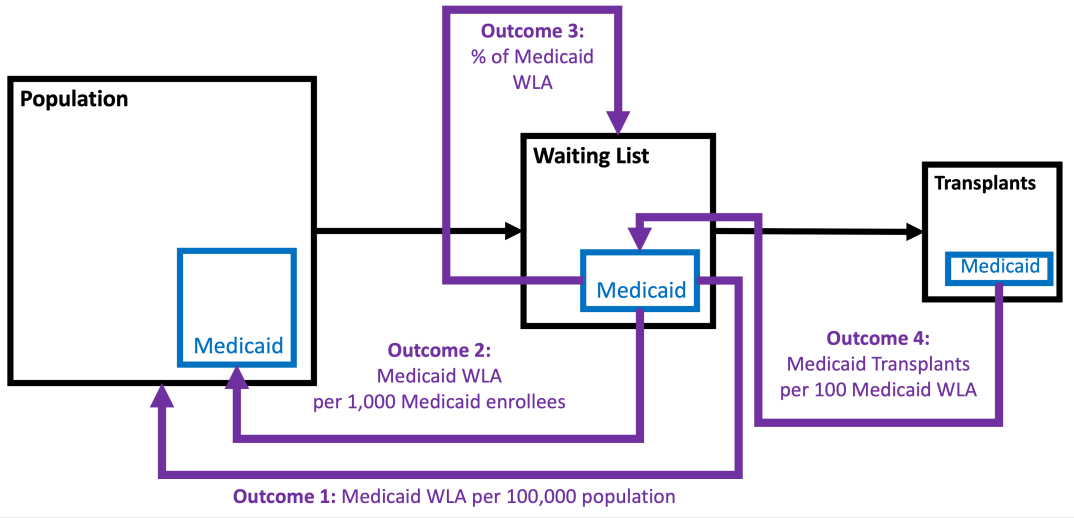


Figure 2: Medicaid expansion treatment groups

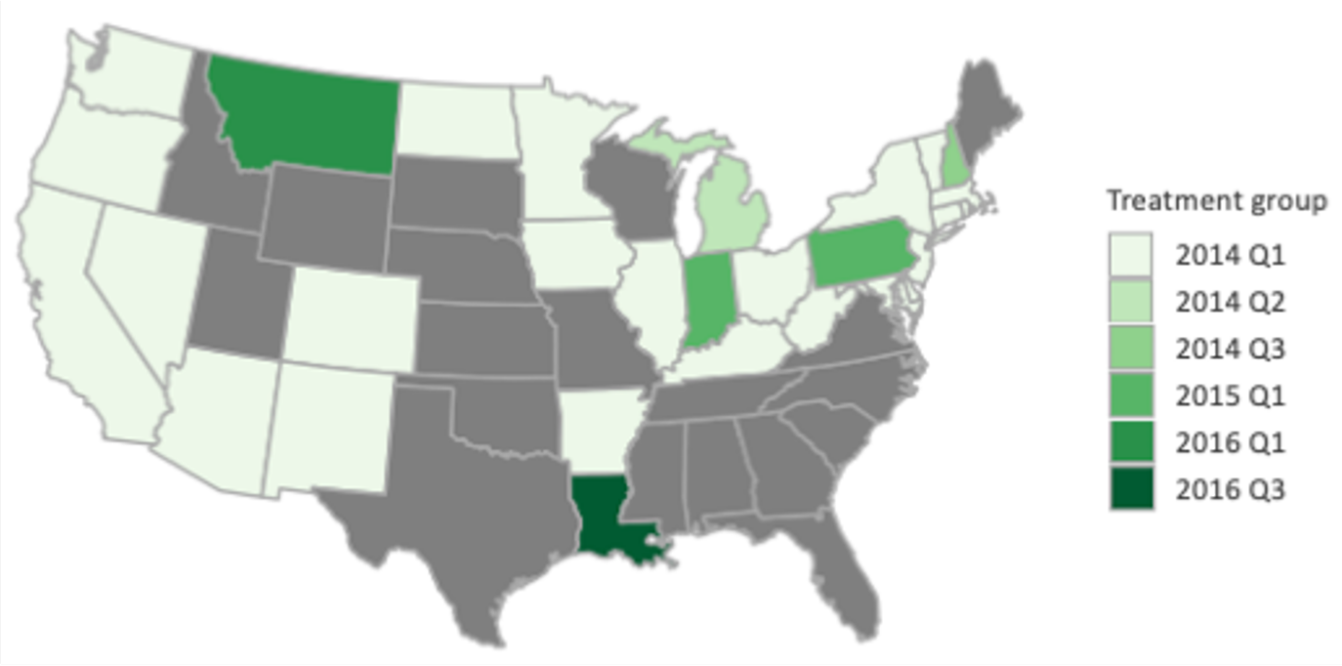


Table 1: Estimated ATT, overall and for 2014:Q1 Expansion states

	Transplant candidates - total				
Outcomes	Mean ω^i	ATT	Std.Err	95% CI	
ω^1	0.384	0.145	0.050	[0.046	0.243]
ω^1_{2014}	0.408	0.151	0.068	[-0.007	0.308]
ω^2	20.62	2.011	2.782	[-3.443	7.465]
ω^2_{2014}	21.55	2.691	3.289	[-4.661	10.09]
ω^3	9.238	3.122	1.394	[0.390	5.855]
ω^3_{2014}	9.637	2.946	1.180	[0.161	5.730]
ω^4	45.53	-3.345	8.311	[-19.63	12.94]
ω^4_{2014}	46.15	-2.717	8.385	[-20.99	15.55]

Notes - Mean ω^i was computed for all pre-treatment quarters. Critical values: $\omega^1 = 2.276$, $\omega^2 = 2.309$, $\omega^3 = 2.321$, $\omega^4 1 = 2.139$.

Figure 3: Outcomes over time by treatment status

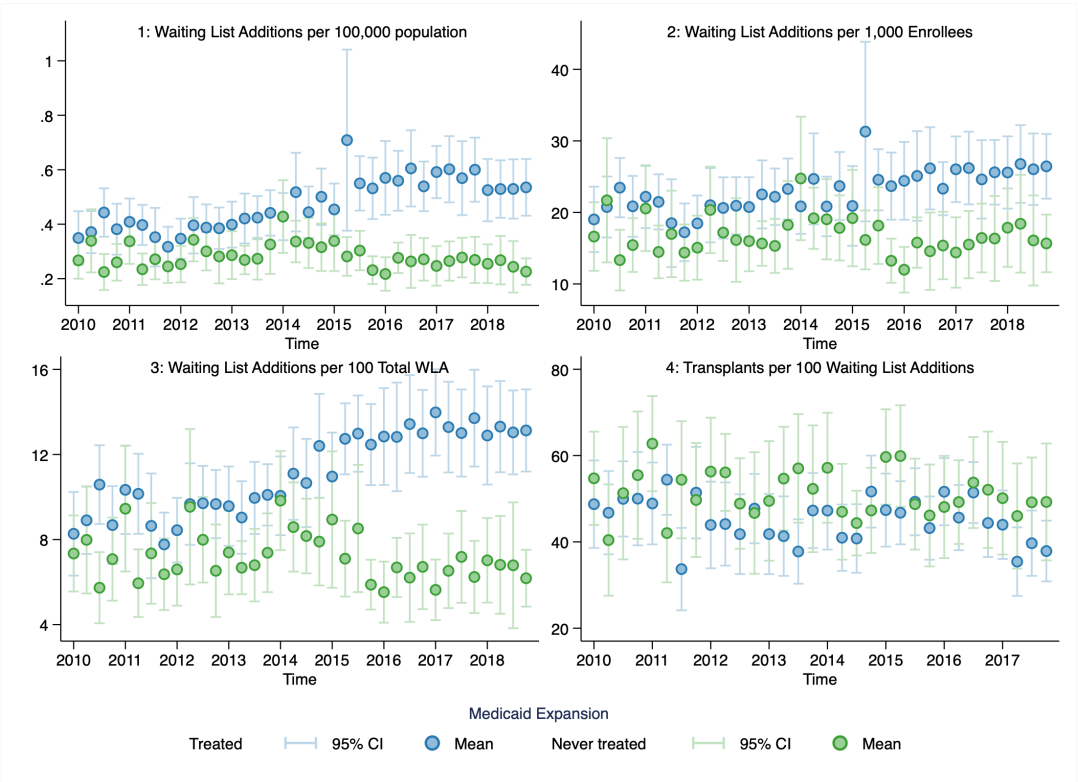
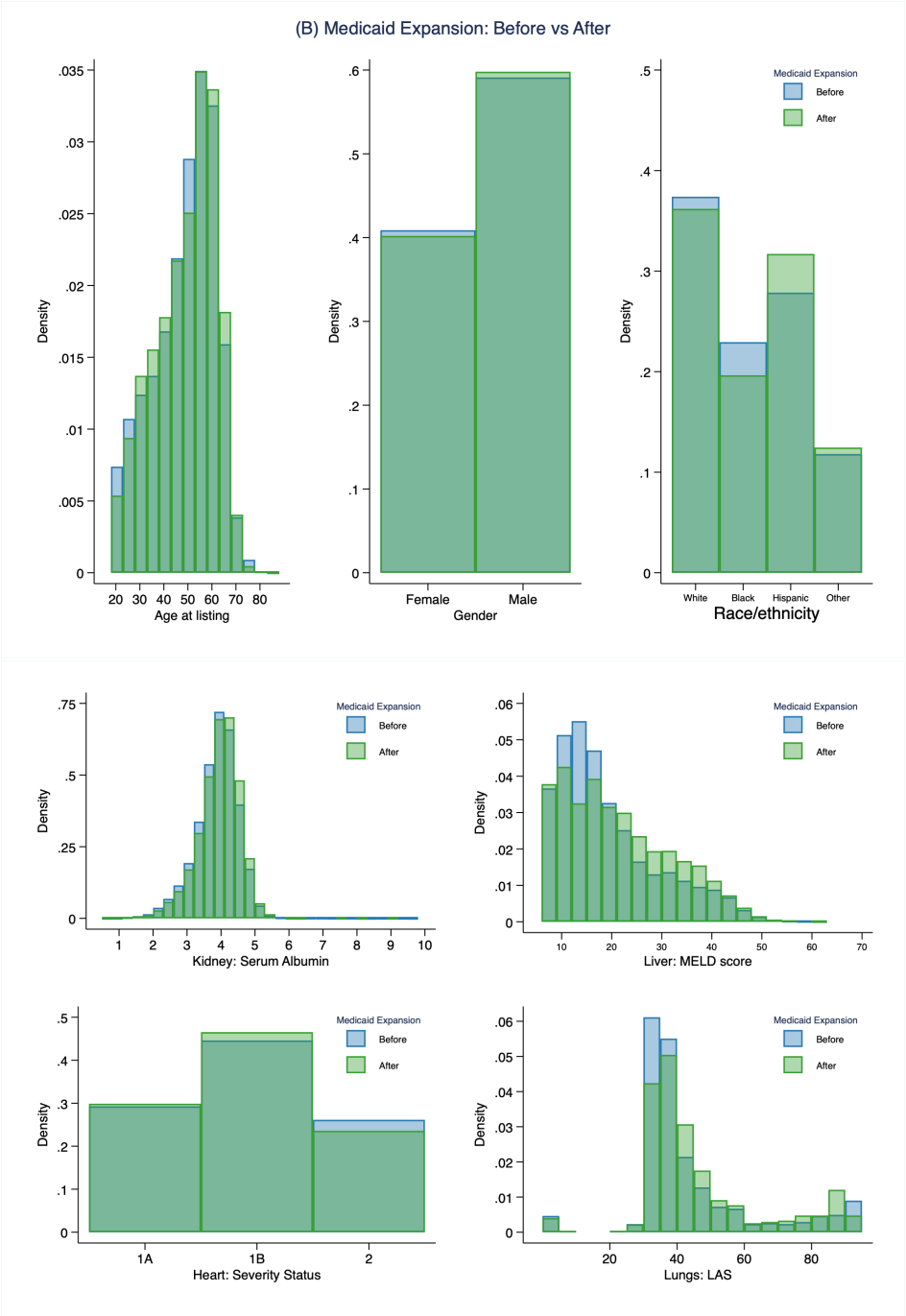


Figure 4: Histogram of Medicaid waiting list patient characteristics in expansion states



Notes - Serum albumin is a commonly used clinical performance marker ans risk factor in patients with end-stage renal disease (see, for example, (8) and National Kidney Foundation's Kidney Disease Outcomes Quality Initiative (KDOQI) Clinical Practice Guidelines (available at `https://www.kidney.org/professionals/guidelines`); more information available at `https://www.kidney.org/content/kidney-failure-risk-factor-serum-albumin`). The figures include information on this indicator for over 95% of kidney transplant candidates (N=270,047). A normal serum albumin is between 3.5 and 5.0 g/dl. An alternative indicator, eGFR, is used to classify kidney disease stage, but is only available for 42% of the transplant candidates. For lung transplant candidates we use their initial Lung Allocation Score (LAS) and for liver transplant candidates we use their MELD score, both routinely measured prior to 2010. Heart transplant candidates are listed based on severity criteria. These have changed in the last quarter of 2018, so we have excluded this quarter from the analysis.

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Appendix

A Two Way Fixed Effects

Given the novelty of our main empirical approach - the Callaway Sant'Anna estimator - and to provide a common ground with most difference-in-difference literature on Medicaid expansion we do also estimate our parameters of interest using a standard two-way fixed effects (TWFE) estimator. The estimator relies on a full set of fixed effects to account for differential timing of Medicaid expansion. In the model we use state and quarter fixed effects and $D_i == 1$ if Medicaid expanded for that state on that quarter:

$$y_{it} = \alpha_i + \gamma_t + \delta D_{it} + X'_{it}\beta + \epsilon_{it} \tag{5}$$

where y_{it} is the outcome variable, α_i and γ_t are the state and year fixed effects and X'_{it} are state level controls, when applicable. Standard errors are clustered at the state-level.

A.1 Goodman-Bacon Decomposition

We test different TWFE model specifications and conduct additional analysis to address concerns by emerging literature on the causal interpretation of TWFE parameters (5; 7). First, we perform the Goodman-Bacon decomposition of the TWFE estimates obtained from model 5. In his work, Goodman-Bacon showed that the TWFE parameter is a weighted average of all possible 2x2 difference-in-difference estimators that compare groups treated in different moments in time. This includes comparisons of treated groups with never treated groups, but also timing comparisons (e.g. using later-treated group as a control before the treatment begins or the earlier-treated group as a control of the late-treatment group when the former is already treated). The weights are proportional to the group size and variance of the treatment dummy in each pair. Using bacondecomp STATA command, we plot the 2x2 difference-in-difference estimators against their weights, to observe the heterogeneity between the components of the weighted average and the most relevant terms/groups for the final TWFE parameter (7).

Figure S2 shows the Goodman-Bacon decomposition for outcomes 1 to 4, for the models without covariates. The analysis of the graphs shows that the TWFE estimate is mostly driven by treated vs. never treated comparisons (weight 0.873), and that among these comparisons one pair has about 0.6 of the weight. This pair corresponds to the comparison of states that expanded Medicaid in 2014, when most expansion occurred, with never treated states.

A.2 Two Way Fixed Effects estimates

TWFE estimates displayed in Figure S3 are consistent with our main estimates of outcome 1 and 3, differing considerably for outcome 4. We test additional TWFE specifications, to address two aspects that have been recently discussed in the literature for the causal interpretation of the TWFE estimator as ATT. First we estimate the models with state-level controls. TWFE assumptions related to covariates (X'_{it}) require homogeneous treatment effects in X'_{it} and no X'_{it}- specific trends in outcomes. Even though our knowledge of the institutional setting make us doubt on whether these assumptions will not hold - for example for the race or age distribution of each state population - we find it informative to test a specification that accounts for the demographic and disease context of the states. Second, we address concerns with the impact of "negative weights" on the the variance-weighted average effect that comes from TWFE. Negative weights might occur when effects vary over time and already-treated units (early groups) act as controls of late groups. In this situation, negative changes in the treatment effects over time get subtracted from the difference-in-difference estimate. According to Goodman-Bacon "this does not imply a failure of the design, but it does caution against summarizing time-varying effects with a single-coefficient". Therefore, we estimate the TWFE only based on treated vs. never treated difference-in-difference comparisons, focusing on states that expanded in 2014. For outcomes 1 to 3, controlling for additional state-level variables implies treatment effects of smaller magnitude. The opposite is seen for outcome 4, where the coefficient with controls is much larger, although remains non-significant. The effects of Medicaid expansion when comparing only states that expanded in 2014 with states that did not expand (up to the end of the study period) are larger for all outcomes. The results are qualitatively similar when we ran a poisson regression estimated by pseudo maximum likelihood (STATA command pplm). All detailed estimates are available upon request.

B Event study

As an alternative to the TWFE models we conduct event studies to estimate dynamic treatment effects for each outcome, overall and by organ. The event of interest is Medicaid expansion, which occurs at different moments in time of the panel:

$$y_{it} = \zeta + Lead_{it}^{K}\beta^{K} + ... + Lead_{it}^{2}\beta^{2} + Lag_{it}^{0}\theta 0 + ... + Lag_{it}^{L}\theta_{L} + \alpha_i + \gamma_t + \epsilon_{it}, \tag{6}$$

where y_{it} is the outcome variable, α_i and γ_t are the state and year fixed effects, and there is a series of K Leads and L Lags, relative to the event of interest.

B.1 Unconditional parallel trends

As discussed in the sections 3.1 and 4.3 of the manuscript, parallel trends is a key identifying assumption across all our empirical approach(es). It implies that control and treated units would follow similar paths in the absence of the intervention. The event-study provides an opportunity to examine this assumption by looking into the pre-trends in outcomes, ahead of Medicaid expansion. This can be done by observing in event-study plots that pre-Medicaid expansion estimates (the leads of the event study) are not different from zero. We tested the joint significance of leads for unconditional pre-trends and find these to be jointly not significant at 5% level for all the outcomes.

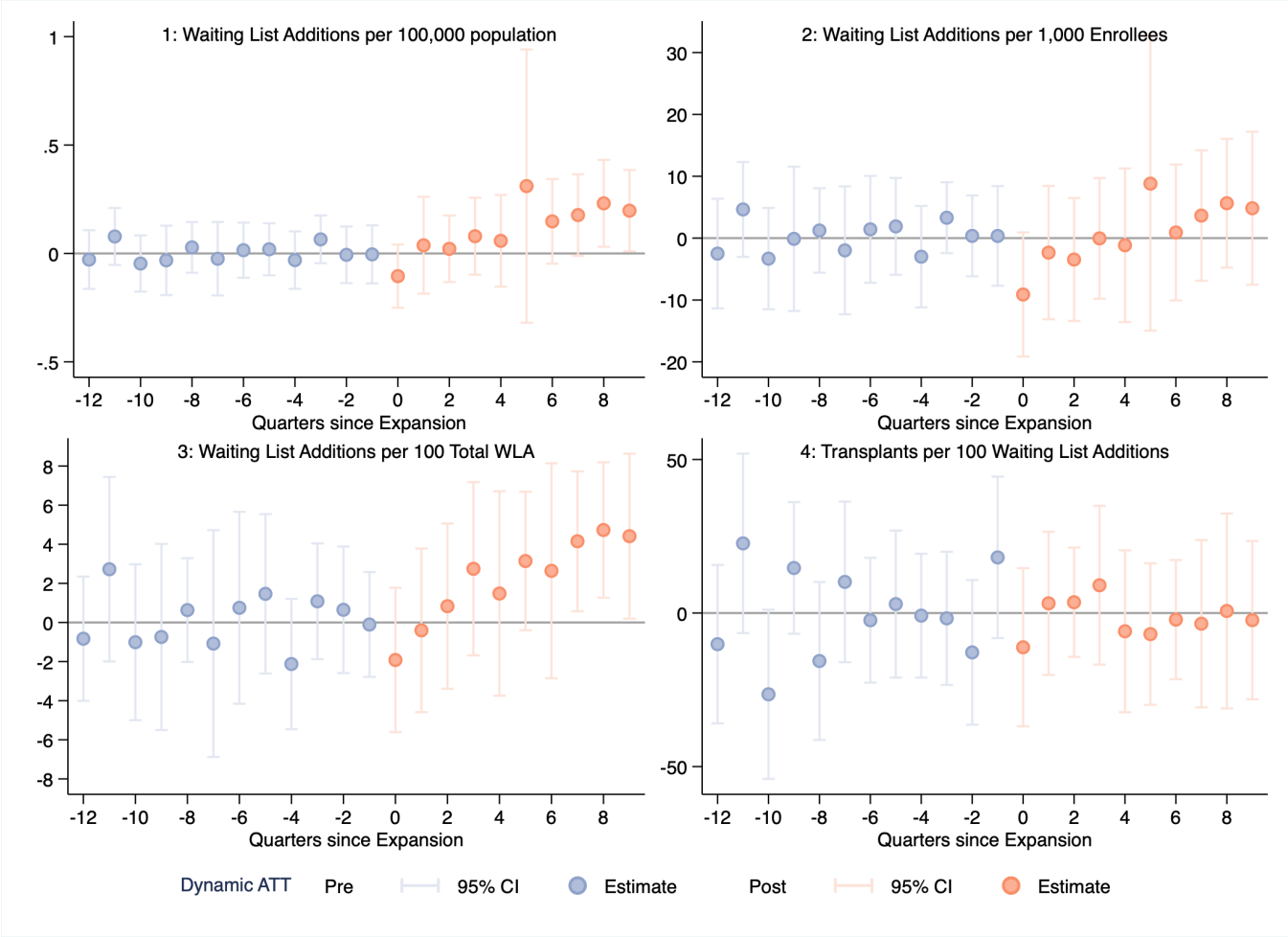
B.2 Estimated dynamic treatment effects

Event study plots report estimates based on equation6. For outcome 1 (Figure S3) we observe a clear increase in effect starting from the second quarter post expansion and stabilizing after one year of Medicaid expansion. For outcome 2 (Figure S3) event study estimates are considerable more imprecise. Even though a trend can also be observed about one year after expansion, effects are never significantly different from zero. For outcome 3 Medicaid expansion leads to a considerable increase in the proportion of Medicaid waiting list additions of transplant candidates, although estimates are also imprecise. As in outcome 1 and eventually 2, effects are only visible one year after Medicaid expansion. Last, for outcome 4 (Figure S3), additional Medicaid transplant candidates do not seem to be negatively affected when it comes to access to transplantation. Treatment effects following Medicaid expansion oscillate between zero and large imprecise positive coefficients, displaying no clear trend or different pattern from the quarters ahead of expansion. Such findings indicate that the organ allocation system may be efficiently incorporating the new added

patients, with no further barriers to access once transplant candidates are added to the waiting list.

Supplementary Tables and Figures

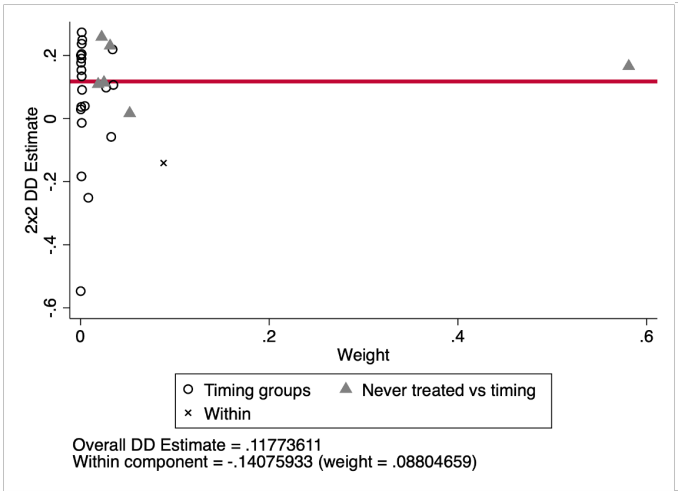
Figure S1: Estimated dynamic treatment effects



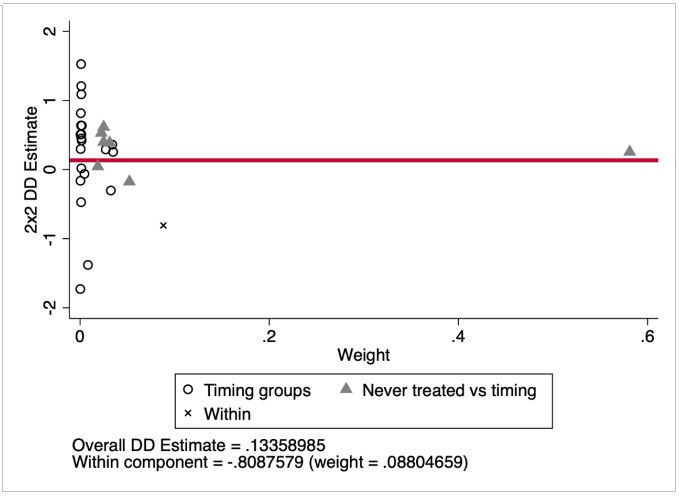
Notes - Estimates based on a balanced sample with 12 pre-treatment quarters and 9 post-treatment quarters. Pre-treatment estimates indicate whether the parallel trends assumption is reasonable based on pre-treatment path.

Figure S2: Goodman-Bacon Decomposition

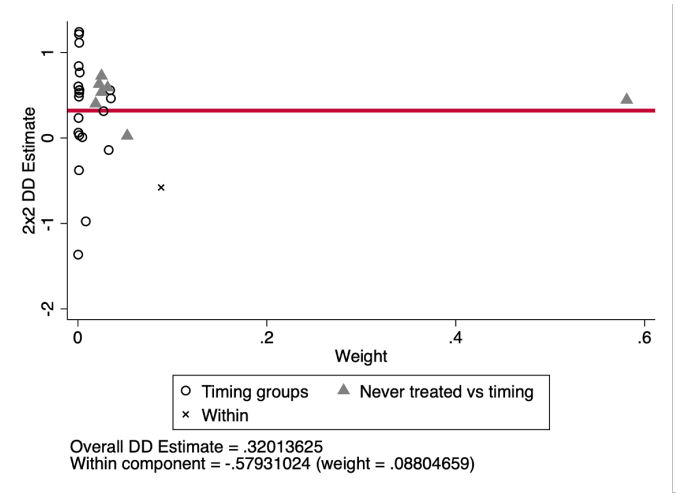
(a) 1: Waiting List Additions per 100,000



(b) 2: Waiting List Additions per 1,000 Enrollees



(c) 3: Waiting List Additions per 100 Total WLA



(d) 4: Transplants per 100 Waiting List Additions

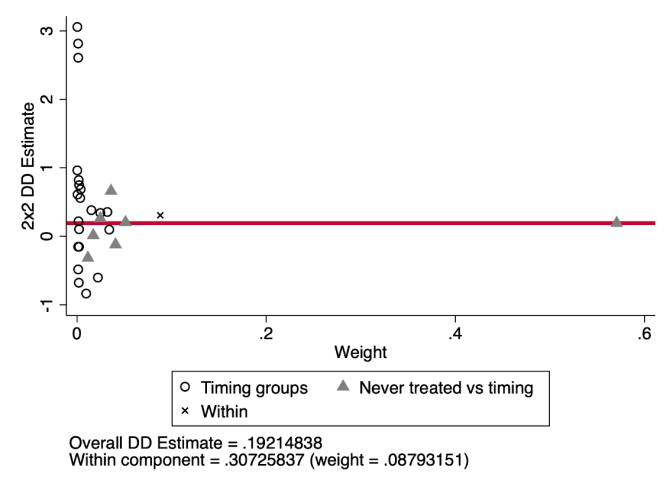


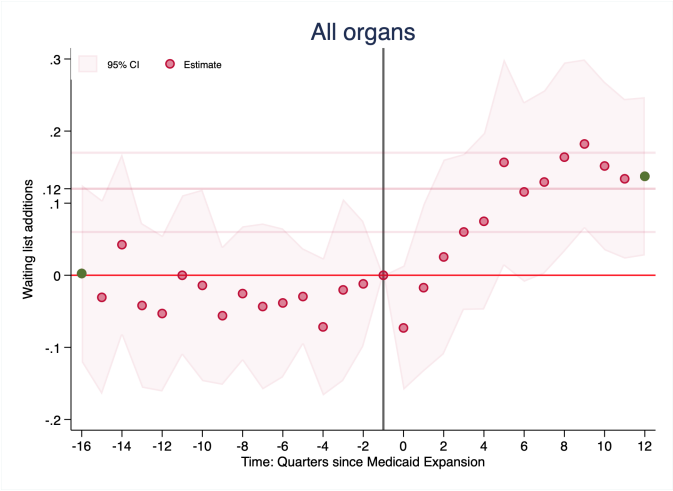
Table S1: Estimated ATT, by organ

		Transplant candidates - by organ				
Outcomes	**Organ**	Mean ω^i	ATT	Std.Err	95% CI	
ω^1	Kidney	0.186	0.085	0.038	[0.010	0.159]
	Liver	0.151	0.051	0.026	[-0.001	0.102]
	Heart (per 1M)	0.338	0.057	0.183	[-0.302	0.415]
	Lungs (per 1M)	0.134	0.039	0.054	[-0.067	0.145]
ω^2	Kidney	10.03	1.854	1.933	[-1.935	5.643]
	Liver	8.094	0.673	1.268	[-1.812	4.655]
	Heart	1.768	-0.575	2.177	[-4.842	3.693]
	Lungs	0.732	0.059	0.326	[-0.580	0.698]
ω^3	Kidney	4.343	1.880	0.846	[0.222	3.537]
	Liver	3.714	1.005	1.137	[-1.223	3.233]
	Heart	0.831	0.109	0.396	[-0.667	0.886]
	Lungs	0.350	0.128	0.140	[-0.146	0.403]
ω^4	Kidney	36.37	-5.730	10.96	[-27.21	15.75]
	Liver	43.21	3.043	6.099	[-8.911	15.00]
	Heart	36.62	5.005	12.12	[-18.75	28.76]
	Lungs	26.37	5.174	13.29	[-20.88	31.22]

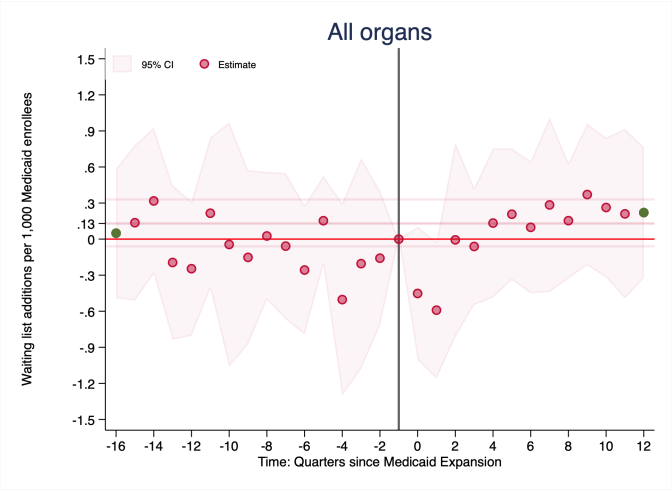
Notes - Mean ω^i was computed for all pre-treatment quarters.

Figure S3: Dynamic treatment effects - event study

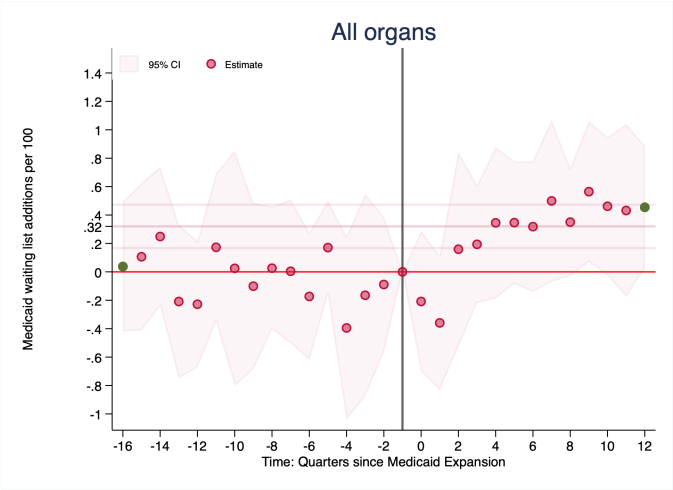
(a) 1: Waiting List Additions per 100,000



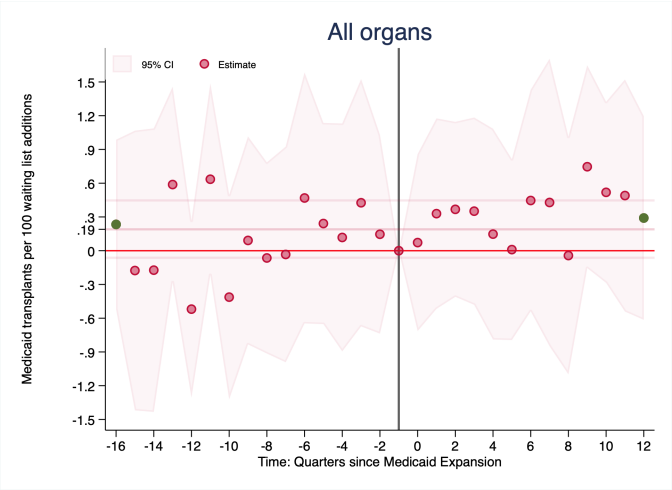
(b) 2: Waiting List Additions per 1,000 Enrollees



(c) 3: Waiting List Additions per 100 Total WLA



(d) 4: Transplants per 100 Waiting List Additions



Notes - Horizontal lines correspond to the TWFE estimate and 95% confidence intervals for each outcome.