Online Appendix to the Paper “Pausing Transplants in the Face of a Global Pandemic: Patient Survival Implications”

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Appendix A: Patient-Level Analyses

In this section, we calculate the threshold probability from a patient's perspective to guide the decision of accepting or declining an offer. When a patient on the waiting list receives an offer, she or he needs to compare the risk of infection due to the pandemic and the risk of health deterioration due to delaying an organ transplant. Because the probability of mortality due to the pandemic is an important parameter for a patient to make a decision, we derive the threshold probability above which a patient should delay an organ transplant by declining the offer.

Before calculating the threshold probability for a patient, we introduce a few new parameters specifically for patient-level analyses. We denote by h_m^{Δ} the probability of a category m patient dying without an organ transplant within Δ days. Unlike the rate of mortality defined in the main analysis (i.e., center-level analysis), the probability of Δ-day mortality describes the likelihood a patient dying within Δ days on the waiting list. We denote by d_{mn}^{Δ} the probability of a patient transitioning from category m to category n within Δ days. We denote by y_{1m}^{Δ} the expected life months of a patient with the organ transplant being delayed by Δ days.

If a center continues organ transplants for a patient in category m and the patient accepts a matched organ, we denote by q_m the probability of the patient dying from the pandemic. The probability of the patient surviving the pandemic and getting additional life months from the organ transplant is $1-q_m$. We calculate the patient's expected life months from accepting an organ transplant during the pandemic as

$$V_m^{NoPause} = -q_m y_{0m} + (1-q_m)(y_{1m} - y_{0m}). \tag{A1}$$

If the patient decides to wait for Δ days because of the pandemic, we denote by h_m^{Δ} the probability of the patient dying without an organ transplant and not getting any additional life months. The probability of the patient surviving and getting additional life months from the organ transplant with a Δ-day delay is $1-h_m^{\Delta}$. We calculate the patient's expected life months from delaying an organ transplant by Δ days as

$$V_m^{Pause} = (1-h_m^{\Delta})(y_{1m}^{\Delta} - y_{0m}). \tag{A2}$$

To calculate the threshold probability q_m^* at which the patient is indifferent between accepting an organ or waiting for Δ days, we let $V_m^{NoPause}$ equal V_m^{Pause} and solve q_m. That is,

$$q_m^* = \frac{y_{1m} - y_{0m} - (1-h_m^{\Delta})(y_{1m}^{\Delta} - y_{0m})}{y_{1m}}. \tag{A3}$$

A.1. Parameters Estimation

In this section, we describe how to estimate the probability of Δ-day mortality and the probability of transition for a patient.

A.1.1. Probability of Mortality We denote by $Death_i$ a binary outcome variable that equals 1 if patient i does not receive a liver transplant and dies within a given period after being added to the waiting list. The independent variable of primary interest is the MELD-Na score (denoted by $MELD\text{-}Na_i$). Note we include the MELD-Na score as a categorical instead of a continuous variable, because the MELD-Na score may affect mortality in a complex nonlinear way.

We include a broad range of patient features (denoted by $PatientFeatures_i$) such as age, gender, race/ethnicity, blood type, diagnoses (e.g., alcoholic liver disease, cholestatic liver disease, and metabolic liver disease), prior transplant, and insurance type. We can describe the relationship between the outcome variable and patient features using a logit model:

$$\mathrm{D}eath_i = f(\beta_0 + \beta_1 MELD\text{-}Na_i + \beta_2 PatientFeatures_i + \epsilon_i), \tag{A4}$$

where f is a function that links the dependent and independent variables and ϵ_i is an idiosyncratic error.

Table A1 summarizes the results from the logistic regression for 30-day mortality probability. From the upper part of the table, we see all coefficients of MELD-Na are negative and significantly different from zero at the 1% significance level, which suggests patients with MELD-Na scores between 5 and 35 have lower mortality probabilities than those with MELD-Na scores above 35 (control group). Comparing the magnitude of the coefficients, we see patients with higher MELD-Na scores are more likely to die than those with lower MELD-Na scores.

From the middle part of the table, we see the coefficient of age is positive and significantly different from zero at the 1% significance level, which suggests older patients are more likely to die than younger patients. Interestingly, patients of blood type AB are more likely to die than those of the other blood types. Finally, we do not find significant effects of gender and malignancy on waitlist mortality probability.

From the lower part of the table, we see the coefficients of cholestatic liver disease, cirrhosis viral hepatitis, malignancy, metabolic liver disease, and others are positive and significantly different from zero at the 5% significance level, which suggests patients with those diagnoses are more likely to die than those with alcoholic liver disease (control group). The coefficient of fatty liver is not significantly different from zero at the 10% significance level, which suggests the mortality probability of patients with fatty liver is not significantly different from that of patients with alcoholic liver disease.

A.1.2. Probability of Transition Recall the probability of Δ-day transition describes how a patient transitions from one category to another within Δ days given that the patient does not receive a liver transplant. We use the probability of transition to calculate the expected life months of a patient with the organ transplant being delayed. The outcome variable is patient category (e.g., MELD-Na score), and independent variables are patient features. Because the outcome variable is categorical, we use the ordered logit model to estimate the transition probability. That is,

$$MELD\text{-}Na_i = g(\beta_0 + \beta_1 PatientFeatures_i + \epsilon_i), \tag{A5}$$

where g is a function that links the dependent and independent variables and ϵ_i is an idiosyncratic error.

Table A2 summarizes the results for the scenario in which we divide patients based on MELD-Na scores into seven categories and let $\Delta = 30$ days. From the table, we see the majority of patients remain in the same category within 30 days. For example, 93.66% of patients in the first category and 90.68% of patients in the second category remain in their respective categories. We also observe the probability of patients remaining in the same category decreases as the MELD-Na score increases, except for the last category. Finally, we see the probability of a patient transitioning from a category to a nearby category is higher than the probability of the patient transitioning to a remote category. For example, the probability of the first category transitioning to the second category is 4% and to the seventh category is 0.04%.

Table A1 Results from the Logit Model

Variable	Coefficient	Standard Error
MELD-Na		
5-10	-6.0939^{***}	0.1718
11-15	-5.1033^{***}	0.1054
16-20	-4.1915^{***}	0.0762
21-25	-3.0133^{***}	0.0593
26-30	-1.6798^{***}	0.0510
31-35	-0.7623^{***}	0.0517
36-40	Control	
Patient Features		
Age	0.0173^{***}	0.0017
GenderFemale	0.0419	0.0380
RaceBlack	0.0210	0.0605
BloodTypeAB	0.4207^{***}	0.1057
BloodTypeB	0.0579	0.0608
BloodTypeO	-0.0474	0.0396
MalignancyAll	-0.0502	0.0653
Diagnoses		
AlcoholicLiverDisease	Control	
CholestaticLiverDisease	0.1817^{**}	0.0843
CirrhosisViralHepatitis	0.2042^{***}	0.0534
FattyLiver	0.0485	0.0665
Malignancy	0.3629^{***}	0.1097
MetabolicLiverDisease	0.3970^{***}	0.1139
Other	0.1007^{**}	0.0503
Number of Observations	86,333	
R Squared	0.3354	

Note: *** $p < 0.01$, ** $p < 0.05$. Insurance type and prior transplant are dropped due to multi-collinearity issues.

A.2. Threshold Probability

Because how long a patient needs to wait for the next offer when she or he declines the current offer is unclear, we perform three scenario analyses by letting $\Delta = 30, 60$, and 90, respectively. Table A3 summarizes the results based on these scenarios.

We illustrate the results by using patients with MELD-Na scores between 16 and 20 as an example. From column "$\Delta = 30$", we see a patient in this category should accept the organ if the probability of mortality due to the pandemic is lower than 4.9% and should decline the organ otherwise. Similarly, from the columns "$\Delta = 60$" and "$\Delta = 90$", we see a patient in this category should accept the organ if the probability of morality due to the pandemic is lower than 7.4% and 8.9%, respectively. Comparing different columns of

Table A2 Results from the Ordered Logit Model

MELD-Na	6-10	11-15	16-20	21-25	26-30	31-35	36-40
6-10	93.66	4.00	1.41	0.66	0.17	0.06	0.04
11-15	0.63	90.68	6.46	1.63	0.39	0.14	0.07
16-20	0.29	2.44	83.22	10.71	2.40	0.59	0.35
21-25	0.21	1.33	9.58	69.41	13.95	3.52	2.01
26-30	0.12	0.68	3.63	18.82	51.51	16.27	8.97
31-35	0.14	0.50	2.24	6.90	18.23	45.68	26.31
36-40	0.11	0.25	0.97	3.03	5.27	11.28	79.09

Note: We estimate the 30-day transition probabilities using the ordered logit model. The sample used for estimation excludes the patients who die or become too sick to receive transplants during the pause.

Table A3 Threshold Probability for Individual Patients

MELD-Na	$\Delta = 30$	$\Delta = 60$	$\Delta = 90$
11-15	0.009	0.015	0.030
16-20	0.049	0.074	0.089
21-25	0.036	0.041	0.061
26-30	0.041	0.080	0.119
31-35	0.136	0.188	0.210
36-40	0.256	0.279	0.280

Note: This table summarizes the threshold probability for the scenarios in which a patient needs to wait 30, 60, or 90 days for another offer.

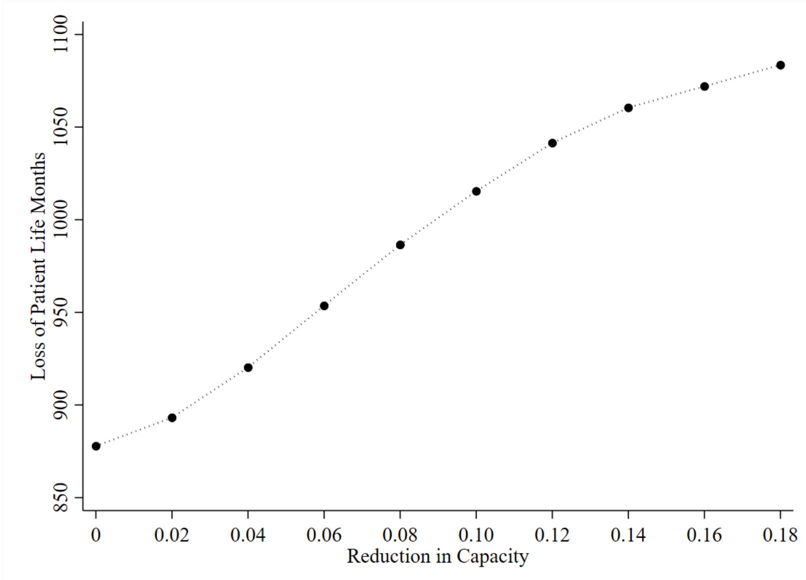
the table, we see the threshold probability increases as the length of the delay increases, which suggests a patient should take more risks to accept an organ if receiving the next organ takes longer.

Appendix B: Impact of Capacity Constraints at Center Level

We follow Kaplan et al. (1992) to analyze the impact of overall-capacity constraints. To describe this approach, we denote by r_m and r'_m the capacity for patient category m before and after the reduction, respectively, and by α the reduction in the overall capacity. Denote by M the number of patient categories. The overall capacity is $\sum_{m=1}^{M} r_m$ before the reduction and $\sum_{m=1}^{M} r'_m$ after the reduction. We derive the optimal pause policy by using equation (10) with an additional constraint that $\sum_{m=1}^{M} r'_m = \sum_{m=1}^{M} r_m - \alpha$.

We first analyze the impact of capacity constraints on the loss of patient life months. Figure B1 depicts the results by using scenario 1 (see Table 6) and the center-specific tiered shutdown policy for a center as an example. The horizontal axis indicates the reduction in the overall capacity, and the vertical axis indicates the loss of patient life months.[1] We see the loss of patient life months increases as the reduction in the overall capacity increases.

Figure B1 Impact of Overall-Capacity Constraints on the Loss of Patient Life Months (Center Level)



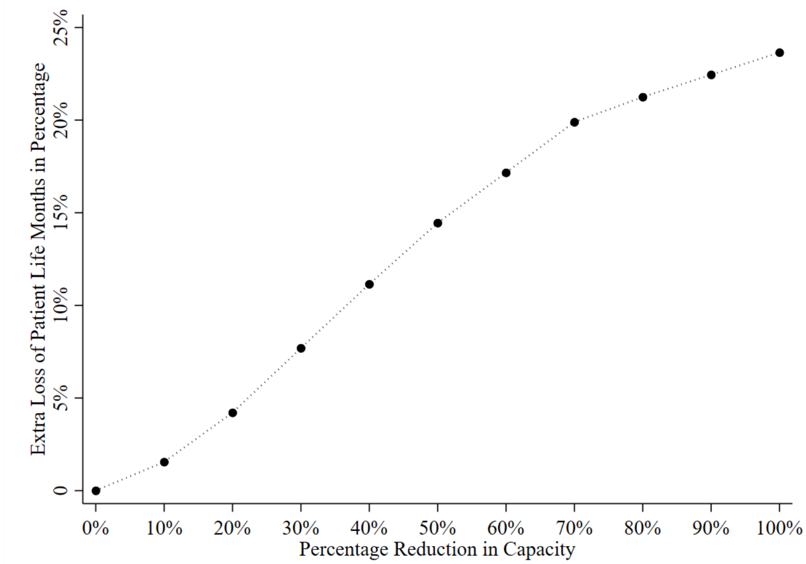
Note: This figure depicts the impact of overall-capacity constraints on the loss of patient life months in absolute numbers. The results are estimated based on scenario 1 (see Table 6) and the center-specific tiered shutdown policy.

We then analyze the impact of capacity constraints on the length of the waiting list. Figure B3 depicts the results by using scenario 1 (see Table 6) and the center-specific tiered shutdown policy for a center as an example. The horizontal axis indicates the reduction in the overall capacity, and the vertical axis indicates the average number of extra patients on the waiting list across the periods under consideration (i.e., $t_1 + t_2$).[2]

[1] Figure B2 depicts the reduction in the overall capacity and the extra loss of patient life months in percentage numbers.

[2] Figure B4 depicts the reduction in the overall capacity and the average number of extra patients on the waiting list in percentage numbers.

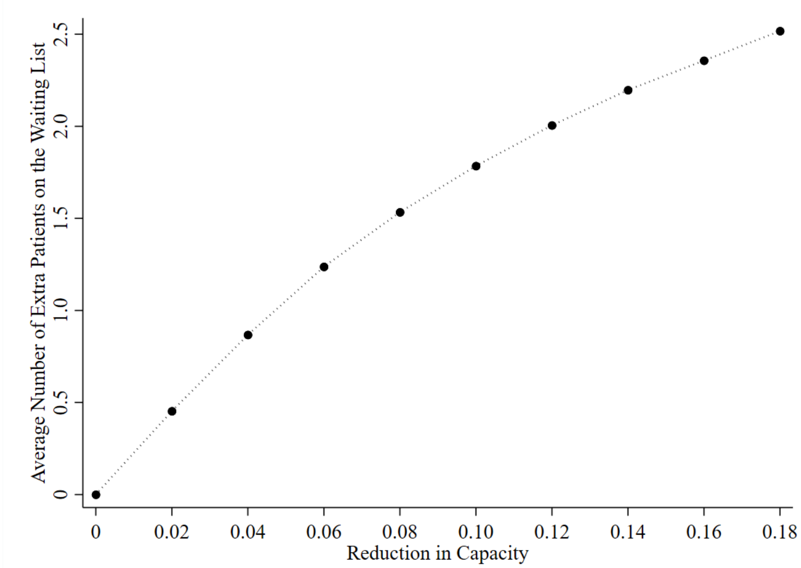
Figure B2 **Impact of Overall-Capacity Constraints on the Loss of Patient Life Months (Center Level)**



Note: This figure depicts the impact of overall-capacity constraints on the loss of patient life months in percentage numbers. The results are estimated based on scenario 1 (see Table 6) and the center-specific tiered shutdown policy.

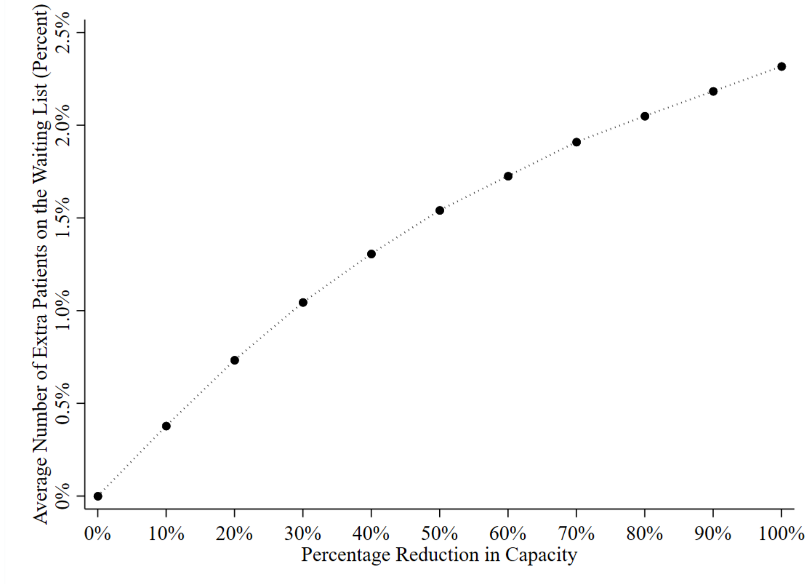
We see the average number of extra patients on the waiting list increases as the reduction in the overall capacity increases.

Figure B3 **Impact of the Overall-Capacity Constraints on Waitlist Length (Center Level)**



Note: This figure depicts the impact of overall-capacity constraints on the average number of extra patients on the waiting list in absolute numbers. The results are estimated based on scenario 1 (see Table 6) and the center-specific tiered shutdown policy.

Figure B4 Impact of the Overall-Capacity Constraints on Waitlist Length (Center Level)

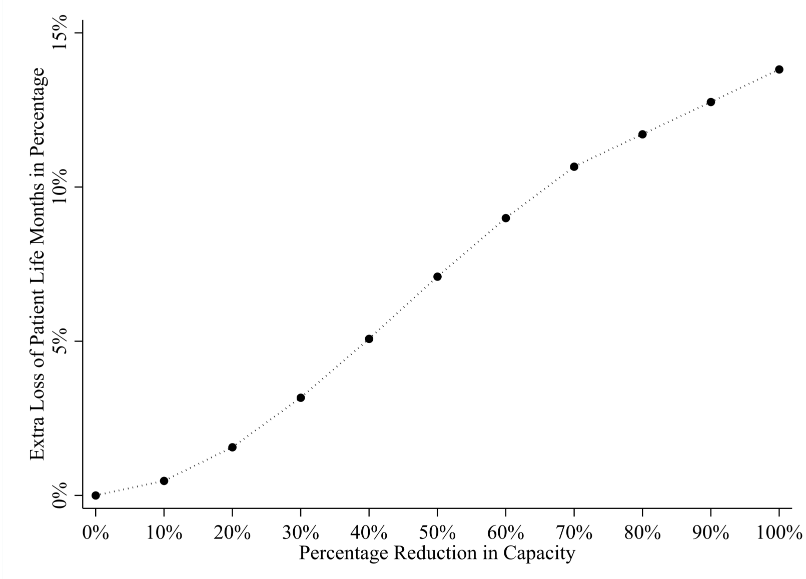


Note: This figure depicts the impact of overall-capacity constraints on the average number of extra patients on the waiting list in percentage numbers. The results are estimated based on scenario 1 (see Table 6) and the center-specific tiered shutdown policy.

Appendix C: Capacity Constraints in Percentage Numbers

Figure C1 depicts the reduction in the overall capacity and the loss of patient life months in percentage numbers. From the figure, we see the extra loss of patient life months increases as the percentage reduction in the overall capacity increases. For example, when the overall capacity reduces by 20%, the extra loss of patient life months increases by $(55,507-54,653)/54,653=1.6\%$, and when the overall capacity reduces by 40%, the extra loss of patient life months increases by $(57,428-54,653)/54,653=5.1\%$.

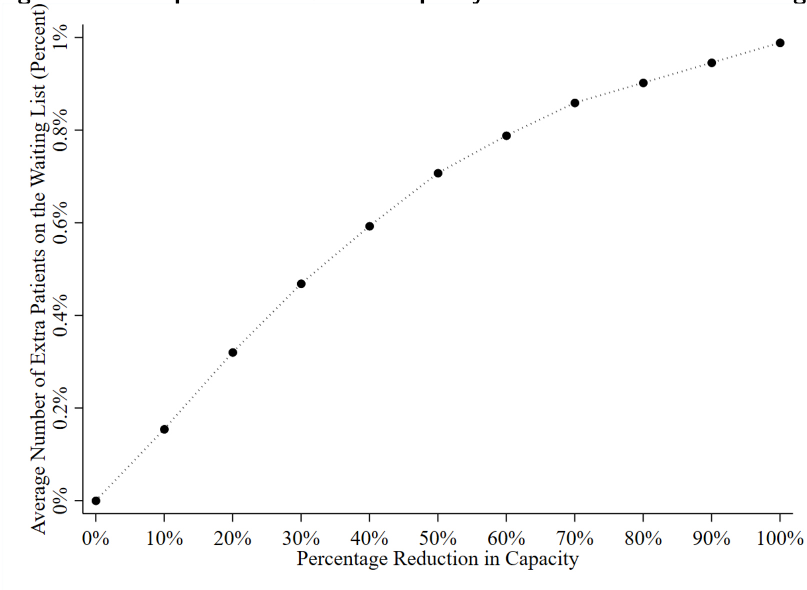
Figure C1 Impact of Overall-Capacity Constraints on the Loss of Patient Life Months



Note: This figure depicts the impact of overall-capacity constraints on the loss of patient life months in percentage numbers. The results are estimated based on scenario 1 (see Table 6) and the nation-guidance tiered shutdown policy.

Figure C2 depicts the reduction in the overall capacity and the average number of extra patients on the waiting list in percentage numbers. From the figure, we see the percentage of the average number of extra patients on the waiting list increases as the percentage reduction in the overall capacity increases. The average number of extra patients on the waiting list (in percentage) is relatively small, because the total number of patients on the waiting list is large.

Figure C2 Impact of the Overall-Capacity Constraints on Waitlist Length



Note: This figure depicts the impact of overall-capacity constraints on the average number of extra patients on the waiting list in percentage numbers. The results are estimated based on scenario 1 (see Table 6) and the nation-guidance tiered shutdown policy.

Appendix D: Loss of Patient Life Months by Patient Category

To understand the nonlinear relationship between the loss of patient life months and the reduction in capacity, we perform sensitivity analyses by reducing the capacity for one patient category at a time. Table D1 summarizes the results based on the scenario in which we reduce the capacity by 0.1 transplants per day for the selected patient category indicated by MELD-Na scores (see column "MELD-Na Score").[3] For ease of interpretation, we decompose the total loss of patient life months (see column "Total Loss") into three parts: (1) loss due to deaths on the waiting list (see column "Waitlist Deaths"), (2) loss due to health deteriorations (see column "Health Deteriorations"), and (3) loss due to the pandemic (see column "The Pandemic").

We now discuss the results from the table. First, the loss of patient life months due to waitlist deaths is larger for patient categories with higher MELD-Na scores, because sicker patients are more likely to die on the waiting list. Second, the loss of patient life months due to health deteriorations is larger for patient categories with medium MELD-Na scores, because these patients are more likely to transition to sicker categories (excluding deaths). Third, the loss of patient life months due to the pandemic is almost the same across different categories, because scenario 1 (see Table 6) specifies the probability of mortality due to the pandemic is the same across different categories. Finally, the total loss is the smallest for patients with low MELD-Na scores and the largest for patients with medium MELD-Na scores.

Table D1 Loss of Patient Life Months by Patient Category

	Loss of Patient Life Months due to			
MELD-Na Score	Waitlist Deaths	Health Deteriorations	The Pandemic	Total Loss
6-10	0.2	16.9	54643.2	54660.3
11-15	10.7	56.3	54645.0	54712.0
16-20	27.6	103.9	54635.5	54767.0
21-25	46.5	137.5	54630.6	54814.6
26-30	64.7	141.2	54635.3	54841.2
31-35	81.7	117.8	54633.9	54833.4
36-40	100.9	41.3	54636.5	54778.7

Note: We calculate the loss by reducing the capacity by 0.1 transplants per day for the selected patient category indicated by MELD-Na scores. The results are estimated based on scenario 1 (see Table 6).

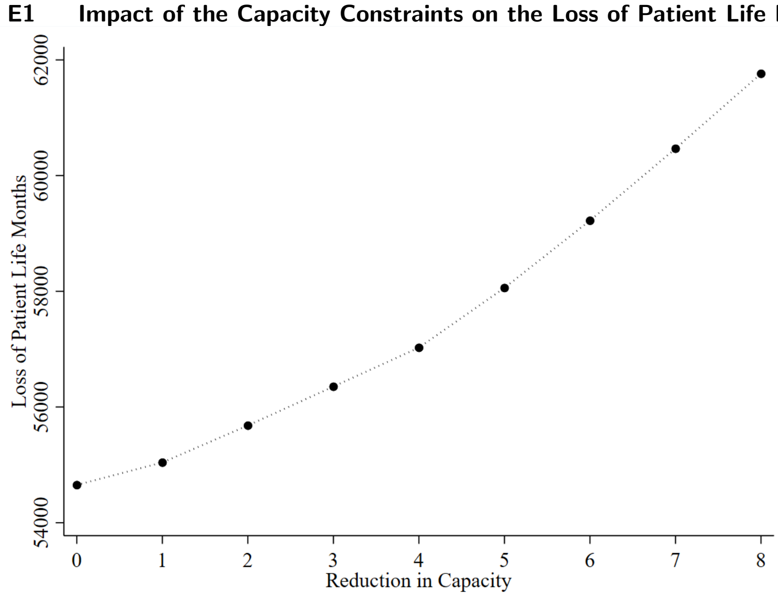
[3] Reducing the capacity by a different amount (e.g., 0.2) does not change the main conclusion of this analysis.

Appendix E: Additional Analyses of Capacity Constraints

In the main analysis, we following existing studies (see, e.g., Kumar et al. 2020) to prioritize sicker patient categories for capacity allocation (designated as "greedy approach"). In this section, we allow different patient categories to have different capacity reductions (designated as "optimal approach"). To describe this approach, we denote by r_m and r'_m the capacity for patient category m before and after the capacity reduction, respectively. We denote by α the reduction in the overall capacity and α_m the reduction in the capacity for patient category m. We derive the optimal pause policy with additional constraints that $r'_m = r_m - \alpha_m$ and $\sum_{m=1}^{M} \alpha_m = \alpha$. Given an overall-capacity reduction α, we find the optimal solution by comparing different combinations of α_m.

We first analyze the impact of capacity constraints on the loss of patient life months. Figure E1 depicts the results by using scenario 1 (see Table 6) and the nation-guidance tiered shutdown policy as an example.[4] The horizontal axis indicates the reduction in the overall capacity, and the vertical axis indicates the loss of patient life months. From the figure, we see the loss of patient life months increases as the reduction in the overall capacity increases. For example, when the overall capacity reduces by two transplants per day, the loss of patient life months increases by $55,681 - 54,653 = 1,028$, and when the overall capacity reduces by four transplants per day, the loss of patient life months increases by $57,027 - 54,653 = 2,374$.

Figure E1 Impact of the Capacity Constraints on the Loss of Patient Life Months



Note: This figure depicts the impact of capacity constraints on the loss of patient life months. The results are estimated based on scenario 1 (see Table 6) and the nation-guidance tiered shutdown policy.

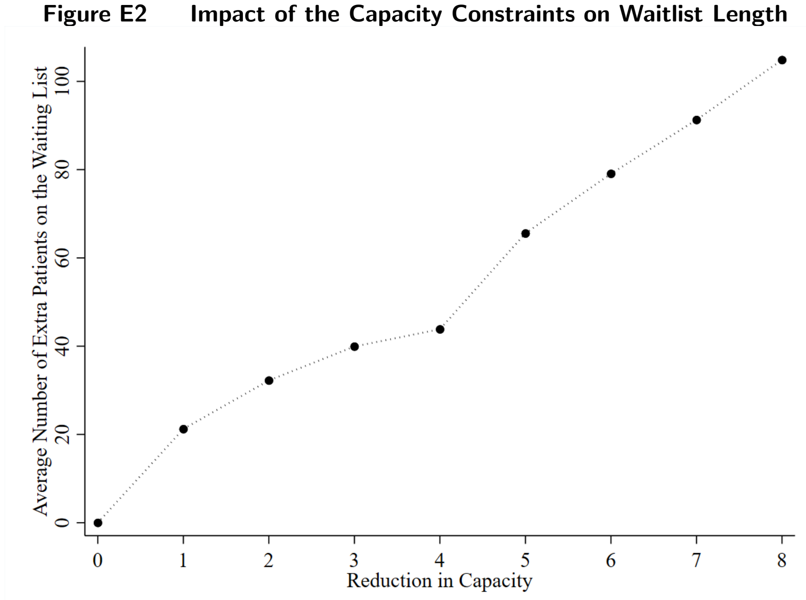
We then analyze the impact of capacity constraints on waitlist length. Figure E2 depicts the results by using scenario 1 (see Table 6) and the nation-guidance tiered shutdown policy as an example. The horizontal

[4] Because the reduction in capacity is continuous, finding the optimal solution is computationally intensive. To address this challenge, we discretize the capacity for each patient category using a bin of 0.1. Using a smaller bin or a percentage number does not change the main conclusion of this analysis.

axis indicates the reduction in the overall capacity, and the vertical axis indicates the average number of extra patients on the waiting list across the periods under consideration (i.e., $t_1 + t_2$). From the figure, we see the average number of extra patients on the waiting list increases as the reduction in the overall capacity increases. For example, when the overall capacity reduces by two transplants per day, the average number of extra patients on the waiting list increases by 32, and when the overall capacity reduces by four transplants per day, the average number of extra patients on the waiting list increases by 44.

Finally, comparing figures E1, E2, 3, and 4, we see the total loss of patient life months from the optimal approach is smaller than that from the greedy approach. For example, when the overall capacity reduces by two transplants per day, the marginal benefit from the optimal approach is $1,162 - 1,028 = 134$ in terms of the loss of patient life months, and $42 - 32 = 10$ in terms of the average number of extra patients on the waiting list. When the overall capacity reduces by four transplants per day, the marginal benefit from the optimal approach is $3,552 - 2,374 = 1,178$ in terms of the loss of patient life months, and $77 - 44 = 33$ in terms of the average number of extra patients on the waiting list. The total loss of patient life months from the optimal approach is smaller because it prioritizes patients with medium MELD-Na scores over those with high MELD-Na scores, whereas the greedy approach prioritizes patients with higher MELD-Na scores over those with lower MELD-Na scores.

Figure E2 Impact of the Capacity Constraints on Waitlist Length



Note: This figure depicts the impact of capacity constraints on the average number of extra patients on the waiting list. The results are estimated based on scenario 1 (see Table 6) and the nation-guidance tiered shutdown policy.

References

Kaplan EH, Hershlag A, DeCherney AH, Lavy G (1992) To be or not to be? That is conception! Managing in vitro fertilization programs. *Management Science* 38(9):1217–1229.

Kumar D, Manuel O, Natori Y, Egawa H, Grossi P, Han SH, Fernández-Ruiz M, Humar A (2020) COVID-19: A global transplant perspective on successfully navigating a pandemic. *American Journal of Transplantation* 20(7):1773–1779.