Online Appendix for "Federal Oversight and Strategic Choices of Kidney Transplant Centers"

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Appendices

A Supplementary Figures

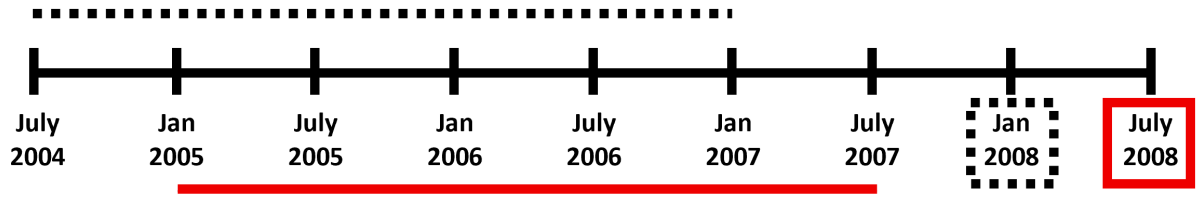


Figure A.I: An illustration of the rolling 2.5-year cohort for CoP

Note: The January 2008 submission (black box) consists of transplants from July 1, 2004, to December 31, 2006 (black line). Similarly, the July 2008 submission (red box) contains transplants from January 1, 2005, and June 31, 2007 (red line).

Line		Center 1 Year	National 1 Year
	Adult (Age 18+)		
1	Transplants (n=number)	90	10,781
2	**Percent (%) of Patients Surviving at End of Period**		
3	Observed at this Center	87.78	86.26
4	Expected, based on national experience	89.41	
5	**Deaths During Follow-up Period**		
6	Observed at this center	11	1,392
7	Expected, based on national experience	8.48	1,392
8	Ratio: Observed to Expected (O/E)	1.30	1.00
9	(95% Confidence Interval)	(0.65-2.32)	
10	P-value (2-sided), observed v. expected	0.469	
11	How does this center's survival compare to what is expected for similar patients?	Not Significantly Different (a)	
12	Percent retransplanted	5.5	4.4
13	Follow-up days reported by center (%)	91.7	93.9
14	Maximum Days of Follow-up (n)	365	365

Figure A.II: An example of a transplant center's CoP report

Note: This table is from Dickinson et al. (2008) and provides an example of a center that did not get penalized for poor performance. The CoP conditions from Section II can be calculated from this table. For example, Condition 1 is in line 8 (e.g., $O/E = 1.3 < 1.5$); Condition 2 is calculated by taking the difference between lines 6 and 7 (e.g., $O - E = 2.52 < 3$); Condition 3 is in line 10 (e.g., $Pr(O = E) = 0.469 > 0.05$).

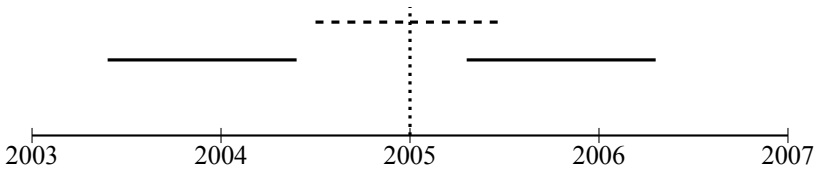
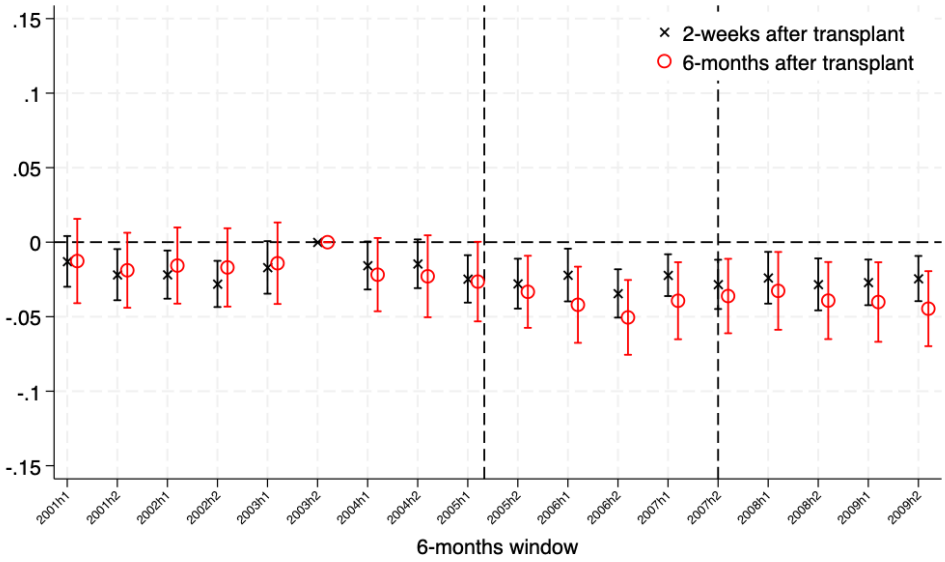


Figure A.III: Non-overlapping (solid) and overlapping (dashed) patients

Note: This figure highlights my regression subsample as described in the section on research design. The length of the lines indicates the patient's post-transplant mortality timeline and varies according to the outcome of interest. Patients whose post-transplant mortality timeline does not overlap with the CoP announcement have solid lines, and those with dashed lines have post-transplant mortality that overlaps with the CoP announcement.

Panel A



Panel B

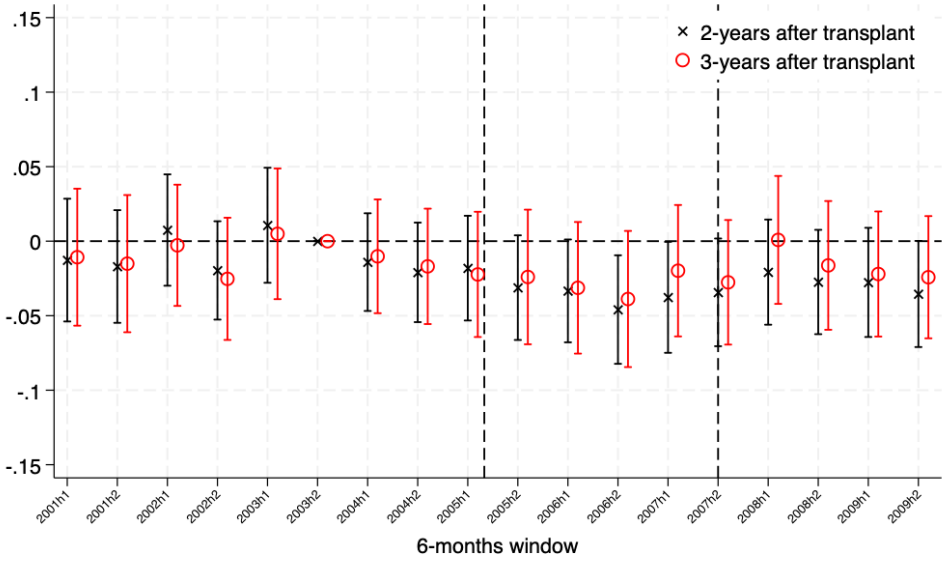
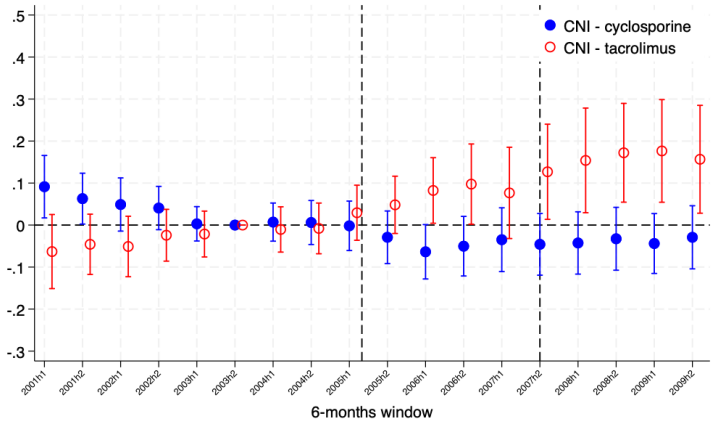


Figure A.IV: Impact on post-transplant mortality at different periods

Note: The figure presents the estimated effect on post-transplant mortality at 2-week/6-month/2-year/3-year, obtained using equation 7 with the instrument Z_c and 2003h2 as the reference 6-month window. I cluster standard errors at the transplant center level. Error bars indicate 95 percent confidence intervals.

Panel A: 6-months follow-up



Panel B: 1-year follow-up

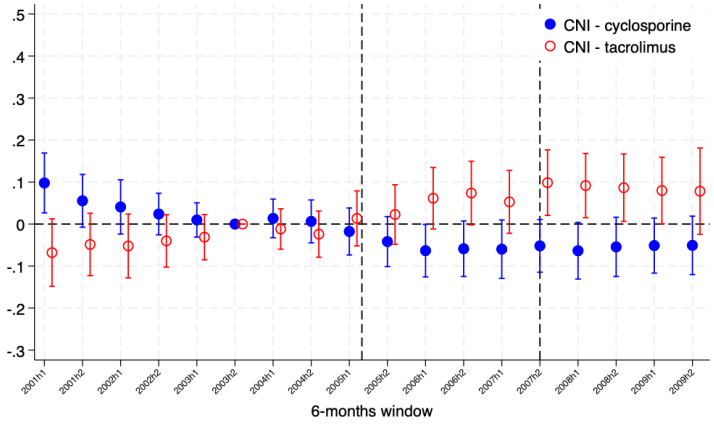


Figure A.V: Impact on maintenance immunosuppressant - tacrolimus and cyclosporine prescription at different follow-up intervals

Note: The figure presents the estimated effect on cyclosporine and tacrolimus prescription at 6-months and 1-year follow-up, obtained using equation 7 with the instrument Z_c and 2003h2 as the reference 6-month window. I cluster standard errors at the transplant center level. Error bars indicate 95 percent confidence intervals.

B Supplementary Tables

Table B.I: Death rates among patients missing follow-up care

Time Period	Pre-CoP	Post-Announce	Post-Implement
Dead within 2 weeks	100.0%	100.0%	100.0%
	(N=593)	(N=398)	(N=357)
Dead within 6 months	92.0%	92.8%	95.3%
	(N=3,078)	(N=1,996)	(N=1,731)
Dead within 1 year	94.0%	95.0%	95.8%
	(N=4,451)	(N=2,950)	(N=2,580)

Notes: This table shows the proportion of patients who missed their follow-up appointments due to death. Death rates are calculated as the proportion of patients who died within the specified timeframe among those who did not show up for their scheduled follow-up care.

Table B.II: Impact of compulsory documentation on mortality and transplant decision

	Post-transplant mortality		Pat-Kid Acceptance	
	(1)	(2)	(3)	(4)
	Teaching Center	Large Center	Teaching Center	Large Center
Post-Ann (Tri)	0.00294	-0.00154	-0.00403	0.00284
	(0.01474)	(0.01833)	(0.00876)	(0.00842)
Post-Imp (Tri)	-0.00543	-0.02449	0.00334	-0.00212
	(0.01528)	(0.01984)	(0.01043)	(0.01201)
Y mean	0.11904	0.11904	0.08273	0.08273
Fixed Effects	Center, 6-months	Center, 6-months	Center, 6-months	Center, 6-months
Observations	74,175	74,175	646,983	646,983

Note: This table relates to the analysis in the section on robustness checks - alternative mechanisms. It presents the estimated effects on post-transplant mortality/ the center's acceptance decision across different subgroups, obtained from triple-differences regression interacted with different administrative capacities. I cluster standard errors at the transplant center level.

Table B.III: Impact on acceptable donor criteria (i)

	(1) Min. Age	(2) Max. Age	(3) HLA Mismatch	(4) Creatinine
Post-Announce	0.02900	-0.53994	0.00647	0.63170
	(0.02441)	(0.16927)	(0.01274)	(0.67081)
Post-Implement	0.04581	1.04754	0.00863	3.41333
	(0.06314)	(0.36648)	(0.01437)	(1.27404)
Y mean	1.23015	80.92366	5.94159	21.81707
Fixed Effects	Patient, Quarters	Patient, Quarters	Patient, Quarters	Patient, Quarters
Observations	43,723	43,723	43,025	43,723

Note: This table relates to the analysis in the section on robustness checks - alternative mechanisms. It presents the estimated effect on centers setting more stringent donor criteria, obtained by estimating equation 8. Each column represents a different modifiable donor criterion. I cluster standard errors at the patient level.

Table B.IV: Impact on acceptable donor criteria (ii)

	(1) Hypertension	(2) Cold Ischemic Time	(3) Warm Ischemic Time	(4) Expanded Criteria
Post-Announce	-0.00006	2.32549	-1.10574	0.00396
	(0.00007)	(1.11263)	(0.55112)	(0.00735)
Post-Implement	-0.00039	9.47421	0.29125	-0.02113
	(0.00039)	(1.89632)	(1.09701)	(0.01041)
Y mean	0.99943	68.08462	65.95272	0.37520
Fixed Effects	Patient, Quarters	Patient, Quarters	Patient, Quarters	Patient, Quarters
Observations	43,723	43,723	35,696	43,723

Note: This table relates to the analysis in the section on robustness checks - alternative mechanisms. It presents the estimated effect on centers setting more stringent donor criteria, obtained by estimating equation 8. Each column represents a different modifiable donor criterion. I cluster standard errors at the patient level.

Table B.V: Impact on admitted patient characteristics (i)

	(1) Age	(2) White	(3) No education	(4) Working	(5) Medicare
Post-Announce	-0.11703	-0.00313	-0.00084	-0.00905	0.01527
	(0.15165)	(0.00413)	(0.01724)	(0.00556)	(0.01053)
Post-Implement	-0.15069	-0.00183	-0.02811	0.00546	0.00573
	(0.16484)	(0.00536)	(0.02463)	(0.00859)	(0.01156)
Y mean	49.16298	0.48686	0.15844	0.18484	0.48499
Fixed Effects	Centers, 6-months	Centers, 6-months	Centers, 6-months	Centers, 6-months	Centers, 6-months
Observations	261,313	261,313	261,313	261,313	261,313

Note: This table relates to the analysis in the section on robustness checks - alternative mechanisms. It presents the estimated effect on admitted patient characteristics, obtained by estimating equation 6. I cluster standard errors at the transplant center level.

Table B.VI: Impact on admitted patient characteristics (ii)

	(1) BMI	(2) Diabetic	(3) On dialysis	(4) Blood type O
Post-Announce	-0.13785	-0.00008	-0.00236	0.12877
	(0.05193)	(0.00606)	(0.00874)	(0.31113)
Post-Implement	-0.18364	-0.00280	0.00498	0.36779
	(0.06640)	(0.00779)	(0.00975)	(0.33629)
Y mean	27.62768	0.39092	0.76889	48.56857
Fixed Effects	Centers, 6-months	Centers, 6-months	Centers, 6-months	Centers, 6-months
Observations	253,962	261,313	261,313	261,313

Note: This table relates to the analysis in the section on robustness checks - alternative mechanisms. It presents the estimated effect on admitted patient characteristics, obtained by estimating equation 6. I cluster standard errors at the transplant center level.

Table B.VII: Impact on the rate of CMV testing

	(1)	(2)	(3)	(4)
	2-weeks	6-months	1-year	2-years
Post-Announce	-0.01628	0.03586	0.03447	0.05219
	(0.01615)	(0.02627)	(0.02904)	(0.04475)
Post-Implement	0.00754	0.02102	0.05379	0.02890
	(0.02026)	(0.03059)	(0.05436)	(0.05679)
Y mean	0.94816	0.11720	0.24254	0.28579
F-statistic	55.20396	54.06380	51.35394	50.61915
Fixed Effects	Center, 6-months	Center, 6-months	Center, 6-months	Center, 6-months
Observations	83,118	72,703	66,157	55,193

Note: This table examines the proposed detection channel in in the section on robustness checks - alternative mechanisms. It presents the estimated effect on the probability of centers performing a CMV test at different follow-up timelines, obtained by jointly estimating equations 5 and 6. Each column uses the subsample of patients whose post-transplant mortality timeline does not overlap with the CoP announcement described in the section on research design. I cluster standard errors at the transplant center level.

Table B.VIII: Impact on patient waitlist experience

	Time on waitlist		Removed from waitlist	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Post-Ann	-0.12311	-0.26940	0.00239	0.00464
	(0.09094)	(0.09930)	(0.00554)	(0.00586)
Y mean	2.79529	2.79529	0.09270	0.09270
F-statistic		134.16039		127.64035
Fixed Effects	Center, 6-months	Center, 6-months	Center, 6-months	Center, 6-months
Observations	107,244	107,247	186,364	186,366

Note: This table relates to the analysis in the section on robustness checks - non-targeted outcomes. It presents the estimated effect on transplant wait time and waitlist mortality, obtained by estimating equations 5 and 6. I cluster standard errors at the transplant center level.

Table B.IX: Full patient sample

	Post-Transplant Death	Tacrolimus Prescription	Cyclosporine Prescription
2-weeks after transplant			
Post-Ann	-0.003	0.049	-0.048
	(0.002)	(0.022)	(0.022)
Post-Imp	-0.006	0.070	-0.061
	(0.002)	(0.029)	(0.024)
6-months after transplant			
Post-Ann	-0.011	0.060	-0.047
	(0.004)	(0.019)	(0.017)
Post-Imp	-0.013	0.072	-0.050
	(0.005)	(0.027)	(0.019)
1-year after transplant			
Post-Ann	-0.011	0.081	-0.027
	(0.006)	(0.038)	(0.017)
Post-Imp	-0.011	0.106	-0.029
	(0.006)	(0.041)	(0.018)

Notes: This table relates to the analysis in the section on robustness checks - alternative specifications. It presents the estimated effect on post-transplant death, as well as the prescription of tacrolimus and cyclosporine, obtained by estimating equations 5 and 6 with the full patient sample. I cluster standard errors at the transplant center level.

Table B.X: Transplant centers have perfect foresight

	Post-Transplant Death	Tacrolimus Prescription	Cyclosporine Prescription
2-weeks after transplant			
Post-Ann	-0.019	0.111	-0.114
	(0.005)	(0.083)	(0.083)
Post-Imp	-0.025	0.106	-0.138
	(0.006)	(0.110)	(0.092)
6-months after transplant			
Post-Ann	-0.052	0.110	-0.067
	(0.012)	(0.075)	(0.067)
Post-Imp	-0.056	0.127	-0.079
	(0.013)	(0.086)	(0.082)
1-year after transplant			
Post-Ann	-0.050	-0.059	-0.030
	(0.022)	(0.102)	(0.076)
Post-Imp	-0.039	-0.046	-0.042
	(0.022)	(0.095)	(0.081)

Notes: This table relates to the analysis in the section on robustness checks - alternative specifications. It presents the estimated effect on post-transplant death, as well as the prescription of tacrolimus and cyclosporine, obtained by estimating equations 5 and 6, but replacing ρ_c with the penalty status of the center in 2007h2 when Medicare implemented CoP. I cluster standard errors at the transplant center level.

Table B.XI: Transplant centers have time-varying penalty beliefs

	Post-Transplant Death	Tacrolimus Prescription	Cyclosporine Prescription
2-weeks after transplant			
Post-Ann	-0.001	0.014	-0.011
	(0.001)	(0.002)	(0.002)
Post-Imp	-0.000	0.024	-0.013
	(0.001)	(0.003)	(0.002)
6-months after transplant			
Post-Ann	-0.005	0.014	-0.012
	(0.002)	(0.003)	(0.002)
Post-Imp	-0.004	0.017	-0.011
	(0.002)	(0.003)	(0.003)
1-year after transplant			
Post-Ann	-0.006	0.020	-0.006
	(0.002)	(0.003)	(0.002)
Post-Imp	-0.003	0.034	-0.006
	(0.003)	(0.004)	(0.003)

Notes: This table relates to the analysis in the section on robustness checks - alternative specifications. It presents the estimated effect on post-transplant death, as well as the prescription of tacrolimus and cyclosporine, obtained by estimating equations 5 and 6, but replacing the ρ_c with time-varying penalty beliefs. I use robust standard errors.

C Stylized model of center behavior without kidney choices

This section provides the proof for Propositions 1 and 2 in the main text. The center chooses its transplant decision $A(\tilde{x})$ and post-transplant care $q(x)$ to maximize its expected payoff:

$$\max_{A(\tilde{x}),q(x)} \int_{\tilde{x}} A(\tilde{x}) \int_{x} \overbrace{\left[\rho \overbrace{\left[\pi + \alpha q(x)\right]}^{\text{center profit}} \quad + \quad (1-\rho) \overbrace{\left[x q(x) - \frac{\gamma}{2} q^2(x) \right]}^{\text{patient utility}} \right]}^{\Pi(x,q(x))} p(x|\tilde{x}) dx dF(\tilde{x}) \tag{C.1}$$

$$\text{s.t.} \int_{\tilde{x}} A(\tilde{x}) \left[\int_{x} P(x, q(x)) p(x|\tilde{x}) dx \right] dF(\tilde{x}) \leq \tau$$

We solve the maximization problem via backwards induction.

A Solving for $q^*(x)$

Let $\lambda \geq 0$ be the Lagrange multiplier on the constraint. Define the Lagrangian:

$$\mathcal{L} = \int_{\tilde{x}} A(\tilde{x}) \int_{x} \Big[\Pi(x, q(x)) \Big] p(x|\tilde{x}) dx \, dF(\tilde{x}) \; - \; \lambda \Big[\int_{\tilde{x}} A(\tilde{x}) \int_{x} P(x, q(x)) p(x|\tilde{x}) dx dF(\tilde{x}) - \tau \Big].$$

Step 1: If the constraint is slack ($\lambda = 0$). For each x, we differentiate $\Pi(x, q(x))$ with respect to $q(x)$:

$$\rho\, \alpha + (1-\rho) \big[x - \gamma\, q(x) \big] = 0 \quad \Longrightarrow \quad (1-\rho)\, \gamma\, q(x) = \rho\, \alpha + (1-\rho)\, x.$$

Hence

$$q^{\text{uncon}}(x) = \frac{\rho\, \alpha + (1-\rho)\, x}{(1-\rho)\, \gamma}.$$

Step 2: If the constraint binds ($\lambda > 0$). For each x, we need

$$\frac{\partial \mathcal{L}}{\partial q} = \int A(\tilde{x}) \frac{\partial \Pi(.)}{\partial q} p(x|\tilde{x}) dx dF(\tilde{x}) - \lambda \int A(\tilde{x}) \frac{\partial P(.)}{\partial q} p(x|\tilde{x}) dF(\tilde{x}) = 0$$

where

$$\frac{\partial}{\partial q} \overbrace{\Big\{ \rho(\pi + \alpha\, q(x)) + (1-\rho) \big[x\, q(x) - \tfrac{\gamma}{2} q^2(x) \big] \Big\}}^{\Pi(x,q(x))} = \rho\, \alpha + (1-\rho) \big[x - \gamma\, q \big].$$

and

$$\frac{\partial}{\partial q(x)} \overbrace{\Big[1 - \Phi\big(\tfrac{x+q(x)}{\sigma} \big) \Big]}^{P(x,q(x))} = - \phi\Big(\tfrac{x+q(x)}{\sigma} \Big) \frac{1}{\sigma},$$

Rearrange for $q^*(x)$:

$$(1-\rho)\,\gamma\,q^*(x) = \rho\,\alpha + (1-\rho)\,x + \lambda\,\frac{1}{\sigma}\,\phi\Big(\tfrac{x+q^*(x)}{\sigma}\Big).$$

Thus we have the *implicit* solution:

$$q^*(x) = \frac{\rho\,\alpha + (1-\rho)\,x}{(1-\rho)\,\gamma} \;+\; \frac{\lambda}{(1-\rho)\,\gamma\,\sigma}\,\phi\Big(\tfrac{x+q^*(x)}{\sigma}\Big). \tag{C.2}$$

If $\lambda = 0$, we revert to the unconstrained optimum. Otherwise, $q^*(x)$ exceeds the unconstrained level, reflecting a desire to reduce mortality.

B Solving for the acceptance rule $A(\tilde{x})$

Define the net benefit function, $NB(\tilde{x})$

$$NB(\tilde{x}) = \int \Pi(x, q(x))p(x|\tilde{x})dx - \lambda \int P(x, q(x))p(x|\tilde{x})dx$$

Since the posterior distribution of $p(x|\tilde{x})$ is increasing in $\tilde{x}$, $NB(\tilde{x})$ is a monotonic function of $\tilde{x}$, $A^*(\tilde{x})$ takes the form of a cutoff strategy:

$$A^*(\tilde{x}) = \begin{cases} 1 & \text{if } \tilde{x} \geq t^* \\ 0 & \text{if } \tilde{x} < t^* \end{cases} \tag{C.3}$$

where t^* is such that $NB(t^*) = 0$. This completes the proof for proposition 1.

C Comparative Statics: Effect of Decreasing τ

As τ decreases, the regulatory constraint tightens, and the Lagrange multiplier λ increases. This forces the center to reduce the product

$$(\#\text{ transplanted}) \times (\#\text{ expected deaths}).$$

They can do this in two ways:

- **Raise t^* (fewer transplants).** Since

  $$NB(\tilde{x}) = \int \Pi(x, q(x))p(x|\tilde{x})dx - \lambda \int P(x, q(x))p(x|\tilde{x})dx$$

  increases in $\tilde{x}$, a higher threshold means fewer people qualify for a transplant.

- **Raise q^* (improve post-transplant care).** From

  $$q^*(x) = \frac{\rho\,\alpha + (1-\rho)\,x}{(1-\rho)\,\gamma} + \frac{\lambda}{(1-\rho)\,\gamma\,\sigma}\,\phi\Big(\tfrac{x+q^*(x)}{\sigma}\Big),$$

a larger λ makes $q^*(x)$ bigger for each x—the center "overspends" on care (relative to the unconstrained level) to reduce mortality.

This completes the proof for proposition 2.

D Stylized model of center behavior with kidney choices

In this section, I formalize the transplant center's incentives and explore how CoP affects decision-making. I present a stylized model where the center observes a noisy signal of patient health and then chooses the transplant eligibility threshold, the kidney type, and the amount of post-transplant care. The center must balance the tradeoffs between profit, patient welfare, and compliance with CoP constraints. Specifically, the center considers the revenue from transplants and post-transplant care, the relative scarcity of good kidneys, and the regulatory penalties from high patient mortality. The model delivers three predictions about the center's response to CoP implementation. First, CoP raises the marginal cost of each transplant by increasing the penalty for poor outcomes, leading centers to reduce transplants. Second, CoP's stricter death constraints increase the marginal benefit of the safer, "expensive" good kidney, resulting in a shift away from bad kidneys. Third, by penalizing poor outcomes, CoP incentivizes centers to increase post-transplant care despite its cost. In subsequent analysis, I model patient mortality in my setting, describe the center's objective function, and characterize the optimal transplant threshold, kidney choice, and post-transplant care. Finally, I provide comparative statics on key parameters and present proofs in the Appendix. Figure D.VI illustrates the center's timeline and decision-making.

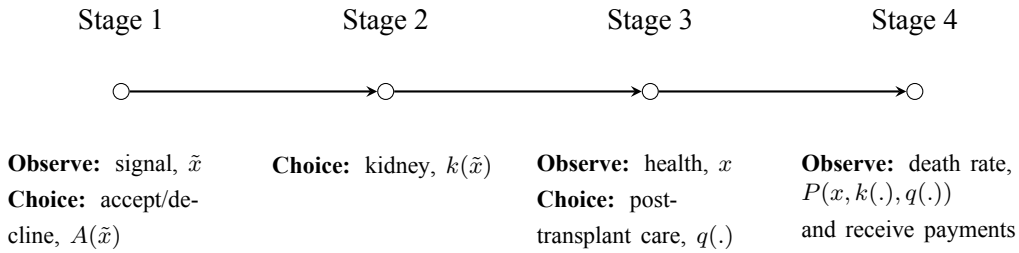


Figure D.VI: Timeline of the center behavior

A Setup

Patient health is denoted as x, where $x \sim N(\mu_x, \sigma_x^2)$ [1]. However, when deciding whether to transplant, centers only observe a noisy signal of patient health, $\tilde{x} = x + u$, where $u \sim N(0, \sigma_u^2)$ is independent of x. Thus, $\tilde{x}$ is an unbiased signal for patient health x. Next, the center matches the patient with the good (g) or bad (b) kidney. The good kidney is less risky $(\sigma_g < \sigma_b)$. After the transplant, centers observe x and decide on post-transplant care $q(x, k)$. Transplant patients die if the latent variable $y > 0$, where $y = \varepsilon_k - x - q(x, k)$ and $\varepsilon_k \sim N(0, \sigma_k^2)$. ε_k is a normally distributed idiosyncratic shocks with mean 0 and variance σ_k^2. Let the likelihood that a patient with health x, kidney k, and post-transplant care $q(x, k)$ die be $P(x, k, q(x, k)) = 1 - \Phi\left(\frac{q(x,k)+x}{\sigma_k}\right)$, which is decreasing in q and x: more post-transplant care or healthier patient reduces the likelihood of transplant deaths. Similarly, the good kidney reduces mortality due to its

[1] Patients with higher x are deemed healthier and more suitable for transplant(OPTN, 2023).

lower variance σ_g^2. Conditional on transplant decision, kidney choice and post-transplant care, the center expects $\int_{\tilde{x}} A(\tilde{x}) \int_x P(x,k,q(x,k))p(x|\tilde{x})dF(\tilde{x})$ patients to die, where $p(x|\tilde{x})$ is the posterior distribution of x given $\tilde{x}$ and can be derived with Bayes' rule.

I follow Clemens and Gottlieb (2014); Dickstein (2017); Alexander (2020); Shi (2023) and model the center's objective function as a weighted combination of profit and concern for patient utility. The weight placed on profit is ρ and can be interpreted as the center's belief in punishment. In my setting, the center becomes more altruistic and places more weight on patient utility when the likelihood of punishment is low (i.e., low ρ). CMS pays the center a fixed reimbursement, π for each transplant, and a reimbursement rate α for each unit of post-transplant care, $q(x,k)$. Thus, the center profit is $\pi + \alpha q(x,k)$. A center's concern for patient welfare can be understood as altruism on behalf of the patient or as the center acting to preserve its reputation (Alexander, 2020).

The patient's utility from post-transplant care is concave in $q(x,k)$, reflecting diminishing returns to care. Healthier patients (higher x) derive greater benefits from transplants, but excessive care imposes costs due to coinsurance or opportunity costs on patient's time (Senanayake et al., 2020). The patient also faces a waiting cost of g to receive a good kidney, reflecting the scarcity of good kidneys. The patient receives zero if centers do not perform a transplant. The center maximizes utility and chooses $A(\tilde{x}), k(\tilde{x}), q(x,k)$ to maximize a weighted average of their profit and the patient's utility from transplant[2]:

$$\max_{A(\tilde{x}),k(\tilde{x})\in\{g,b\},q(x,k)} \int_{\tilde{x}} A(\tilde{x}) \int_x \left[\rho \overbrace{[\pi + \alpha q(.)]}^{\text{center profit}} + (1-\rho) \overbrace{\left[xq(.) - \frac{\gamma}{2} q^2(.) - \mathbf{1}_{\{k=g\}} g \right]}^{\text{patient utility}} \right] p(x|\tilde{x}) dx dF(\tilde{x})$$

$$\text{s.t.} \quad \overbrace{\int_{\tilde{x}} A(\tilde{x})}^{\text{"small center discount"}} \quad \overbrace{\int_x P(x,k,q(.))p(x|\tilde{x})dx \, dF(\tilde{x})}^{\text{"not too many deaths"}} \leq \tau \tag{D.1}$$

τ is the CoP limit, and the rest of the terms in the constraint reflect the CoP conditions in Section 2.4. $\int_x P(x,k,q(x,k))p(x|\tilde{x})dx$ mimics conditions 1 and 2: there cannot be too many post-transplant deaths. However, even if it does, the center is exempted if condition 3 fails (i.e., the sample size is so small that differences between observed and expected deaths are statistically insignificant). $\int_{\tilde{x}} A(\tilde{x})dF(\tilde{x})$ mimics condition 3 and serves as a scaling factor that makes it less likely for small centers to exceed the CoP limit, τ.

Intuitively, the center balances competing incentives. On one hand, it seeks to maximize profit by performing more transplants, using cheaper bad kidneys, and providing reimbursable care. On the other hand, performance concerns and patient welfare impose constraints: (i) transplanting too many patients and using the bad kidney increases the likelihood of exceeding the CoP mortality limit; (ii) patients dislike

[2] **Note:** The notation $q(x,k)$ is to indicate that post-transplant care is chosen when x and k are observed.

excessive post-transplant care due to the marginal cost $\gamma > 0$. The center optimally trades off these incentives by adjusting the transplant decision $A(\tilde{x})$, kidney choice $k(\tilde{x})$, and post-transplant care $q(x,k)$. Next, I characterize $A^*(\tilde{x}), k^*(\tilde{x}), q^*(x,k)$ and present the proofs in Appendix.

Proposition 1. *The optimal $q^*(x,k)$ is an implicit solution to the equation D.3. $A^*(\tilde{x})$ takes the form of a cutoff strategy D.6 and t^* is the transplant threshold where patients with $\tilde{x} \geq t^*$ will receive transplants and post-transplant care. Conversely, patients with $\tilde{x} < t^*$ will receive no transplants nor post-transplant care. The optimal kidney allocation $k^*(\tilde{x})$ is defined as:*

$$k^*(\tilde{x}) = \begin{cases} g & t^* \leq \tilde{x} < t_g^*, \\ b & \tilde{x} \geq t_g^*, \\ \textit{(no transplant)} & \tilde{x} < t^*. \end{cases}$$

where t_g^*, the good kidney threshold, is the root to equation D.5.

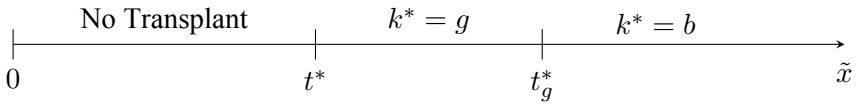
Because the center cannot observe a patient's true health x and instead relies on the noisy signal $\tilde{x}$, Proposition 1 implies a negative□sorting allocation rule based on $\tilde{x}$. Specifically, patients whose signals lie in an intermediate range, $\tilde{x} \in [t^*, t_g^*)$, receive the safer (good) kidney, while patients with strong signals, $\tilde{x} \geq t_g^*$, receive the riskier (bad) kidney. The intuition is that for borderline (moderate) signals, the good kidney's lower mortality risk ($\sigma_g < \sigma_b$) provides a significant survival benefit that justifies incurring its waiting cost g. By contrast, for sufficiently high signals $\tilde{x} \geq t_g^*$, that survival benefit diminishes and no longer outweighs g, prompting the center to assign the cheaper (bad) kidney. This tradeoff in expected benefit versus cost naturally yields a cutoff $\tilde{x} = t_g^*$ above which the center switches from good to bad kidneys.

B Comparative statics

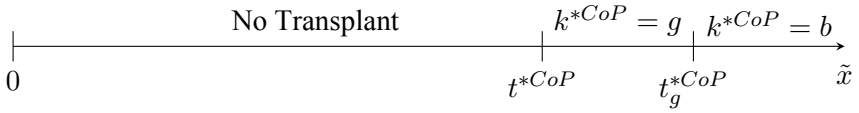
In this stylized model, the pre-CoP announcement reflects $\tau \to \infty$, meaning no effective regulatory constraints on the product of transplants and mortality, allowing centers to optimize without restrictions. The post-CoP announcement reflects $\tau < \infty$, introducing binding regulatory constraints. The following result illustrates the comparative statics for the transplant threshold t^*, kidney choice t_g^*, and post-transplant care $q^*(x,k)$ as CMS announces CoP (i.e., τ decreases). I present the proofs in the Appendix.

Proposition 2. *As CMS announces CoP (i.e., τ decreases), the transplant threshold t^* increases $\left(\frac{\partial t^*}{\partial \tau} < 0\right)$; post-transplant care $q^*(x,k)$ increases $\left(\frac{\partial q^*(x,k)}{\partial \tau} < 0\right)$; the good kidney threshold t_g^* increases $\left(\frac{\partial t_g^*}{\partial \tau} < 0\right)$.*

Proposition 2 predicts that as CMS announces CoP, the fraction of patients receiving a transplant decreases. However, this does not imply that enters are actively selecting healthier patients. Instead, the higher threshold t^* makes it more likely for a patient with better true health x to surpass it. Consequently, average health among the smaller set of transplanted patients rises (i.e., $E[x|\tilde{x} > t^*)$ is increasing in t^*). The extent of this rise depends on the informativeness of the noisy signal $\tilde{x}$. When $\tilde{x}$ closely tracks x (i.e., low



(a) Kidney matching when CoP limit, $\tau \to \infty$ (before CoP)



(b) Kidney matching when CoP limit, $\tau < \infty$ (after CoP)

Figure D.VII: Kidney matching before CoP v.s. after CoP

Note: Panel A depicts the scenario when the CoP limit is not stringent (e.g., $\tau \to \infty$). Panel B depicts the scenario when the CoP limit is very stringent (e.g., $\tau < \infty$). The model predicts fewer bad kidney transplants because centers substitute the bad kidneys for the good kidneys for patients with a strong signal, $\tilde{x} \in [t_g^*, t_g^{*CoP}]$. On the other hand, patients with intermediate signal, $\tilde{x} \in [t^*, t^{*CoP}]$, do not receive a transplant. Thus, the effect of CoP on good kidney transplants is ambiguous and depends on the parameter value of the model (e.g., high/low waiting cost, g).

Var(u)), the stricter threshold effectively excludes less-healthy patients, strongly skewing the transplanted group toward high health. Conversely, if $\tilde{x}$ is weakly informative (i.e., high Var(u)), the higher threshold barely alters the health composition of transplanted patients.

Furthermore, Proposition 2 predicts fewer bad kidney transplants after CMS implements CoP. Using Figure D.VII as an example, this decrease is because the center substitutes the bad kidneys with the good kidneys for patients with a strong signal, $\tilde{x} \in [t_g^*, t_g^{*CoP}]$. However, this does not imply more good kidney transplants because patients with intermediate signal, $\tilde{x} \in [t^*, t^{*CoP}]$ will not receive a transplant due to more stringent performance limits. Thus, the effect of CoP on good kidney transplants is ambiguous and depends on the model's parameter values (e.g., high/low waiting cost, g).

C Proofs for Proposition 1 and 2

From equation D.1, the center's objective function is

$$\max_{A(\tilde{x}),k\in\{g,b\},q} \int_{\tilde{x}} A(\tilde{x}) \int_{x} \overbrace{\left[\rho \overbrace{\left[\pi + \alpha q\right]}^{\text{center profit}} \quad + \quad (1-\rho) \overbrace{\left[xq - \frac{\gamma}{2}q^2 - \mathbf{1}_{\{k=g\}} g \right]}^{\text{patient utility}} \right]}^{\Pi(x,k,q)} p(x|\tilde{x}) dx dF(\tilde{x}) \tag{D.2}$$

$$\text{s.t.} \int_{\tilde{x}} A(\tilde{x}) \left[\int_{x} P(x,k,q) p(x|\tilde{x}) dx \right] dF(\tilde{x}) \leq \tau$$

We solve the maximization problem via backwards induction.

C.1 Solving for q^*

Let $\lambda \geq 0$ be the Lagrange multiplier on the constraint. Define the Lagrangian:

$$\mathcal{L} = \int_{\tilde{x}} A(\tilde{x}) \int_{x} \Big[\Pi(x,k,q) \Big] p(x|\tilde{x}) dx \, dF(\tilde{x}) \; - \; \lambda \Big[\int_{\tilde{x}} A(\tilde{x}) \int_{x} P(x,k,q) p(x|\tilde{x}) dx dF(\tilde{x}) - \tau \Big].$$

Step 1: If the constraint is slack ($\lambda = 0$). For each x, we differentiate $\Pi(x,k,q)$ with respect to q:

$$\rho\,\alpha + (1-\rho)\big[x - \gamma\, q\big] = 0 \quad \Longrightarrow \quad (1-\rho)\,\gamma\, q = \rho\,\alpha + (1-\rho)\,x.$$

Hence

$$q^{\text{uncon}}(x) = \frac{\rho\,\alpha + (1-\rho)\,x}{(1-\rho)\,\gamma}.$$

Step 2: If the constraint binds ($\lambda > 0$). For each x, we need

$$\frac{\partial \mathcal{L}}{\partial q} = \int A(\tilde{x}) \frac{\partial \Pi(.)}{\partial q} p(x|\tilde{x}) dx dF(\tilde{x}) - \lambda \int A(\tilde{x}) \frac{\partial P(.)}{\partial q} p(x|\tilde{x}) dF(\tilde{x}) = 0$$

where

$$\frac{\partial}{\partial q} \overbrace{\Big\{ \rho(\pi + \alpha\, q) + (1-\rho)\big[x\, q - \tfrac{\gamma}{2} q^2 - \mathbf{1}_{\{k=g\}} g\big] \Big\}}^{\Pi(x,k,q)} = \rho\,\alpha + (1-\rho)\big[x - \gamma\, q\big].$$

and

$$\frac{\partial}{\partial q} \overbrace{\Big[1 - \Phi\big(\tfrac{x+q}{\sigma_k}\big) \Big]}^{P(x,k,q)} = -\,\phi\Big(\tfrac{x+q}{\sigma_k}\Big)\,\frac{1}{\sigma_k},$$

Rearrange for q^*:

$$(1-\rho)\,\gamma\, q^* = \rho\,\alpha + (1-\rho)\,x + \lambda\,\frac{1}{\sigma_k}\,\phi\Big(\tfrac{x+q^*}{\sigma_k}\Big).$$

Thus we have the *implicit* solution:

$$q^*(x,k) = \frac{\rho\,\alpha + (1-\rho)\,x}{(1-\rho)\,\gamma} \;+\; \frac{\lambda}{(1-\rho)\,\gamma\,\sigma_k}\,\phi\Big(\tfrac{x+q^*(x,k)}{\sigma_k}\Big). \tag{D.3}$$

If $\lambda = 0$, we revert to the unconstrained optimum. Otherwise, $q^*(x,k)$ exceeds the unconstrained level, reflecting a desire to reduce mortality.

C.2 Solving for $k^*(\tilde{x})$

Upon seeing $\tilde{x}$, the center forms a posterior over x, where $p(x|\tilde{x})$ is derived from Bayes' rule, with priors $x \sim N(\mu_x, \sigma_x^2)$ and $u \sim N(0, \sigma_u^2)$. x and u are assumed to be independent. $\Pi(x,k,q^*)$ is the payoff for a transplanted patient of true health x given kidney k as defined in the previous section. Thus, the center chooses k^* at each $\tilde{x}$ such that:

$$k(\tilde{x}) = \arg\max_{k\in\{g,b\}} \overbrace{\int \left[\Pi(x,k,q^*) \;-\lambda P(x,k,q^*)\right] p(x|\tilde{x})\,dx}^{\widetilde{\Pi}(x,k,q^*)} \tag{D.4}$$

Next, we define:

$$D(\tilde{x}) = \widetilde{\Pi}(x,g,q^*) - \widetilde{\Pi}(x,b,q^*) \tag{D.5}$$

As $\tilde{x}$ increases, the posterior shifts to higher x. Since $\widetilde{\Pi}(x,g,q^*)$ and $\widetilde{\Pi}(x,b,q^*)$ differ mainly by the cost g and the difference in survival benefits, then $D(\tilde{x})$ is decreasing in $\tilde{x}$: when $\tilde{x}$ is large, the expected incremental survival benefit of g is smaller, so $D(\tilde{x})$ may become negative, favoring kidney b. Thus, $D(\tilde{x})$ crosses zero exactly once, giving a unique cutoff t_g^*. We have the following cutoff rule:

$$k^*(\tilde{x}) = \begin{cases} g & t \le \tilde{x} < t_g^*, \\ b & \tilde{x} \ge t_g^*, \\ \text{(no transplant)} & \tilde{x} < t^*. \end{cases}$$

C.3 Solving for the acceptance rule $A(\tilde{x})$

Define the net benefit function, $NB(\tilde{x})$

$$NB(\tilde{x}) = \int \Pi(x,k,q)p(x|\tilde{x})dx - \lambda \int P(x,k,q)p(x|\tilde{x})dx$$

Since the posterior distribution of $p(x|\tilde{x})$ is increasing in $\tilde{x}$, $NB(\tilde{x})$ is a monotonic function of $\tilde{x}$, $A(\tilde{x})$ takes the form of a cutoff strategy:

$$A(\tilde{x}) = \begin{cases} 1 & \text{if } \tilde{x} \ge t^* \\ 0 & \text{if } \tilde{x} < t^* \end{cases} \tag{D.6}$$

where t^* is such that $NB(t^*) = 0$. This completes the proof for proposition 1.

C.4 Comparative Statics: Effect of Decreasing τ

As τ decreases, the regulatory constraint tightens, and the Lagrange multiplier λ increases. This forces the center to reduce the product

$$(\#\text{ transplanted}) \times (\#\text{ expected deaths}).$$

They can do this in two ways:

- **Raise t^* (fewer transplants).** Since

$$NB(\tilde{x}) = \int \Pi(x, q(x))p(x|\tilde{x})dx - \lambda \int P(x, q(x))p(x|\tilde{x})dx$$

  increases in $\tilde{x}$, a higher threshold means fewer people qualify for a transplant.

- **Raise t_g^* (fewer bad kidney transplants).** From

$$D(\tilde{x}) = \widetilde{\Pi}(x, g, q^*) - \widetilde{\Pi}(x, b, q^*)$$

  a larger λ means centers can afford fewer expected deaths than before. This reduces the marginal benefit of the bad kidney and raises t_g^*

- **Raise q^* (improve post-transplant care).** From

$$q^*(x, k) = \frac{\rho\,\alpha + (1-\rho)\,x}{(1-\rho)\,\gamma} + \frac{\lambda}{(1-\rho)\,\gamma\,\sigma_k}\,\phi\Big(\tfrac{x+q^*(x)}{\sigma_k}\Big),$$

  a larger λ makes $q^*(x, k)$ bigger for each x—the center "overspends" on care (relative to the unconstrained level) to reduce mortality.

This completes the proof for proposition 2.

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