Discussion of:
"Optimizing Patient Placement in Normal Care Units: An Instrumental Causal Forest Approach Minimizing Mortality"
by Johannes Cordier

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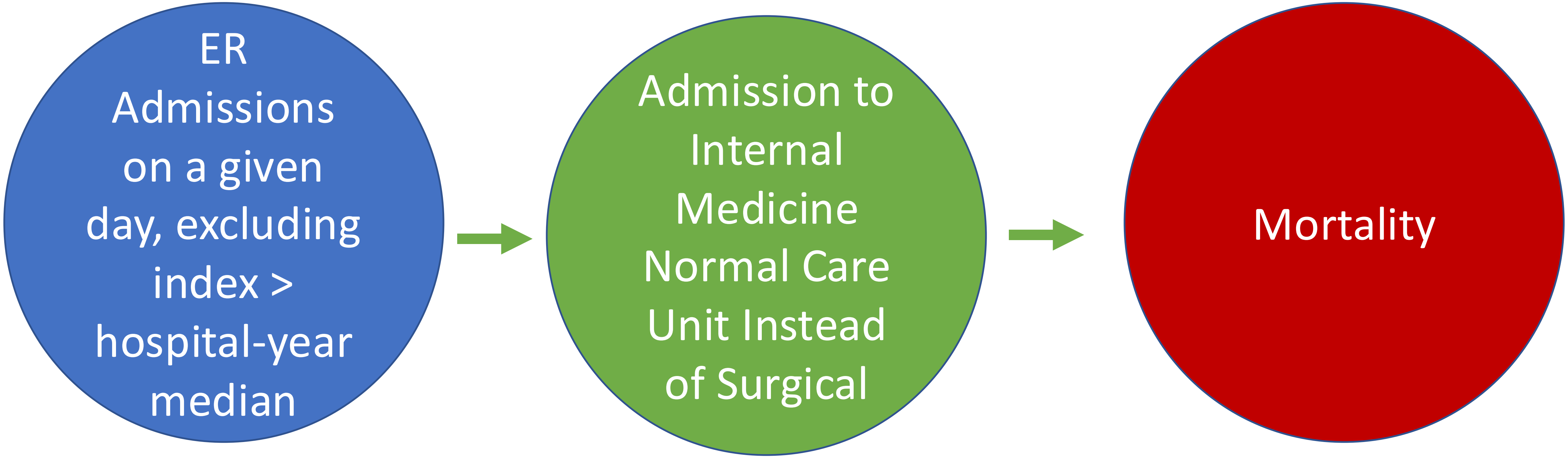
Great paper!

How can we optimize patient placement in normal care units – internal medicine units vs. surgical units?

Identification Strategy



Empirical Approach

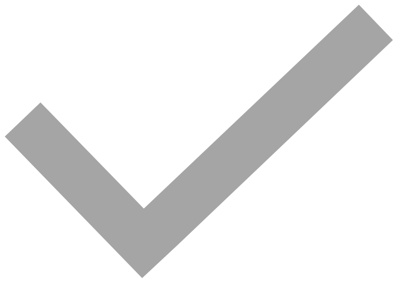
Instrumental Causal Forest

+

Minimax Regret Policy

Results

Mortality decreases



Capacity unchanged

Switzerland

Optimizing Patient Placement in Normal Care Units: An Instrumental Causal Forest Approach Minimizing Mortality

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Motivation and Problem Statement

- Patient placement in NCUs impacts mortality, length of stay, and costs (Sharma et al., 2022; Handel et al., 2018).
- High NCU utilization increases risk of adverse outcomes (Abir et al., 2020; Boyle et al., 2013; Schilling et al., 2010).
- Trade-off: specialization vs. utilization.
- Status: Empirical analysis, Swiss university hospitals, 74,355 cases.

Medical and Hospital Background

- Focus: Cardiovascular and oncological diagnoses (ICD-10: I2, I3, I6, I7, C1–C4, C7).
- NCUs: Internal medicine vs. surgical units.
- Placement decisions influenced by diagnosis, resource constraints, and hospital policies.
- Out-lying (suboptimal placement) increases risk.

Data Overview

- Source: Swiss Federal Statistical Office, Medical Statistics of Hospitals.
- Years: 2012–2020, 278 hospitals, 13 million cases.
- Sample: 5 university hospitals, 74,355 cases, selected ICD-10 groups.

Variables

- **Outcome:** In-hospital mortality (binary).
- **Treatment:** NCU type (Internal Medicine $W = 1$, Surgical $W = 0$).
- **Controls:** Age, sex, diagnoses, procedures, time/hospital fixed effects.
- **Instrument:** Daily emergency admissions (binary, above hospital-specific median).

Double ML and Causal Forests

- Instrumental variable causal forest estimates heterogeneous treatment effects (Wager and Athey, 2018; Athey and Imbens, 2016).
- Instrument: Exogenous variation in daily emergency admissions (above median adjusted for hosptial and year).
- Controls for confounding and selection bias.

$$\hat{\tau} = \frac{1}{n}\sum_{i=1}^{n} \hat{\Gamma}_i + \hat{\Psi}_i \tag{1}$$

$$\hat{\Psi}_i = \frac{Z_i - \hat{Z}_i(X_i)}{\hat{Z}_i(X_i)(1 - \hat{Z}_i(X_i))}(Y_i - \hat{\mu}(X_i) * \hat{\Gamma}_i(d_i - \hat{e}(X_i))) \tag{2}$$

$$\hat{\Gamma}_i = \hat{\mu}_{(1)}(X_i) - \hat{\mu}_{(0)}(X_i) + \frac{d_i}{\hat{e}(X_i)}\left(Y_i - \hat{\mu}_{(1)}(X_i)\right) - \frac{1 - d_i}{1 - \hat{e}(X_i)}\left(Y_i - \hat{\mu}_{(0)}(X_i)\right) \tag{3}$$

Minimax Regret Policy

- Policy optimizes daily assignment of P patients to NCUs.
- Minimizes worst-case regret across all assignment configurations.

$$R_i(\boldsymbol{\pi}) = \max_{\boldsymbol{\pi}' \in \boldsymbol{\Pi}} \tilde{Y}_i(\boldsymbol{\pi}') - \tilde{Y}_i(\boldsymbol{\pi}) \tag{4}$$

$$\mathrm{R}(\boldsymbol{\pi}) = \sum_{i=1}^{P} \left[\max_{\boldsymbol{\pi}' \in \boldsymbol{\Pi}} \tilde{Y}_i(\boldsymbol{\pi}') - \tilde{Y}_i(\boldsymbol{\pi}) \right] \tag{5}$$

Welfare Effects

- Welfare: Expected sum of patient outcomes under chosen assignment.

$$W(\boldsymbol{\pi}) = \sum_{i=1}^{P} \tilde{Y}_i(\boldsymbol{\pi}) \tag{6}$$

$$W(\boldsymbol{\pi}) = \sum_{i=1}^{P} \left\{ \tilde{Y}_i(0) + (\hat{\Gamma}_i + \hat{\Psi}_i)\boldsymbol{\pi}_i \right\} \tag{7}$$

Stacked Bar Plot: ICD-10 and NCU Placement

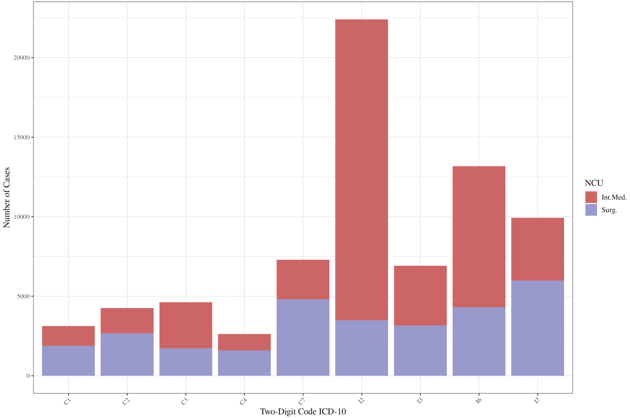


Figure 1: Cases by ICD-10 code and NCU placement

Panel Stacked Bar Plot by Hospital

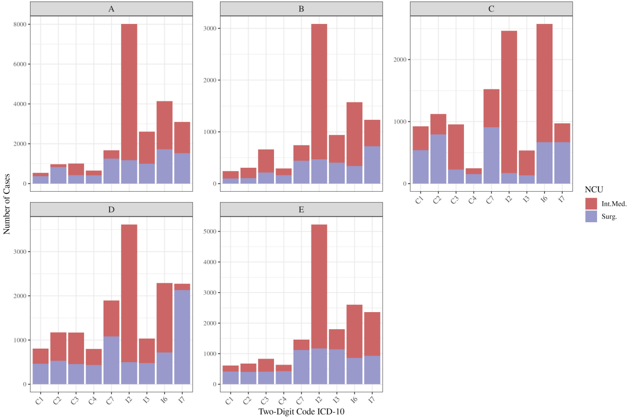


Figure 2: Cases by ICD-10 code, NCU placement, and hospital

Busyness Time Series by Hospital

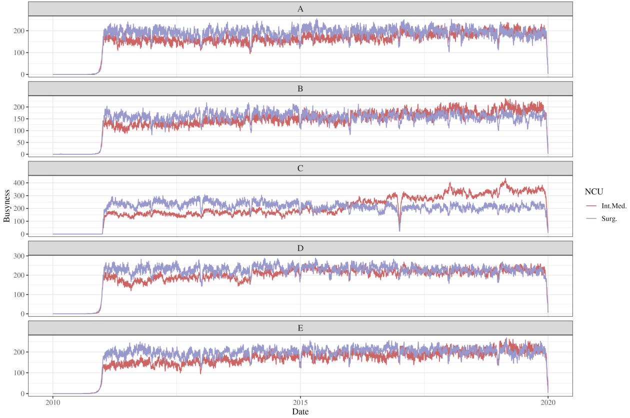


Figure 3: Time series of NCU busyness by hospital

Common Support Plot

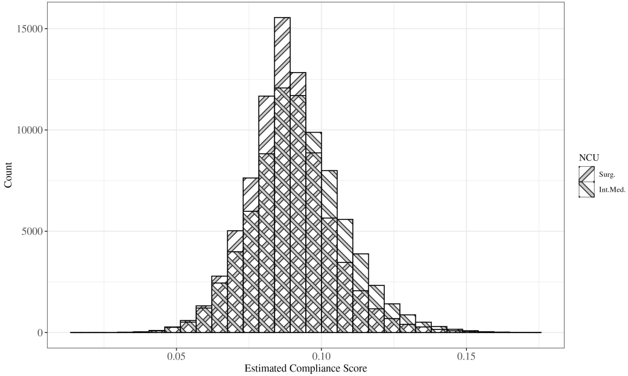


Figure 4: Compliance scores for the instrument

Policy Busyness Time Series

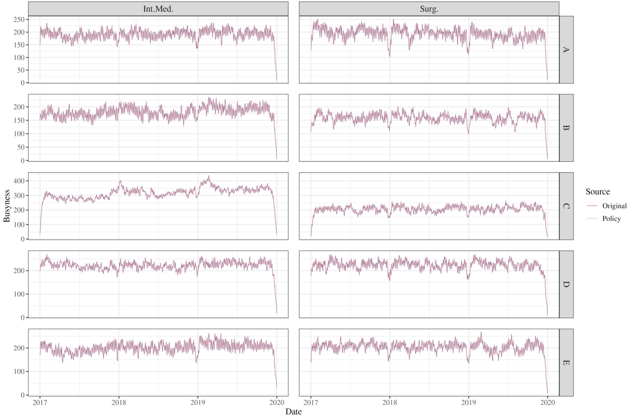


Figure 5: Busyness time series under policy and observed assignment

Instrument Strength

- First Stage R-squared (LM): 0.348
- First Stage R-squared (CF): 0.308
- First Stage F-statistic (LM): 117.314
- Instrument: Emergency admissions, exogenous variation.

Average Treatment Effects

- Causal Forest ATE: -0.09 (SE: 0.032)
- Linear Model ATE: 0.035 (SE: 0.051)
- Large heterogeneity; effect driven by surgical NCU patients.

Frame Title

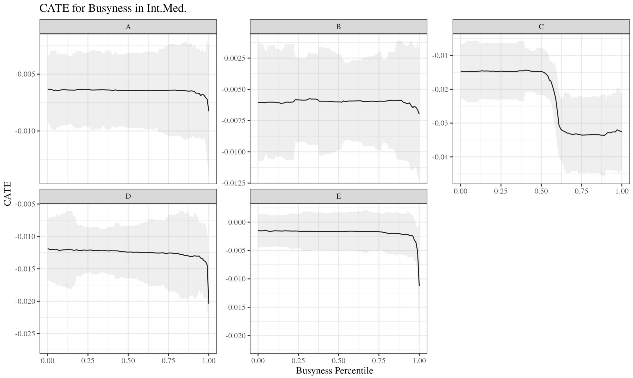


Figure 6: CATE over Busyness levels by Hospital

Policy Impact: Confusion Matrix

- 13863 patients remained in surgical NCUs.
- 17273 patients remained in internal medicine NCUs.
- 30985 patients (49.9%) reassigned under policy.

Busyness and Welfare Effects

Metric	Observed	Policy	Relative Change	Absolute Change
Total Welfare	2032	1879	0.075	-153
Average Welfare	0.033	0.03	0.075	-0.002

Table 1: Comparison of Observed and Policy Welfare Metrics

Hospital-Specific Welfare Effects

Hospital	Observed	Policy	Relative Change	Absolute Change
A	277	246	0.111	-31
B	182	142	0.218	-40
C	604	572	0.052	-32
D	381	402	-0.056	21
E	588	516	0.122	-72

Table 2: Comparison of Observed and Policy Welfare Metrics by UH Canton

Limitations

- No direct data on staff availability or real-time resource constraints.
- Restricted to subset of NCUs and patients.
- Instrument assumes similar effect across NCUs; possible deviations.
- Focus on selected ICD-10 diagnoses.
- Limited number of hospitals; external validity may be limited.

Implications

- Data-driven placement policies can improve outcomes and efficiency.
- Minimax regret framework balances specialization and utilization.
- Policy can be tailored to local contexts.
- Potential for broader system-level improvements.

Conclusion

- Instrumental causal forest + minimax regret policy optimizes NCU placement.
- Improves mortality, balances busyness, maintains welfare.
- Framework is robust, scalable, and policy-relevant.

Compliance Score Descriptive Plot

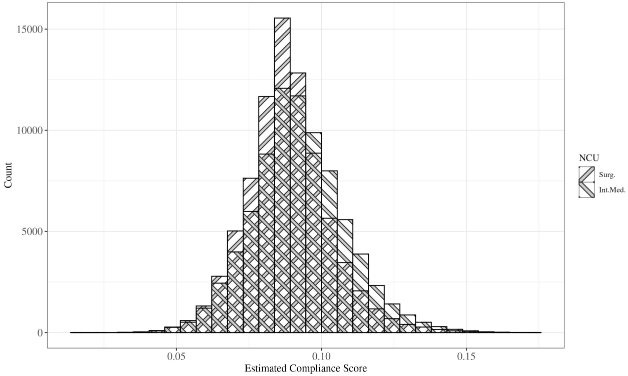


Figure 7: Compliance score descriptive plot

Busyness Difference Histogram

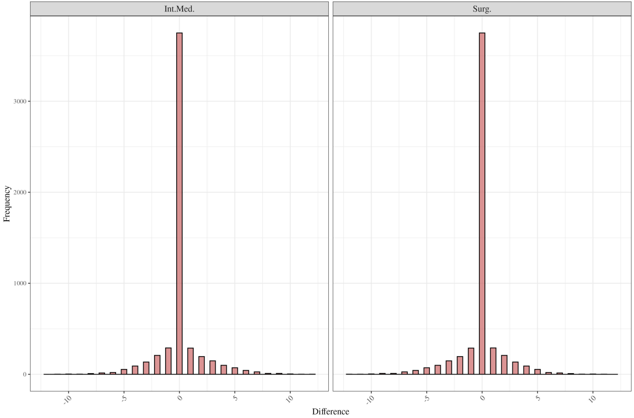
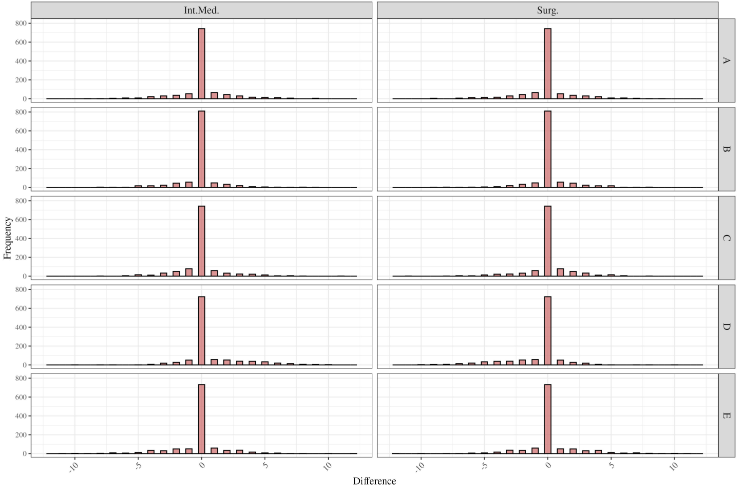


Figure 8: Busyness difference

Busyness Difference by Hospital



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Discussion

Do doctors/nurses see things you do not?

Why are you using regret?

Why wouldn't you just implement the optimal policy?

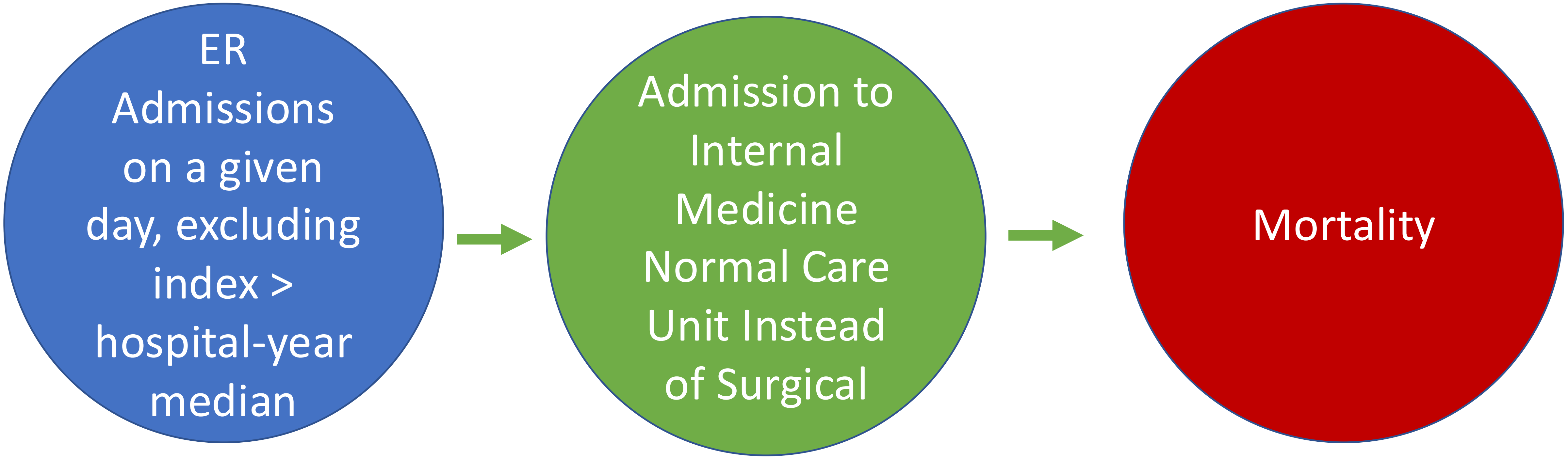
How hard is this to implement?

The policy operates in the following steps:

1. **Daily Patient Assignment:** Each day, P patients arrive and must be assigned to one of the two NCUs.
2. **Outcome Prediction:** Use the instrumental variable causal forest to predict individual average treatment effects (IATEs) for each patient under both possible assignments, incorporating the EWM welfare framework.
3. **Welfare Calculation:** Compute estimated welfare $\hat{W}(\boldsymbol{\pi})$ for each possible assignment configuration using the predicted outcomes from the causal forest.
4. **Regret Minimization:** Calculate regret for each possible assignment by comparing predicted welfare against the optimal feasible assignment, following the minimax regret criterion.
5. **Decision Rule:** The optimal assignment is determined by finding the configuration $\boldsymbol{\pi}^*$ that minimizes the maximum regret across all assignments: $\boldsymbol{\pi}^* = \arg\min_{\boldsymbol{\pi}\in\boldsymbol{\Pi}} \max_{\boldsymbol{\pi}'\in\boldsymbol{\Pi}}[\hat{W}(\boldsymbol{\pi}') - \hat{W}(\boldsymbol{\pi})]$.
6. **Assignment Implementation:** The optimal allocation is implemented by updating patient records with the best NCU placement, balancing specialization needs with utilization effects.

This implementation framework ensures that the policy integrates causal inference with operational decision-making, providing a data-driven approach to patient placement that accounts for both individual treatment effects and system-wide welfare optimization.

Can you do more to justify monotonicity? (Do you need it?)



How Exactly Are You Thinking about Capacity?

Is capacity just a covariate? How about SUTVA?

Why just use binary variation in the instrument?

Statement of Contributions

- What is novel and what is "off the shelf"?
- "extend the minimax regret into a case with multiple decisions affecting multiple patients at once"

Potential for Scalability is Exciting