Meaningful Use of Electronic Health Record and Patient Utilization Outcomes within 30 Days of Hospital Discharge

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Outline

- Causal Inference and Observational Data
- Background
- Study Goals & Design
- Data, Measures & Analytic Approach
- Principal Findings
- Limitations
- Policy Implications
- Conclusions
- Q & A

Causal Inference and Observational Data

- Randomized Controlled Trial (RCT) is the **gold standard** for causal inference
- However, RCT data may be unavailable for several reasons, e.g., ethics, feasibility with respect to cost and timing, and other considerations
- Observational data, despite their major limitations—e.g., confounding, selection—may be the only source of information available
- When rigorously and carefully analyzed, they may provide invaluable insights into the worth of programs and interventions implemented (*Rubin 2008*)

Background

- The HITECH Act authorized financial incentives to physicians and hospitals for adopting and using EHR to improve patient care
- Through the Meaningful Use (MU) Programs, launched in 2011 and to be implemented through 2021, hundreds of thousands of providers received incentives for complying with requirements that aim to stimulate the integration of EHR into daily practice
- MU policy priorities target, for instance, improvements in quality, safety, efficiency, and patient/caregiver education—while focusing on clinical information exchange and care coordination
- However, there is limited evidence supporting that compliance with MU requirements translates into better patient outcomes

Study Goals & Design

To investigate the pattern of patient utilization outcomes to evaluate whether being admitted to MU vs. non-MU hospitals could:

1) Raise patient odds of timely ambulatory follow-up
2) Reduce patient odds of 30-day emergency department (ED) utilization
3) Further reduce patient odds of 30-day readmission—beyond a direct effect on readmission—via a timely ambulatory follow-up

Posttest Only Quasi-Experimental Design NR X O_{MU}

(*Shadish et al. 2002*) ------------------------

NR indicates Nonrandom assignment. X: Treatment; O: outcomes NR $O_{Non\text{-}MU}$

Data, Measures & Analytic Approach

Data Sources

- Medicare enrollment and claims files (2012), for roughly 180,000 patients
- Publicly available MU records for 160 hospitals (2011-2012), corresponding to MU Stage-1
- Hospital data (e.g., Provider of Services file, Healthcare Cost Report Information System)
- Market data (e.g., American Community Survey, Dartmouth Atlas of Health Care)

Data, Measures & Analytic Approach

Outcomes

Patient utilization outcomes, including

1) Timely ambulatory follow-up, defined as an evaluation and management service in ambulatory setting occurring within 14 days of discharge—*before* readmission *or* ED visit occurs
2) 30-day ED utilization
3) 30-day Readmission

All outcomes are binary and coded '1' for event occurrence, and '0' otherwise

Data, Measures & Analytic Approach

Exposure

Being admitted to MU hospital

- **Challenge**: Non-randomization of patients into MU vs. non-MU hospitals (or to receive or not a timely follow-up) suggests potential confounding at patient, market, and hospital level that could obscure relationship between exposure and outcome

Analytic approach

To address these threats to internal validity, we use a propensity score-based analysis for bias reduction, that could mitigate potential imbalance at baseline and improve comparability between the two groups of patients

Data, Measures & Analytic Approach

Inverse Probability Weighting (*with stabilized weights*)

- *Inverse probability of treatment weighing* (IPTW) using the inverse of estimated propensity scores (PS)

Single-level logistic regression controlling for patient, market, and hospital covariates to obtain estimated PS

(*Guo & Fraser 2015; Thoemmes & West 2011*)

- *Variable selection approach*

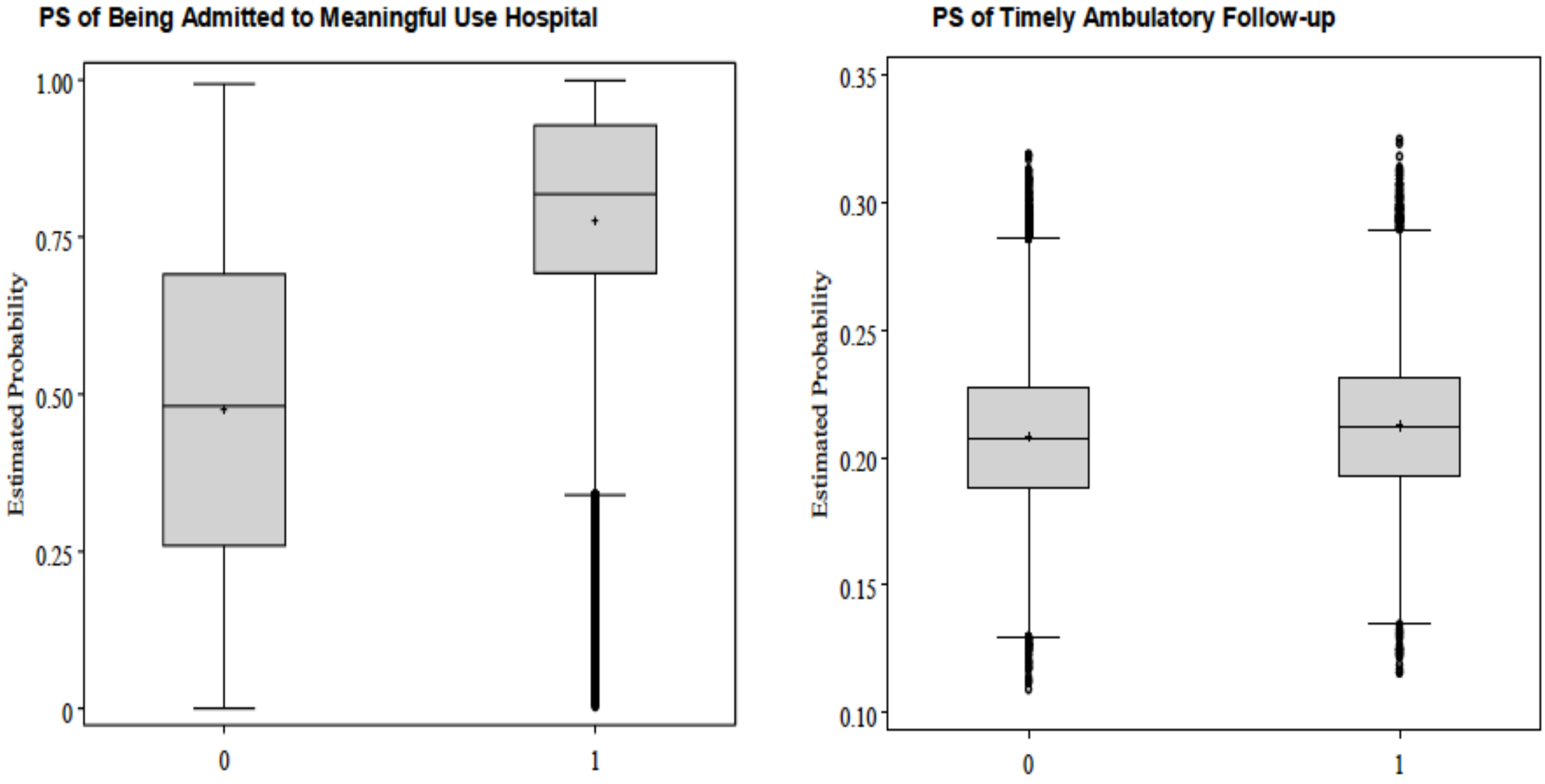
Variables selected are of known theoretical or empirical or policy relevance—measured at baseline—that could potentially influence exposure and utilization outcomes

Data, Measures & Analytic Approach

Outcomes analysis

- Two-level weighted logistic regressions with patient, market and hospital controls to evaluate the associations of exposure with utilization outcomes
- Two-level weighted structural equation modeling (SEM) with regression adjustment—using the propensity scores of timely follow-up—to test mediation hypothesis of an indirect effect of being admitted to MU hospitals on 30-day readmission—via a timely ambulatory follow-up
- SAS 9.4 version 14.1 and MPlus 7.4 to estimate intervention effects using generalized linear mixed models (GLMM)

Figure 1. Distribution of Propensity Scores Among Hospitalized Patients



PS: propensity score. 0 = admitted to non-MU hospital vs. 1 = admitted to MU hospital. 0 = without timely follow-up vs. 1 = with timely follow-up.

Principal Findings

- No evidence that patients admitted to MU hospitals had better utilization outcomes, including 1) higher odds of timely ambulatory follow-up; 2) lower odds of 30-day ED utilization; or 3) lower odds of 30-day readmission
- No evidence of a protective effect of a timely ambulatory follow-up against 30-day readmission
- However, strong associations of patient characteristics—e.g., prior utilization, illness severity—with utilization outcomes
- Strong associations of physicians' adoption of EHR with 30-day ED utilization and 30-day readmission

Table 1. Predictors of Patient Utilization Outcomes within 30 Days of Hospital Discharge to Home

Variable	***Timely Ambulatory Follow-up****	***p-value***	***30-Day ED Utilization***	***p-value***	***30-Day Readmission***	***p-value***
Admitted to MU hospital	**1.00 (0.95-1.07)**	**.873**	**1.07(0.94-1.21)**	**.294**	**1.00 (0.93-1.06)**	**.919**
Prior Utilization	-	-	1.11 (1.10-1.12)	<.0001	1.24 (1.21-1.27)	<.0001
Dually Eligible for Medicare/Medicaid	1.06 (1.01-1.12)	.020	0.93 (0.87-0.99)	.015	1.18 (1.12-1.24)	<.0001
Female Gender	1.07 (1.04-1.11)	<.0001	0.99 (0.95-1.04)	.694	0.92 (0.88-0.96)	<.0001
Patient Cohort						
Medicine	*Reference*		*Reference*		*Reference*	
Cardiovascular	0.96 (0.89-1.04)	.317	1.37 (1.29-1.46)	<.0001	0.88 (0.80-0.96)	.007
Cardiorespiratory	0.93 (0.88-0.98)	.010	1.14 (1.07-1.21)	<.0001	1.05 (0.99-1.11)	.126
Neurology	1.07 (0.97-1.18)	.187	0.98 (0.91-1.06)	.684	0.82 (0.76-0.88)	<.0001
Surgery	0.86 (0.81-0.91)	<.0001	0.92 (0.86-0.98)	.007	0.63 (0.59-0.68)	<.0001
Patient MS-DRGs Weight						
Quartile 1 (lowest illness severity)	*Reference*		*Reference*		*Reference*	
Quartile 2	0.92 (0.88-0.97)	.004	0.93 (0.88-0.98)	.008	1.29 (1.19-1.39)	<.0001
Quartile 3	0.81 (0.77-0.86)	<.0001	0.82 (0.78-0.8)	<.0001	1.43 (1.28-1.59)	<.0001
Quartile 4	0.92 (0.86-0.98)	.007	0.81 (0.74-0.88)	<.0001	1.55 (1.40-1.71)	<.0001

Limitations

Data, population, and other interventions

- Evaluation focused on

1) *Hospitals with Meaningful Use Stage-1*

➢ Increased requirements, under future stages, may likely produce significant improvements in transitional care

2) *Elderly patients in some specific markets*

➢ Findings may not generalize to a younger, technologically savvier population, or to other areas

3) *Patient follow-up using claims data*

➢ Other methods of follow-up, e.g., phone calls & e-communications, not assessed

- Other interventions, such as the Hospital Readmissions Reduction Program (HRRP), may have biased results toward the null.

Limitations

Methods

- There are risks of model misspecifications, possibly associated with unmeasured confounders and/or omission of interactions or higher order terms, that can potentially bias the findings

➢ However, a comprehensive set of covariates was used and most plausible interactions tested

- Finally, the study is observational

➢ Cannot establish a definitive claim of causality

Policy Implications

MU Program, in its early stages,

- Emphasizes data capture
- Does not address key patient-centered elements of care

➢ MU Program should focus on patient/caregiver health education and engagement

Improving care transitions will likely require additional interventions beyond timely clinical follow-up and hospitals using EHR systems

Conclusions

- Observational data are invaluable sources of information for program evaluation
- RCT and observational data: Not a dichotomy; but differ in terms of strength of evidence: from well suited to poorly suited for drawing causal inferences (*Rubin 2008*)
- Critically important to separate design from analysis for objective causal inferences (*Rubin 2008*)
- PS methods aim to mimic RCTs. And like RCTs, they work best in large samples. How large?

References

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Thank You!