Meaningful Use and Hospital Performance on Post-Acute Utilization Indicators

Yanick N. Brice, Karen E. Joynt, Christopher P. Tompkins, and Grant A. Ritter

---

Objectives. To examine trends in hospital post-acute utilization indicators and to determine whether improvement in these indicators is associated with attesting to meaningful use (MU).

Data Sources. Medicare claims-based, repeated measures on 30-day hospital-wide all-cause readmission and emergency department (ED) utilization rates for 160 short-stay hospitals (2009–2012); Medicare EHR Incentive Program Payments files (2011–2012); and other hospital and market data.

Study Design. Interrupted time series with concurrent comparison group.

Principal Findings. Propensity score-weighted multilevel models for change demonstrate that 30-day readmission rates (unadjusted) fell from 13.4 percent in 2009 to 12.1 percent in 2012. Similarly, 30-day ED utilization declined from 18.9 percent to 17.3 percent during the same period. However, MU and non-MU hospitals were indistinguishable vis-à-vis performance. Controlling for hospital and market characteristics, MU was unrelated to 30-day readmission. In contrast, 30-day ED utilization deteriorated.

Conclusions. Hospitals with MU Stage 1 designation did not show significantly higher improvement on post-acute utilization compared to their counterparts without. To achieve gains in quality and safety, potentially associated with EHRs, and to advance care coordination and patient engagement, the regulators should strengthen accountability by linking comprehensive, outcomes-based performance measures to specific MU objectives.

Key Words. Meaningful use, EHRs, 30-day readmission, 30-day ED utilization

---

There is widespread belief that health information technology (health IT) can help address the enormous quality gaps and spending growth, in health care, and contribute to increasing efficiency and creating value (IOM 2000, 2001; Hillestad et al. 2005; CBO 2008). To that end, the United States Congress, via the Health Information Technology for Economic and Clinical Health (HITECH) Act, appropriated funds—estimated at \$32 billion—to launch a

program aimed at encouraging investments in nationwide technological infrastructure for electronic use and exchange of health information (Blumenthal 2010, 2011; Buntin, Jain, and Blumenthal 2010). Specifically, the HITECH Act directed the Centers for Medicare and Medicaid Services (CMS) to incentivize providers to adopt and use certified electronic health records (EHRs) in ways that can improve patient care, referred to by the CMS as “Meaningful Use” (Blumenthal 2010; Blumenthal and Tavenner 2010; CMS 2010; Jha 2010; Stark 2010).

The Meaningful Use (MU) Program is designed in three successive stages—associated with increasing requirements and potential financial penalties. Under Stage 1 of the program, which was launched in May 2011, participating providers can receive an incentive payment if they attest to MU by satisfying a set of policy objectives and measures during a continuous 90-day reporting period. These objectives and measures encapsulate performance criteria related to quality, safety, efficiency, care coordination, patient and family engagement, and other public health priorities. Some of these criteria are qualitative—for instance, using EHRs to produce patient lists with specific conditions for purposes of quality improvement or research. Others are quantitative—for example, performing medication reconciliation for more than 50 percent of transitions of care. In subsequent years, the MU Program becomes mandatory, and the reporting period covers the full year, with higher thresholds of use. Noncompliers faced payment reductions as early as 2015 (CMS 2010; Stark 2010).

In short, MU measures the degree to which eligible professionals and hospitals have adopted certified EHRs and integrated them into daily practice. As of November 2015, under the CMS Medicare EHR Incentive Program, over \$21 billion in incentives has been disbursed to providers meeting MU criteria (CMS 2015). Hence, concerning adoption and use, the program is by all means a success (Adler-Milstein et al. 2013; Kaushal and Blumenthal 2014; Wright et al. 2014). However, even well into its fifth year of implementation, empirical evidence is limited regarding whether meeting MU criteria translates into measurable improvement in hospital performance. Such

---

Address correspondence to Yanick N. Brice, Ph.D., M.P.A., Department of Health Services, Policy, and Practice; CER/PCOR Scholar, Center for Evidence Synthesis in Health; Brown University School of Public Health, Providence, RI; e-mail: yanick_brice@brown.edu. Karen E. Joynt, M.D., M.P.H., is with the Harvard T. H. Chan School of Public Health, Harvard Medical School; Harvard University, Boston, MA. Christopher P. Tompkins, Ph.D., and Grant A. Ritter, Ph.D., are with The Heller School for Social Policy and Management, Brandeis University, Waltham, MA.

evidence is critical for policy makers using policy levers such as MU to improve patient care and outcomes.

Therefore, in this study, we aim to examine trends in hospital post-acute utilization indicators, including 30-day hospital-wide all-cause readmission and 30-day emergency department (ED) utilization rates, from 2009 to 2012, and to determine whether improvement in these indicators is associated with attesting to MU. We anticipate that effective use of certified EHRs may strengthen hospital structural capabilities and, by doing so, improve processes of care and clinical outcomes (Donabedian 2005). Specifically, we hypothesize that the MU era will coincide with an improvement in post-acute utilization indicators and that hospitals with MU Stage 1 designation will show significantly higher reduction in 30-day readmission and 30-day ED utilization rates compared to their counterparts without.

We focus on post-discharge health events, particularly ED use and readmissions, for several reasons. First, 10 to 55 percent of readmissions are deemed potentially preventable because of their associations with substandard care during the initial inpatient stay, implying there is significant potential for improvement (Ashton et al. 1995, 1997; Benbassat and Taragin 2000). In fact, previous research suggests that EHRs can enhance the quality of inpatient care, including increased adherence to medication and evidence-based guidelines, reduced complications, and patient safety—albeit in limited settings (Chaudhry et al. 2006; Menachemi et al. 2008; Amarasingham et al. 2009; Parente and McCullough 2009; Yu et al. 2009; McCullough et al. 2010; Appari, Johnson, and Anthony 2014). Second, major deficits in communication between hospital-based and ambulatory physicians create potentially harmful gaps in care during transitions (Kripalani et al. 2007a,b). Many believe that these gaps can possibly be addressed by a robust health IT infrastructure (Coleman and Boulton 2003). Third, prior research suggests that appropriate patient education, among other interventions, can prevent 12 to 75 percent of readmissions (Benbassat and Taragin 2000). The MU Program specifically targets patient and family engagement in health (ONC June 2013), which essentially aims to get patients to be more actively involved in care and health care to drive better outcomes of care (Berwick, Nolan, and Whittington 2008; Hibbard and Greene 2013).

On the other hand, we examine 30-day ED utilization because it is not publically monitored. Yet it is critically important to know its prevalence and whether it may be influenced by the same factors as those determining readmission. ED utilization post-discharge could signal additional waste in the

health system, possibly a much-overlooked opportunity to promote accountability during care transitions and increase value.

METHODS

Study Design

We exploited an interrupted time series design—with a concurrent comparison group—to examine trends over time and to test associations of MU with change in hospital performance on post-acute utilization. This is one of the strongest quasi-experimental designs to assess program effectiveness (Shadish, Cook, and Campbell 2002). We assumed that implementation of the MU Program, starting May 2011, introduced two distinct classes of hospitals: those with MU designation and those without. We expected the intervention to be effective, with no delayed effects. And we hypothesized that postintervention observations of the outcomes of interest would show a different *level* and *slope* from those before intervention.

Sample Description and Data Sources

We used 100 percent Medicare Research Identifiable Inpatient and Outpatient Files for our sample of 160 nonfederal, short-stay hospitals located in 21 markets. Seventeen of the markets are labeled as Beacon Communities because they include grant recipients from the Office of the National Coordinator for Health IT's (ONC's) Beacon Community initiative. The Beacon Community initiative was a three-year demonstration project also funded under the HITECH Act. It aimed to show that the National Quality Strategy triple aim of better care, improved population health, and lower cost can be advanced through health IT investments, combined with meaningful use of certified EHR technology (ONC June 2013).

We linked hospitals with their performance data on the Hospital Value-Based Purchasing (HVBP) program from CMS's Hospital Compare database; organizational characteristics from CMS's Provider of Services file; number of Medicare, Medicaid, and total discharges generated by CMS's Healthcare Cost Report Information System; EHR incentive payments from CMS's Eligible Hospital Recipients of Medicare EHR Incentive Program Payments public files; and supplemental security income (SSI) ratios downloaded from websites maintained by the CMS, which capture the percent of low-income beneficiaries served by a hospital.

We also matched hospitals with market characteristics obtained from three additional sources. EHR adoption rates among providers, measured at the state level, were downloaded from the ONC's website. Health system statistics, including provider density, measured at the hospital referral region (HRR), were obtained from The Dartmouth Atlas of Health Care. Sociodemographic data were taken from the American Community Survey (ACS). The Brandeis University Institutional Review Board approved the research protocol.

Outcomes

The 30-day hospital-wide all-cause readmission measure is claims-based, and it comprises five mutually exclusive specialty patient cohorts, including medicine, surgery/gynecology, cardiorespiratory, cardiovascular, and neurology. In contrast to condition-specific measures, it is intended as a broader assessment of the quality of care for hospitalized patients (YNHHSC/CORE 2013). Our measure was calculated as the ratio of the number of readmitted Medicare fee-for-service patients, older than 65, attributable to a hospital to the total number of Medicare admissions. To ensure each hospital had an observation at each measurement occasion, we included hospitals with 300 or more admissions from 2009 to 2012. Following the CMS methodology, we excluded the following:

1. Admissions transferred to another acute care facility.
2. Admissions to Prospective Payment System (PPS)-exempt hospitals (specialty hospitals, critical access hospitals).
3. Admissions with fewer than 30 days of post-discharge follow-up.
4. Admissions discharged against medical advice.
5. Admissions for medical treatment of cancer, primary psychiatric diagnoses, and rehabilitation.

We then constructed repeated measures on 30-day readmission rates. The time series is a sequence of yearly observations pre- and post-MU Program, which provide a fairly strong quasi-experimental design to assess program impact. Thus, each hospital contributed four observations, resulting in a total of 640 hospital-by-time observations.

Similarly, we computed repeated measures on 30-day ED utilization rates, with each hospital contributing four observations to the time series for a total of 640 hospital-by-time observations.

Key Independent Variables

The primary predictor of interest is whether a hospital attested to MU under the Medicare EHR Incentive Program. We introduced two binary indicators to assess effectiveness: The first one captures the hypothesized *change in level* in the outcomes, and the second one captures any differential *change in slope*, that is, in the rate of improvement (or deterioration) over time. We assumed that once a hospital attained MU, at any given time during the performance period covering May 2011 to December 2012, it maintained the status for the duration of the study.

Control Variables

To control for secular changes in our key outcomes over time, we included a variable for time in our models (Singer and Willett 2003). We also adjusted for hospital structural characteristics. They comprised geographic location (urban) and organizational factors, including size (small, medium, and large) and profit status. Likewise, we adjusted for teaching status. These characteristics have been associated with hospital performance in previous work (Jha et al. 2005), and they are relatively stable over time and treated as time-invariant covariates. We accounted for hospital quality (expressed in quartile) using total performance score on the HVB program. Higher scorers are expected to exhibit better performance.

Hospital patient profile is likely to influence performance. Specifically, hospitals treating large volumes of low-income or publically funded patients, as reflected in their SSI ratio or payer mix (measured as the share of Medicare and Medicaid discharges in total discharges), may exhibit poorer performance. Previous research has shown that patient socioeconomic status (SES) is linked to utilization outcomes, including readmission (Weissman, Stern, and Epstein 1994; Joynt and Jha 2011; Hu, Gonsahn, and Nerenz 2014). Likewise, illness severity (Andersen and Newman 2005)—as measured by a weighted severity diagnosis related group (DRG) index—can negatively affect performance (Conway et al. 2015). These factors (divided into quartiles) could change from year to year and hence were treated as time-varying covariates.

We also adjusted for market characteristics. Primary care physicians' availability (PCPs/100,000 residents) may improve access to, comprehensiveness of, and continuity of care, which may contribute to reducing unnecessary utilization and improved outcomes (Starfield, Shi, and Macinko 2005;

Bodenheimer 2008). In contrast, previous work on geographic variation has shown that hospital supply (acute care hospital beds/1,000 residents) may increase pressure to fill up these beds, thus leading to more utilization (Fisher et al. 1994). Other market characteristics comprised EHR adoption rates among physicians and hospitals, respectively. It is widely held that a robust health IT infrastructure can potentially increase communication among providers, improve care coordination, and reduce unnecessary utilization (Coleman and Boulton 2003). Similarly, community sociodemographic profile, including educational attainment, unemployment, and poverty status, may be associated with utilization. Previous research suggests community factors accounted for more than half of the variation in hospital readmissions (Herrin et al. 2015). All continuous covariates were centered on their mean.

Analytic Approach

Descriptive Statistics. We computed univariate summary measures describing hospital and market characteristics. We visually inspected the time series to (1) examine shape of individual hospital's trajectory of change in performance and (2) explore relationship between change and potential predictors of among-hospital differences in such change (Appendix SA4).

The Multilevel Model for Change. Given the limited number of time points, we fit a linear growth curve, within the multilevel model (MLM) tradition, to describe a hospital's trajectory of change in post-acute utilization indicators (Raudenbush and Bryk 2002; Singer and Willett 2003). The MLM for change is typically specified as a pair of linked statistical models, with the level 1 model describing the variation in outcome, or *within-unit change*, as a function of time and two unit-specific growth trajectory parameters: the intercept and the slope (or rate of change). The intercept and slope are modeled, at level 2, as outcomes describing the variation among units, or *among-hospital change*. Substitution of the level 2 model into the level 1 yields the composite specification of the MLM for change in its simplest formulation (Appendix SA2). Of note, a proper choice of centering constant for the temporal predictor can facilitate interpretation of the level 1 intercept (Raudenbush and Bryk 2002; Singer and Willett 2003).

Measuring Hospital Performance at Study Endpoint. To examine trends in hospital post-acute utilization indicators, we parameterized time using two distinct

centering constants (Appendix SA3). This parameterization of time allowed us to measure performance at the beginning and end of the study, using efficiently all available data (Singer and Willett 2003).

We also assessed the extent of variability in the outcomes across the sample by calculating the 95 percent confidence interval. And, to evaluate the role of technology use in explaining trends, we controlled for MU in the multilevel weighted regressions (to be discussed later).

Assessing MU Impact on Hospital Performance on Post-Acute Utilization, 2010–2012. To evaluate the full effects of the MU Program, we centered the temporal predictor on 2010. And to control for potential residual imbalances in characteristics between MU and non-MU hospitals, we fit a series of models of increasing complexity, which included our key predictors of a change in level and trend of each outcome. Specifically, we adjusted for hospital and market characteristics. We assessed model adequacy, at the 5 percent threshold, in terms of statistical significance of individual parameters and overall model performance, using deviance and information criteria.

Model Estimation. The repeated measures are correlated within hospitals and represent proportions, which follow a binomial distribution. Therefore, for parameter estimation and valid statistical inferences, we employed generalized linear mixed models (GLMMs). Given the number of observations, we used the normal distribution and identity link (Bolker et al. 2009). Empirical sandwich variance estimators were implemented to address potential misspecifications in the error structure (Fitzmaurice, Laird, and Ware 2011) and accommodate the use of stabilized weights (Guo and Fraser 2015). SAS 9.4 version 14.1 was used for all analyses.

Computing Weights. Using a single-level logistic regression, we estimated a propensity score model, including hospital and market characteristics, to predict selection into MU status (Appendix SA5). Previous research suggests EHR adoption differs by hospital bed size, teaching status, location, and quality (Jha et al. 2009; Elnahal et al. 2011; DesRoches et al. 2013; Joynt et al. 2015) and thus may influence the odds of attaining MU (Adler-Milstein et al. 2013). We posited that market characteristics, such as sociodemographic

profile, providers' density, and EHR adoption, could predict selection (Gold and McLaughlin 2016).

We used the inverse of the estimated propensity scores to calculate the weights. To correct for potentially influential observations, we multiplied the inverse probability of treatment weights (IPTW) by a constant proportional to the mean value of hospitals being in their respective classes, MU versus non-MU. We integrated the stabilized weights in the multilevel regressions and estimated the resulting models (Guo and Fraser 2015).

RESULTS

Hospital and Market Characteristics

There were 160 hospitals in our sample. Of these, 63 percent achieved MU designation in 2011–2012 (Table 1). Nineteen percent were for-profit and 79 percent were located in urban areas. Forty-two percent of hospitals had teaching status (18 percent limited teaching and 24 percent major teaching). More than half were of medium size (56 percent), with the remaining ones split nearly equally between small and large providers (not reported). Hospitals differed in terms of their patient population profile. The share of low-income patients was on average below 10 percent, but ranged as high as 40 percent. Nearly half of hospital patient discharges were publically funded (not reported).

The average HVBP total performance score was 46.9, with a range of 11.9 to 78.3. With respect to utilization outcomes, performance varied across hospitals and across years. The 30-day readmission rate across the four years averaged 13 percent and 30-day ED utilization averaged 18 percent. In terms of market characteristics, the mean EHR adoption among hospitals, at 47 percent, was slightly higher than the national average (Charles et al. 2013). The mean EHR adoption among physicians was at 43 percent. The mean number of PCPs per 100,000 residents was 74, and the number of hospital beds per 1,000 residents was about 2 (Table 1).

Measuring Trends in Hospital Performance between 2009 and 2012

Propensity score-weighted MLMs for change demonstrate that, between 2009 and 2012, hospital performance on post-acute utilization indicators improved, with rates falling by more than one full percentage point by the end of the study. However, there were no differences related to technology use: MU and

Table 1:   Sample Descriptive Statistics (Select Variables)

<i>Variable Label</i>	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>Minimum</i>	<i>Maximum</i>
Hospital-level					
Meaningful use (MU)	160	0.63	0.48	0.00	1.00
For-profit status	160	0.19	0.40	0.00	1.00
Urban location	160	0.79	0.41	0.00	1.00
Teaching status	160	0.42	0.49	0.00	1.00
HVBP total performance score	160	46.88	10.98	11.90	78.27
Readmission rate*	160	0.13	0.03	0.03	0.20
ED utilization rate*	160	0.18	0.07	0.03	0.46
Market-level					
Hospital EHR adoption (basic notes) [†]	21	0.47	0.14	0.12	0.69
Physician practice adoption of basic EHR [†]	21	0.43	0.12	0.25	0.71
Hospital beds per 1,000 residents [‡]	34	2.46	0.61	1.64	4.36
PCPs per 100,000 residents [‡]	34	74.15	12.37	46.87	100.96

*Rates represent the grand mean across the 4 years of the study.
†Variable is measured at state level. Of note, EHR adoption rates changed from year to year. However, due to unavailability for the early years of the study, only 2012 data are used and reported. These variables were treated as time-invariant covariates, although these metrics changed over time.
‡Variable is measured at the hospital referral region (HRR) level. These variables were assumed to be time-invariant during the study period, an assumption that is reasonable, at least in the short run.
ED, emergency department; EHR, electronic health record; HVBP, hospital value-based purchasing; PCP, primary care physician; SD, standard deviation.

non-MU hospitals were indistinguishable in terms of their performance on 30-day readmission or 30-day ED utilization in 2012.

In particular, raw overall 30-day readmission rates fell from 13.4 percent in 2009 to 12.1 percent in 2012 (Model 1, Table S1). There was variability in performance, with 95 percent of hospitals exhibiting rates between 8.2 and 18.5 percent at study onset, and between 7.2 and 17.1 percent by the end.

Adjusting for technology use, MU was unrelated to performance. Indeed, compared to their non-MU counterparts, MU hospitals experienced an increase in readmissions of nearly half a full percentage point (0.4 percent, $p = .46$) in 2012 (Model 2, Table S1). However, the estimated differential was not statistically significant. Hence, MU and non-MU hospitals had similar performance on 30-day readmission rates in 2012 (11.9 percent, $p < .0001$).

Regarding 30-day ED utilization, the estimated mean declined from 18.9 percent in 2009 to 17.3 percent in 2012 (Model 1, Table S2). Ninety-five percent of hospitals had rates of 30-day ED utilization between 5.7 and 32.1 percent in 2009, compared to 7.6 and 27.0 percent in 2012. Interestingly, adjusting for technology use, there was no statistically significant difference in

performance on 30-day ED utilization between MU and non-MU hospitals in 2012 (Model 2, Table S2). The MU differential was nonsignificant (1 percent, $p = .41$). Hence, MU and non-MU hospitals had similar performance on ED utilization in 2012 (16.7 percent, $p < .0001$).

MU and Change in Hospital Performance on 30-Day Readmission

Controlling for hospital and market characteristics, we found that hospital performance on 30-day readmission rates did not improve following implementation of the MU Program, with a nonsignificant coefficient for a within-hospital change in performance (-0.1 , $p = .65$; Table 2). Hence, contrary to our hypothesis, there was no statistically significant difference in 30-day readmission rates before and after implementation of the MU-certified EHR program, after controlling for other factors.

Similarly, the MU Program was not associated with any improvement in rate of change in 30-day readmission between 2010 and 2012. MU hospitals exhibited a constant yearly rate of decline of less than two-tenths of a full percentage point (-0.2 percent, $p = .07$) compared to their non-MU counterparts (Table 2), a finding that does not support our hypothesis of a favorable MU effect. Thus, MU and non-MU hospitals exhibited the same constant annual rate of improvement in readmission between 2010 and 2012, with a slope of -0.4 percent ($p = .03$).

MU and Change in Hospital Performance on 30-Day ED Utilization

The MU Program was associated with an increase in within-hospital change in 30-day ED utilization rates—after adjusting for hospital and market

Table 2: Meaningful Use and Change in 30-Day Readmission Rates, 2010–2012

<i>Fixed Effects</i>	<i>Estimate</i>	<i>p-Value</i>
Within-hospital change	-0.10 (-0.54 to 0.34)	.6520
Status in 2010		
Intercept	14.96 (13.71 to 16.22)	<.0001
MU Differential	0.55 (-0.09 to 1.19)	.0898
Rate of change		
Intercept	-0.42 (-0.8 to -0.04)	.0289
MU differential	-0.16 (-0.33 to 0.02)	.0746

Notes. Boldface figures represent estimates of interest. Propensity score-weighted multilevel regression estimating MU impact on 30-day readmission.

MU, meaningful use. (See Table S3 for full regression results.)

Table 3: Meaningful Use and Change in 30-Day ED Utilization Rates, 2010–2012

<i>Fixed Effects</i>	<i>Estimate</i>	<i>p-Value</i>
Within-hospital change	3.98 (2.61 to 5.34)	<.0001
Status in 2010		
Intercept	21.42 (17.14 to 25.71)	<.0001
MU differential	−0.05 (−1.98 to 1.89)	.9628
Rate of change		
Intercept	−4.01 (−6.15 to −1.86)	.0003
MU differential	0.71 (−0.12 to 1.54)	.0941

Notes. Boldface figures represent estimates of interest. Propensity score-weighted multilevel regression estimating MU impact on ED utilization.
MU, meaningful use. (See Table S4 for full regression results.)

characteristics (Table 3). And the change in level was substantial: 4.0 full percentage points (4 percent, $p < .0001$). Thus, all else being equal, implementation of a certified EHR program was actually associated with higher ED use.

In contrast, the MU Program was unrelated to change in hospital performance on 30-day ED utilization rates from 2010 to 2012. In fact, compared to their non-MU counterparts, MU hospitals experienced deterioration in performance, with a constant yearly rate of increase of nearly one full percentage point (0.71 percent, $p = .09$; Table 3). However, the estimated differential in yearly rate of change was obtained by chance alone. This suggests that MU and non-MU hospitals exhibited the same constant annual rate of improvement in 30-day ED utilization between 2010 and 2012 (−4.0 percent, $p < .0003$), all else being equal.

DISCUSSION

We examined trends in post-acute utilization indicators for a geographic sample of 160 hospitals, from 2009 to 2012. We tested associations of MU with change in hospital performance—using propensity score-weighted multilevel regressions—and found surprising results. Hospital performance on crude 30-day readmission and 30-day ED utilization rates improved. However, the improvement was not related to technology use. Moreover, controlling for hospital and market factors, we found that MU was not associated with a reduction in 30-day readmission rates. This finding adds to previous work on the associations of EHR with readmission, which has produced mixed results (DesRoches et al. 2010; Jones, Friedberg, and Schneider 2011; Lee, Kuo, and

Goodwin 2013). On the other hand, performance on 30-day ED utilization rates deteriorated over the study period, potentially suggesting further distortions in providers' behavior as a result of the CMS targeting a restricted set of metrics for improvement. Targeting a restricted set of metrics can potentially redirect focus and scarce resources from important outcomes.

Although this evaluation concerns MU Stage 1, our findings suggest that CMS should consider moving away from a process-based monitoring framework and, instead, focusing regulation on what matters the most to improve patient care and impact clinical and health outcomes. In this regard, a combined outcomes-based regulation may be more productive than one exclusively oriented toward process measures, as is currently done under the MU Programs. CMS and ONC could potentially strengthen accountability by linking comprehensive, outcomes-based performance measures to specific MU objectives, hence mitigating potential perverse effects, including teaching to the test, which shifts providers' behavior toward what is measured and rewarded.

New Contributions

Analyzing the relationship between MU and hospital performance on post-acute utilization is critical to gauge whether the massive investments in health IT will, one day, pay off to society. One in five Medicare hospitalized, elderly patients is readmitted within 30 days of discharge, costing Medicare alone roughly \$17 billion annually (Jencks, Williams, and Coleman 2009). The prevalence of ED utilization, within 30 days post-discharge, and related costs have not been documented as extensively but are likely high. Thus, these measures are critical ones to assess the extent to which providers are effectively using certified EHR technology to enhance patient care and coordinate across settings to optimize clinical outcomes. Besides a limited number of studies on systems during the era preceding that of certified EHR programs (DesRoches et al. 2010; Jones, Friedberg, and Schneider 2011; Lee, Kuo, and Goodwin 2013), little is known about the impact of EHRs on comprehensive measures of utilization or quality that can generate the anticipated benefits of large-scale adoption—notably the huge efficiency savings.

This study adds to the body of empirical work on the effectiveness of MU in improving hospital performance on post-acute utilization indicators. Specifically, it is among the first to investigate the impact of MU using health data concurrent with its implementation. And it extends previous evaluations by exploiting a comprehensive measure of health IT, rather than a simple measure of whether a hospital has an EHR, which may mitigate the effects that

substantial variations in type, sophistication, and thresholds of use may have had on variations in outcomes reported in published work. The scope of benefits of effective use of health IT remains an area with much uncertainty (CBO 2008; Jones et al. 2012).

Relatedly, we focus on nearly all admitted patients—not just select groups, such as those treated for acute myocardial infarction, pneumonia, or heart failure (Jones, Friedberg, and Schneider 2011), which represent only 10 percent of all Medicare hospitalizations (Joynt and Jha 2012). To the extent that hospitals are using certified EHRs to improve patient care, the benefits should apply to all categories, regardless of diagnoses or conditions. And current evaluations should aim to measure associated results. The anticipated efficiency savings to the health system can materialize when provision of high-quality care becomes universal (Hillestad et al. 2005; Jones et al. 2012).

Study Limitations

Our findings must be interpreted with caution in light of the limitations associated with the research. First, the MU Program was not the only quality improvement program occurring during the study period, and thus, we cannot be certain that changes associated with MU were not superseded by other programs. Specifically, with respect to 30-day readmission, the null finding may be partially explained by the fact that hospitals had been actively working to reduce readmissions in anticipation of the Hospital Readmissions Reduction Program (HRRP). The HRRP is mandated by the Affordable Care Act (ACA) of 2010, and it imposes financial penalties on hospitals having higher-than-expected readmission rates for select conditions, starting fiscal year 2013. Indeed, national estimates point to significant reductions in 30-day readmission rates coinciding with ACA implementation (Zuckerman et al. 2016). Nevertheless, we ruled out selection, at baseline, because our findings reveal that both MU and non-MU hospitals had identical performance on 30-day readmission (Table 2) and 30-day ED utilization rates (Table 3), even in 2010.

Second, while we found no positive impact of MU on post-acute utilization, others have found evidence of success in other areas, particularly improvement in inpatient quality indicators and patient satisfaction (Adler-Milstein, Everson, and Lee 2015). Further, we evaluated the first 18 months of the Medicare EHR Incentive Program. Hence, as providers become savvier at using EHR and MU requirements increase over time, it is plausible that performance in post-acute care may improve. Besides, the current policy landscape, with various pay-for-performance initiatives—including the new

CMS's Quality Payment Program—could stimulate effective use of EHRs by physicians, in general, which may help increase the effectiveness of the Medicare EHR Incentive Program for hospitals.

Other limitations concern generalizability of the findings. In particular, the sample consists of self-selected providers concentrated in geographic markets with advanced EHR capabilities, suggesting that their performance may not be representative of that of providers from a national random sample. Nonetheless, this sample represents a good laboratory for testing MU impact. Relatedly, another limitation concerns the patient population. Because the study focuses on the elderly, the findings may not generalize to hospitals treating a younger or more diverse population.

Regarding the methods, there are risks of model misspecifications, which can potentially bias the results. Propensity score-based methods for bias reduction cannot adequately correct for misspecification due to unmeasured covariates (Austin 2011). Our study uses observational data, which rarely include all relevant covariates. Hence, the risk of omitted variables is present because, in practice, an analyst can never control for all possible confounders. However, efforts were made to control for a comprehensive set of covariates. And, as long as those factors do not change over time, the longitudinal design protects against bias (Fitzmaurice, Laird, and Ware 2011).

Along the same line, misspecification can also occur because of nonlinearity. Omitting higher order terms or possible interactions when estimating a selection model can bias results (Austin and Stuart 2015). Nonetheless, as long as the propensity score model or the outcome regression is correctly specified, the method of doubly robust estimation, which combines IPTW with regression adjustment, offers protections against misspecifications, while increasing precision of estimation (Funk et al. 2011; Sloczynski and Wooldridge 2014). At any rate, the final models are deemed reasonable. The more complex ones, involving interactions or complex error structures, did not offer a better fit based on comparison of model fit indices.

CONCLUSION

Hospitals with MU Stage 1 designation, during the first 18 months of the Medicare EHR Incentive Program, did not show significantly higher improvement on post-acute utilization compared to their counterparts without. Whether MU supports payment and delivery system innovations, which may contribute to advancing better care, improved population health, and

lower cost, and ultimately to the benefits many have hoped for from large-scale EHR implementation, will hinge on whether the more stringent MU requirements, under later stages of the program, produce greater benefits.

ACKNOWLEDGMENTS

Joint Acknowledgment/Disclosure Statement: This research was partially funded by a dissertation support award to Yanick N. Brice from the Institute on Healthcare Systems of the Schneider Institutes for Health Policy at Brandeis University through a collaborative agreement with the Jewish Healthcare Foundation. We are particularly thankful to Dr. Xiaodong Liu for his helpful advice on growth curve modeling. We acknowledge the anonymous reviewers for their thoughtful feedback that substantially improved our work.

Disclosures: None.

Disclaimers: None.

REFERENCES

- Adler-Milstein, J., J. Everson, and S.-Y. D. Lee. 2015. "EHR Adoption and Hospital Performance: Time-Related Effects." *Health Services Research* 50 (6): 1751–71.
- Adler-Milstein, J., M. F. Furukawa, J. King, and A. K. Jha. 2013. "Early Results from the Hospital Electronic Health Record Incentive Programs." *American Journal of Managed Care* 19 (7): e273–84.
- Amarasingham, R., L. Plantinga, M. Diener-West, D. J. Gaskin, and N. R. Powe. 2009. "Clinical Information Technologies and Inpatient Outcomes: A Multiple Hospital Study." *Archives of Internal Medicine* 169 (2): 108–14.
- Andersen, R., and J. F. Newman. 2005. "Societal and Individual Determinants of Medical Care Utilization in the United States." *Milbank Quarterly* 83 (4): 1–28.
- Appari, A., E. M. Johnson, and D. L. Anthony. 2014. "Information Technology and Hospital Patient Safety: A Cross-Sectional Study of US Acute Care Hospitals." *American Journal of Managed Care* 20(11 Spec No. 17): eSP39–47.
- Ashton, C. M., D. H. Kuykendall, M. L. Johnson, N. P. Wray, and L. Wu. 1995. "The Association between the Quality of Inpatient Care and Early Readmission." *Annals of Internal Medicine* 122 (6): 415–21.
- Ashton, C. M., D. J. Del Junco, J. Soucek, N. P. Wray, and C. L. Mansyur. 1997. "The Association Between the Quality of Inpatient Care and Early Readmission: A Meta-Analysis of the Evidence." *Medical Care* 35 (10): 1044–59.
- Austin, P. C. 2011. "An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies." *Multivariate Behavioral Research* 46 (3): 399–424.

- Austin, P. C., and E. A. Stuart. 2015. "Moving Towards Best Practice When Using Inverse Probability of Treatment Weighting (IPTW) Using the Propensity Score to Estimate Causal Treatment Effects in Observational Studies." *Statistics in Medicine* 34 (28): 3661–79.
- Benbassat, J., and M. Taragin. 2000. "Hospital Readmissions as a Measure of Quality of Health Care: Advantages and Limitations." *Archives of Internal Medicine* 160 (8): 1074–81.
- Berwick, D. M., T. W. Nolan, and J. Whittington. 2008. "The Triple Aim: Care, Health, and Cost." *Health Affairs* 27 (3): 759–69.
- Blumenthal, D. 2010. "Launching HITECH." *New England Journal of Medicine* 362 (5): 382–5.
- Blumenthal, D. 2011. "Wiring the Health System — Origins and Provisions of a New Federal Program." *New England Journal of Medicine* 365(24): 2323–9.
- Blumenthal, D., and M. Tavenner. 2010. "The "Meaningful Use" Regulation for Electronic Health Records." *New England Journal of Medicine* 363 (6): 501–4.
- Bodenheimer, T. 2008. "Coordinating Care—A Perilous Journey through the Health Care System." *New England Journal of Medicine* 358 (10): 1064–71.
- Bolker, B. M., M. E. Brooks, C. J. Clark, S. W. Geange, J. R. Poulsen, M. H. H. Stevens, and J.-S. S. White. 2009. "Generalized Linear Mixed Models: A Practical Guide for Ecology and Evolution." *Trends in Ecology & Evolution* 24 (3): 127–35.
- Buntin, M. B., S. H. Jain, and D. Blumenthal. 2010. "Health Information Technology: Laying The Infrastructure For National Health Reform." *Health Affairs* 29 (6): 1214–9.
- CBO. 2008. *Evidence on the Costs and Benefits of Health Information Technology*. Washington, DC: Congressional Budget Office.
- Charles, D., J. King, V. Patel, and M. F. Furukawa. 2013. *Adoption of Electronic Health Records Among U.S. non-Federal Acute Care Hospitals: 2008-2012*. ONC. Washington, DC: Office of the National Coordinator for Health Information Technology.
- Chaudhry, B., J. Wang, S. Y. Wu, M. Maglione, W. Mojica, E. Roth, S. C. Morton, and P. G. Shekelle. 2006. "Systematic Review: Impact of Health Information Technology on Quality, Efficiency, and Costs of Medical Care." *Annals of Internal Medicine* 144 (10): 742–52.
- CMS. 2010. "Medicare & Medicaid EHR Incentive Program Meaningful Use Stage 1 Requirements Overview" [accessed on October 22, 2016]. Available at https://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/downloads/MU_Stage1_ReqOverview.pdf
- CMS. 2015. "Medicare Incentive Payments" [accessed on January 11, 2016]. Available at https://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/Downloads/November2015_MedicareEHRIncentivePayments.pdf
- Coleman, E. A., and C. Boulton. 2003. "Improving the Quality of Transitional Care for Persons with Complex Care Needs." *Journal of the American Geriatrics Society* 51 (4): 556–7.

- Conway, R., D. Byrne, D. O’Riordan, and B. Silke. 2015. “Emergency Readmissions are Substantially Determined by Acute Illness Severity and Chronic Debilitating Illness: A Single Centre Cohort Study.” *European Journal of Internal Medicine* 26 (1): 12–7.
- DesRoches, C. M., E. G. Campbell, C. Vogeli, J. Zheng, S. R. Rao, A. E. Shields, K. Donelan, S. Rosenbaum, S. J. Bristol, and A. K. Jha. 2010. “Electronic Health Records’ Limited Successes Suggest More Targeted Uses.” *Health Affairs* 29 (4): 639–46.
- DesRoches, C. M., D. Charles, M. F. Furukawa, M. S. Joshi, P. Kralovec, F. Mostashari, C. Worzala, and A. K. Jha. 2013. “Adoption of Electronic Health Records Grows Rapidly, But Fewer Than Half of US Hospitals Had at Least a Basic System in 2012.” *Health Affairs* 32 (8): 1478–1485.
- Donabedian, A. 2005. “Evaluating the Quality of Medical Care.” *Milbank Quarterly* 83 (4): 691–729.
- Elnahal, S. M., K. E. Joynt, S. J. Bristol, and A. K. Jha. 2011. “Electronic Health Record Functions Differ between Best and Worst Hospitals.” *American Journal of Managed Care* 17 (4): E121–47.
- Fisher, E. S., J. E. Wennberg, T. A. Stukel, and S. M. Sharp. 1994. “Hospital Readmission Rates for Cohorts of Medicare Beneficiaries in Boston and New Haven.” *New England Journal of Medicine* 331 (15): 989–95.
- Fitzmaurice, G. M., N. M. Laird, and J. H. Ware. 2011. *Applied Longitudinal Analysis*. Hoboken, NJ: John Wiley and Sons Inc.
- Funk, M. J., D. Westreich, C. Wiesen, T. Stürmer, M. A. Brookhart, and M. Davidian. 2011. “Doubly Robust Estimation of Causal Effects.” *American Journal of Epidemiology* 173 (7): 761–7.
- Gold, M., and C. McLaughlin. 2016. “Assessing HITECH Implementation and Lessons: 5 Years Later.” *Milbank Quarterly* 94 (3): 654–87.
- Guo, S., and M. W. Fraser. 2015. *Propensity Score Analysis: Statistical Methods and Applications*. Thousand Oaks, CA: Sage.
- Herrin, J., J. St. Andre, K. Kenward, M. S. Joshi, A.-M. J. Audet, and S. C. Hines. 2015. “Community Factors and Hospital Readmission Rates.” *Health Services Research* 50 (1): 20–39.
- Hibbard, J. H., and J. Greene. 2013. “What the Evidence Shows about Patient Activation: Better Health Outcomes and Care Experiences; Fewer Data on Costs.” *Health Affairs* 32 (2): 207–14.
- Hillestad, R., J. Bigelow, A. Bower, F. Girosi, R. Meili, R. Scoville, and R. Taylor. 2005. “Can Electronic Medical Record Systems Transform Health Care? Potential Health Benefits, Savings, and Costs.” *Health Affairs (Millwood)* 24 (5): 1103–17.
- Hu, J., M. D. Gonsahn, and D. R. Nerenz. 2014. “Socioeconomic Status and Readmissions: Evidence from an Urban Teaching Hospital.” *Health Affairs* 33 (5): 778–85.
- IOM. 2000. *To Err Is Human: Building a Safer Health System*. Washington, DC: The National Academies Press.
- IOM. 2001. *Crossing the Quality Chasm: A New Health System for the 21st Century*. Washington, DC: The National Academies Press.

- Jencks, S. F., M. V. Williams, and E. A. Coleman. 2009. "Rehospitalizations among Patients in the Medicare Fee-for-Service Program." *New England Journal of Medicine* 360 (14): 1418–28.
- Jha, A. K. 2010. "Meaningful use of Electronic Health Records: The Road Ahead." *Journal of the American Medical Association* 304 (15): 1709–10.
- Jha, A. K., Z. Li, E. J. Orav, and A. M. Epstein. 2005. "Care in U.S. Hospitals — The Hospital Quality Alliance Program." *New England Journal of Medicine* 353 (3): 265–74.
- Jha, A. K., C. M. Desroches, E. G. Campbell, K. Donelan, T. G. Ferris, A. Shields, S. Rosenbaum, and D. Blumenthal. 2009. "The Use of Electronic Health Records in Us Hospitals." *Journal of General Internal Medicine* 24: 195–6.
- Jones, S. S., M. W. Friedberg, and E. C. Schneider. 2011. "Health Information Exchange, Health Information Technology Use, and Hospital Readmission Rates." *AMIA Annual Symposium Proceedings* 2011: 644–53.
- Jones, S. S., P. S. Heaton, R. S. Rudin, and E. C. Schneider. 2012. "Unraveling the IT Productivity Paradox — Lessons for Health Care." *New England Journal of Medicine* 366 (24): 2243–5.
- Joynt, K. E., and A. K. Jha. 2011. "Who Has Higher Readmission Rates for Heart Failure, and Why?: Implications for Efforts to Improve Care Using Financial Incentives." *Circulation: Cardiovascular Quality and Outcomes* 4(1): 53–9.
- . 2012. "Thirty-Day Readmissions — Truth and Consequences." *New England Journal of Medicine* 366(15): 1366–9.
- Joynt, K. E., D. L. Bhatt, L. H. Schwamm, Y. Xian, P. A. Heidenreich, G. C. Fonarow, E. E. Smith, M. L. Neely, M. V. Grau-Sepulveda, and A. F. Hernandez. 2015. "Lack of Impact of Electronic Health Records on Quality of Care and Outcomes for Ischemic Stroke." *Journal of the American College of Cardiology* 65 (18): 1964–72.
- Kaushal, R., and D. Blumenthal. 2014. "Introduction and Commentary for Special Issue on Health Information Technology." *Health Services Research* 49(1pt2): 319–24.
- Kripalani, S., A. T. Jackson, J. L. Schnipper, and E. A. Coleman. 2007a. "Promoting Effective Transitions of Care at Hospital Discharge: A Review of Key Issues for Hospitalists." *Journal of Hospital Medicine* 2 (5): 314–23.
- Kripalani, S., F. LeFevre, C. O. Phillips, M. V. Williams, P. Basaviah, and D. W. Baker. 2007b. "Deficits in Communication and Information Transfer between Hospital-Based and Primary Care Physicians: Implications for Patient Safety and Continuity of Care." *Journal of the American Medical Association* 297 (8): 831–41.
- Lee, J., Y. F. Kuo, and J. S. Goodwin. 2013. "The Effect of Electronic Medical Record Adoption on Outcomes in US Hospitals." *BMC Health Services Research* 13: 39.
- McCullough, J. S., M. Casey, I. Moscovice, and S. Prasad. 2010. "The Effect of Health Information Technology on Quality in U.S. Hospitals." *Health Affairs (Millwood)* 29 (4): 647–54.
- Menachemi, N., A. Chukmaitov, C. Saunders, and R. G. Brooks. 2008. "Hospital Quality of Care: Does Information Technology Matter? The Relationship Between Information Technology Adoption and Quality of Care." *Health Care Management Review* 33 (1): 51–9.

- ONC. June 2013. *Update on the Adoption of Health Information Technology and Related Efforts to Facilitate Electronic Use and Exchange of Health Information: A Report to Congress*. Washington, DC.
- Parente, S. T., and J. S. McCullough. 2009. "Health Information Technology and Patient Safety: Evidence from Panel Data." *Health Affairs* 28 (2): 357–60.
- Raudenbush, S. W., and A. S. Bryk. 2002. *Hierarchical Linear Models: Applications and Data Analysis Methods*. Newbury Park, CA: Sage Publications.
- Shadish, W. R., T. D. Cook, and D. T. Campbell. 2002. *Experimental and Quasi-Experimental Designs for Generalized Causal Inference*. Boston: Houghton Mifflin.
- Singer, J. D., and J. B. Willett. 2003. *Applied Longitudinal Analysis: Modeling Change and Event Occurrence*. New York: Oxford University Press.
- Sloczynski, T., and J. M. Wooldridge. 2014. *A General Double Robustness Result for Estimating Average Treatment Effects*. Bonn, Germany: The Institute for the Study of Labor (IZA).
- Starfield, B., L. Shi, and J. Macinko. 2005. "Contribution of Primary Care to Health Systems and Health." *Milbank Quarterly* 83 (3): 457–502.
- Stark, P. 2010. "Congressional Intent for the HITECH Act." *American Journal of Managed Care* 16: SP24–8.
- Weissman, J. S., R. S. Stern, and A. M. Epstein. 1994. "The Impact of Patient Socioeconomic Status and Other Social Factors on Readmission: A Prospective Study in Four Massachusetts Hospitals." *Inquiry* 31 (2): 163–72.
- Wright, A., J. Feblowitz, L. Samal, A. B. McCoy, and D. F. Sittig. 2014. "The Medicare Electronic Health Record Incentive Program: Provider Performance on Core and Menu Measures." *Health Services Research* 49 (1pt2): 325–46.
- YNHHSC/CORE. 2013. "Yale New Haven Health Services Corporation/Center for Outcomes Research & Evaluation March 2013. Hospital-Wide (All-Condition) 30-Day Risk-Standardized Readmission Measure. Draft Measure Methodology Report (Version 2.0)."
- Yu, F. B., N. Menachemi, E. S. Berner, J. J. Allison, N. W. Weissman, and T. K. Houston. 2009. "Full Implementation of Computerized Physician Order Entry and Medication-Related Quality Outcomes: A Study of 3364 Hospitals." *American Journal of Medical Quality* 24 (4): 278–86.
- Zuckerman, R. B., S. H. Sheingold, E. J. Orav, J. Ruhter, and A. M. Epstein. 2016. "Readmissions, Observation, and the Hospital Readmissions Reduction Program." *New England Journal of Medicine* 374 (16): 1543–51.

SUPPORTING INFORMATION

Additional supporting information may be found online in the supporting information tab for this article:

Appendix SA1: Author Matrix.

Table S1. Technology Use and 30-Day Readmission Rates, 2009–2012.

Table S2. Technology Use and 30-Day ED Utilization Rates, 2009–2012.

Table S3. Meaningful Use and Predictors of 30-Day Readmission Rates, 2010–2012.

Table S4. Meaningful Use and Predictors of 30-Day ED Utilization Rates, 2010–2012.

Appendix SA2: Multilevel Model for Change Specification.

Appendix SA3: Measuring Hospital Performance on Post-Acute Utilization in 2009 and 2012.

Appendix SA4: Exploratory Data Analysis.

Appendix SA5: Propensity Score Model Estimation.