METHODS

How Pooling Fragmented Healthcare Encounter Data Affects Hospital Profiling

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Evaluating hospital performance based on patient outcomes, such as complications, readmissions, and mortality, has become a mainstay of ongoing healthcare quality improvement initiatives in the United States.[1-3] Hospital performance measures have traditionally been used for monitoring outcomes of high-risk patients, and more recently, for public reporting and determining financial incentives.[1,4,5] The CMS Hospital Compare program evaluates nearly all US acute care hospitals based on their patients' risk of 30-day mortality and readmission following an admission for acute myocardial infarction (AMI), heart failure, or pneumonia.[6]

Ideally, such evaluations would rely on detailed clinical information on patient morbidity and severity at admission. However, due to issues with completeness, access, and comparability with such data, many profiling programs, including Hospital Compare, use administrative discharge data ("billing" or "encounter" records).[7-9] A potential shortcoming—the consequences of which have not been previously explored—is that some individuals receive substantial care in multiple systems, making the data in any single system incomplete.[10,11] Dual or triple eligibility for Medicare, Medicaid, and Veterans Health Administration (VA) healthcare; changes in Medicaid coverage; and switches into and among private managed care plans are common sources of "fragmentation" of patient data into payer-specific silos.[12-15] This problem of incompleteness could also arise when hospital profiling is based only on records of patient care obtained at that hospital. The 2 most common current strategies are: 1) to use the data at hand, ignoring its incompleteness; and 2) to exclude patients with dual coverage. Neither is ideal.[16,17]

When patients use different systems for distinct medical problems, single data source assessments can miss important differences in patient risk that could bias performance measures; in this case, pooled data should add consequential new clinical information.[10,11] If hospitals vary substantially in how much of their patients' data is unobserved, single-source

ABSTRACT

Objectives

People receiving healthcare from multiple payers (eg, Medicare and the Veterans Health Administration [VA]) have fragmented health records. How the use of more complete data affects hospital profiling has not been examined.

Study Design

Retrospective cohort study.

Methods

We examined 30-day mortality following acute myocardial infarction at 104 VA hospitals for veterans 66 years and older from 2006 through 2010 who were also Medicare beneficiaries. Using VA-only data versus combined VA/Medicare data, we calculated 2 risk-standardized mortality rates (RSMRs): 1 based on observed mortality (O/E) and the other from CMS' Hospital Compare program, based on model-predicted mortality (P/E). We also categorized hospital outlier status based on RSMR relative to overall VA mortality: average, better than average, and worse than average. We tested whether hospitals whose patients received more of their care through Medicare would look relatively better when including those data in risk adjustment, rather than including VA data alone.

Results

Thirty-day mortality was 14.8%. Adding Medicare data caused both RSMR measures to significantly increase in about half the hospitals and decrease in the other half. O/E RSMR increased in 53 hospitals, on average, by 2.2%, and decreased in 51 hospitals by –2.6%. P/E RSMR increased, on average, by 1.2% in 56 hospitals, and decreased in the others by –1.3%. Outlier designation changed for 4 hospitals using O/E measure, but for no hospitals using P/E measure.

Conclusions

VA hospitals vary in their patients' use of Medicare-covered care and completeness of health records based on VA data alone. Using combined VA/Medicare data provides modestly different hospital profiles compared with those using VA-alone data.

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Take-Away Points

- Evaluation of hospital performance in terms of risk-adjusted outcomes (eg, 30-day mortality rate) can be biased if patient health records are incomplete due to fragmentation of data across multiple healthcare systems.
- For Medicare-covered veterans admitted to Veterans Health Administration (VA) hospitals for acute myocardial infarction, we found that using VA-only data substantially undercounts patient comorbidity compared with combined VA-Medicare data.
- Using combined VA-Medicare data, instead of VA-only data, resulted in a modest change in relative hospital performance based on risk-adjusted 30-day mortality as the outcome.

hospital profiles could disadvantage facilities whose patients' data are particularly incomplete.

To explore this, we examined hospital profiling in the VA—the largest integrated healthcare provider system in the United States—which offers comprehensive healthcare to 7.9 million enrollees (2010).[18] The VA's highly integrated, comprehensive, and systematized healthcare information system has been used extensively to evaluate patient outcomes and hospital performance.[17,19] However, VA data can still be missing important diagnoses since 77% of veterans have dual or multiple coverage, involving Medicare (51%), Medicaid (7%), TRICARE (16%), or commercial insurance (29%).[12-14,18,20-22] How might evaluations of VA hospital performance based on only VA data differ from those based on more complete data? We compared VA only–based profiles with VA-Medicare-based profiles for veterans 66 years and older who are receiving Medicare's Fee for Service (FFS) benefit; this cohort receives the vast majority of its healthcare within these 2 systems.[18]

We selected 30-day mortality for patients admitted for AMI to evaluate VA hospitals, as it remains a key performance criterion for stakeholder groups nationally.[6,23-25] We examined the effects under 2 population evaluation methods, including CMS' Hospital Compare, to facilitate comparability and enhance relevance.

METHODS

Study data for 2006 to 2010 were obtained from the VA and Medicare administrative inpatient and outpatient files. We used VA patient treatment files; outpatient clinical files; and vital status files; and Medicare FFS beneficiary, inpatient/skilled nursing facility, carrier, and outpatient files. Our goal was to compare VA hospitals on their AMI admissions (found in the VA inpatient file), based on their risk-adjusted 30-day survival. Because "risk" is calculated from diagnoses recorded on claims incurred during the 365 days prior to admission, we obtained Medicare FFS data during this period (to add to VA data) to create "complete" risk profiles. We applied the protocol adopted by CMS Hospital Compare and endorsed by the National Quality Forum to identify the study cohort and calculate risk.[6]

Study Cohort

Using VA acute inpatient discharge data for fiscal years 2006 to 2010, we identified all admissions, henceforth termed "index admissions," for patients 66 years or older with the principal diagnosis of AMI (all *International Classification of Diseases, NinthRevision, Clinical Modification* [*ICD-9-CM*] 410.xx codes, except 410.x2).[6] We only retained hospitalizations for veterans who were both continuously enrolled in Medicare FFS and never enrolled in a VA hospice program during the 12 months preceding the admission date. We additionally excluded admissions that: a) were transfers from another acute care hospital; b) resulted in discharges against medical advice or discharges alive on the same or next day following admission; or c) had missing data on key measures. For patients with multiple, otherwise eligible admissions in a year, we randomly selected 1 for our study sample so as to avoid survival bias.[6] Following VA Hospital Compare methodology, we excluded admissions from hospitals with fewer than 25 otherwise eligible admissions during the 5-year study period.

Patient Outcome and Risk Factors

We examined patient death within 30 days of the index admission date. Risk factors consisted of demographics and comorbid conditions identified using *ICD-9-CM* diagnosis codes in the index admission record and in records of inpatient discharges and outpatient visits during the 12 months preceding the index admission date.[6] Following CMS Hospital Compare protocols, we excluded selected secondary diagnosis codes in the index record identified as potential complications of the admission itself.[6] The diagnosis codes were then classified using DxCG condition categories.[26,27] To examine the impact of combining patient data from Medicare records, we produced 2 sets of risk factors: 1 based on VA data alone and the other based on combined VA and Medicare data.

Medicare Utilization Measures

To quantify patient- and hospital-level differences in Medicare utilization, we identified all acute inpatient care and outpatient visits in the 12 months preceding the index admission, separately in VA and Medicare data.

For each index admission, we defined 2 measures: 1) a categorical grouping of the relative volume of Medicare use: a) no Medicare-covered inpatient or outpatient care ("none"), b) at least some, but less than 25% of outpatient visits covered by Medicare ("moderate"), and c) at least 25% of outpatient visits covered by Medicare ("high"); and 2) the proportion (%) of a patient's outpatient visits that had been covered by Medicare. Using the latter measure, we grouped hospitals into tertiles by increasing the proportion of Medicare-covered outpatient use.

Risk Adjustment Models

To obtain the weight associated with each risk factor and the adjusted discharge-level predicted probability of 30-day mortality, we estimated: a) a logistic regression model (GLM); and b) a hierarchical logistic regression model (HLM) wherein the log-odds of the dichotomous outcome of 30-day mortality was specified as a linear function of patient risk factors—HLM also included unobserved hospital effect.[4,28,29] We reported odds ratios (ORs) associated with each risk factor. For both models, overall model fit was evaluated by the area under the receiver operating characteristic curve (C statistic), the percentage of outcome variation explained, and the observed outcome rate in the lowest and highest deciles of predicted probability of death.[30] We calculated 2 predicted numbers of deaths for each hospital: the first, denoted E, is an expected number of deaths at that hospital, assuming average VA care, but adjusted for its patients' risk (from GLM and HLM models); and the second, denoted P, is an expected number of deaths in that hospital that accounts for both patient risk and hospital effect (from the HLM model).[30]

As a potential measure of the incremental patient risk captured in Medicare data, we estimated a separate hierarchical logistic regression model in which we added a patient discharge-level categorical indicator of Medicare use as a covariate.

Risk-Standardized Mortality Rates (RSMRs)

Hospital performance was expressed in terms of risk standardized mortality rates (RSMRs).[28,30] Two measures of RSMR are commonly used for hospital profiling: a) the traditional measure, based on the ratio of observed number of hospital deaths (O) to E[28,30]; and b) the Hospital Compare measure, based on the ratio of P to E.[28,29] Each ratio is multiplied by the overall observed death rate across all hospitals to obtain O/E RSMR and P/E RSMR estimates, respectively. Since the 2 RSMR measures behave differently in profiling, primarily because the P/E ratio "shrinks" estimates toward an overall average, we separately examined the impact of adding Medicare data when profiling hospitals using each measure.[28]

Analysis of Impact of Pooling Medicare Data

The direct impact of adding Medicare data is through finding risk factors not documented in VA records. Accordingly, we first calculated the prevalence of individual risk factors in VA data alone and in combined VA/Medicare data. Changes in risk factor prevalence require recalibrating the mortality model, leading to new risk weights. We refer to the changes in E associated with changing risk weights as an indirect effect. We estimated the direct, indirect, and overall changes in RSMR from adding Medicare data. The direct effect was measured by the change in RSMRs due to the change in risk prevalence, holding risk weights unchanged, while the indirect effect was measured by the change due to changing in risk weights, keeping risk prevalence unchanged.

Importantly, when a risk prediction model is calibrated to data, the sum of the expected probabilities equals the observed mortality; therefore, the sums of the expected probabilities of mortality from a model with and without Medicare data are equal. Thus, if adding Medicare data causes the expected probabilities in some hospitals to increase, it must decrease in others. Given this, we reported overall change in RMSRs for hospitals that experience an increase or decrease in RSMR separately.

Our core measures of the impact of adding Medicare data are absolute and relative (%) overall RSMR change. We calculated 95% CIs for these, defined as the (2.5th, 97.5th) percentile range of the RSMR change, from 1000 bootstrap resamplings, with each stratified by hospital.[31,32] A second outcome of interest is change in *outlier status*, defined by RSMR bootstrap CI, lying either entirely above ("worse-than-average"), or entirely below ("better-than-average") the VA national average mortality rate. We examined changes in outlier status after adding Medicare data. Further, to evaluate associations with extent of Medicare utilization, we estimated RSMRs and outlier-status changes for hospitals within tertiles of Medicare utilization.

All analyses were performed using Stata version 11.1 (StataCorp, College Station, Texas).[33] This study was approved by the Boston VA Healthcare System Institutional Review Board.

Sensitivity Analysis

We used all discharges for both estimation and prediction in order to ensure the largest sample size for each hospital for obtaining RSMR CIs. However, predictions

Table 1. Medicare Utilization of Patients Admitted for AMI to a VA Hospital, 2006-2010

		Patients by Hospital Tertiles Based on Proportion of Aggregate Outpatient Visits of Hospital Patients Covered by Medicare		
A. Admission-Level Statistics (N = 11,373)	**All Patients**	**1st Tertile**	**2nd Tertile**	**3rd Tertile**
No. index admissions	11,373	4477	4423	2473
No. hospitals	104	43	31	30
Mean 30-day mortality rate (%)	14.8%	13.4%	15.5%	16.2%
Mean age (years)	77.7	77.6	77.8	78.0
Mean share of patient outpatient visits covered by Medicare (%)	17%	15%	17%	23%
Patients with various proportions of care being covered by Medicare (%)				
None: no Medicare utilization	51%	55%	52%	43%
Moderate: no more than 25% of outpatient visits	24%	24%	23%	24%
High: more than 25% of outpatient visits	25%	21%	25%	33%
B. Hospital-Level Statistics (N = 104)	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Mean no. of index admissions	109	86	25	639
Mean 30-day observed mortality (%)	16.0%	6.8%	3.8%	40%
Mean age (years)	78.1	1.6	74.8	82.3
Mean share of patient outpatient visits covered by Medicare (%)	23%	8%	10%	47%
Medicare utilization (%)				
Patient without Medicare use (inpatient or outpatient care)	49%	10%	23%	71%
Moderate Medicare use patient (≤25% of outpatient visits Medicare-covered)	25%	7%	8%	45%
High Medicare use patient (>25% of outpatient visits Medicare-covered)	26%	8%	12%	55%

AMI indicates acute myocardial infarction.
The shares of outpatient visits covered by Medicare are based on all outpatient physician visits that occurred during the 365 days prior to the index AMI admission date.
In Table 1a, the mean of each measure (eg, mean 30-day mortality rate) is based on pooling the experience of all the people in all the hospitals (overall and by tertile), while in Table 1b the corresponding mean is obtained by taking the average over all hospital means.

on the same data used to estimate the model may overestimate model predictive power. To examine the extent of overprediction, we divided discharges into 2 halves by randomly allocating discharges in each hospital, and calculated model performance after using risk weights estimated for each half to obtain predictions on the other. We then compared the performance measures using this approach with our initial estimates.

RESULTS

We identified 28,700 AMI discharges for patients aged 66 years or older from 138 VA hospitals in the inpatient VA administrative records from 2006 to 2010. The aforementioned exclusions resulted in a final study population of 11,373 index admissions at 104 hospitals. Of the discharges excluded, the main reasons were noncontinuous enrollment in Medicare FFS during the 12 months prior to index admission (45%), live discharge on the same/next day (11%), and transfer from another acute care hospital (10%) (see **eAppendix Table 1**, available at **www.ajmc.com**). The mean observed 30-day mortality rate during the years 2005 to 2009 was 14.8% (**Table 1**).

Medicare Utilization

Although all patients were enrolled in Medicare, 51% received no Medicare-covered inpatient or outpatient care (ie, all their care was obtained in the VA); another 24% and 25% were in the "moderate" and "high" user categories of Medicare-covered outpatient visits, respectively. The Medicare-covered share of all outpatient visits varied considerably, from 8% to 47%, across hospitals. In addition, the proportion of patients in the high Medicare-user category averaged 26% (Table 1, section B) (standard deviation = 8%).

Impact of Pooling Medicare Data on Direct and Indirect Effects

Table 2 details the 2 ways in which adding Medicare data can affect the risk associated with 30-day mortality: first, the direct effect of higher prevalence of risk factors,

Table 2. Demographics, Risk Prevalence, and Risk Weights With and Without Medicare Data

(N = 11,373 index admissions from 104 hospitals)	Risk Prevalence			Risk Weights (Odds Ratio)		
	VA data (1)	VA & Medicare data (2)	Ratio (2)/(1)	VA data (3)	VA & Medicare data (4)	Ratio (4)/(3)
Age (years), mean (SD)	78 (7)					
Female (%)	2%	2%	1.00	1.09	1.10	1.01
Heart failure (CC80)	32%	37%	1.15	**1.18**	**1.19**	1.00
AMI (CC81)	22%	25%	1.15	**1.23**	**1.26**	1.02
Unstable angina (CC82)	21%	25%	1.19	**1.59**	**1.45**	0.91
Cardiopulmonary-respiratory failure and shock (CC79)	6%	10%	1.53	**2.44**	**1.94**	0.79
Valvular and rheumatic heart disease (CC86)	11%	14%	1.35	**1.34**	**1.18**	0.88
Stroke (CC95-96)	9%	11%	1.23	1.10	1.08	0.99
Cerebrovascular disease (CC97-99,103)	12%	16%	1.29	0.95	0.91	0.96
History of renal failure (CC131)	27%	30%	1.11	**1.27**	**1.29**	1.02
Pneumonia (CC111-113)	13%	17%	1.35	1.09	1.10	1.01
Peripheral vascular disease (CC104-105)	24%	28%	1.18	1.09	1.07	0.98
Trauma in last year (CC154-156,158-162)	17%	23%	1.31	1.03	1.01	0.98
Major psychiatric disorders (CC54-56)	8%	9%	1.21	1.02	1.08	1.05
Coronary artery bypass graft (*ICD-9-CM* 3610, 3611, 3612, 3613, 3614, 3615, 3616)	0.4%	1%	1.27	0.63	1.24	1.95
Percutaneous transluminal coronary angioplasty (*ICD-9-CM* 0066, 3601, 3602, 3605, 3606, 3607)	2%	3%	1.55	**0.65**	0.78	1.18
Anterior MI (*ICD-9-CM* 410.00-410.19)	2%	2%	1.58	1.30	0.94	0.73
Other location MI (*ICD-9-CM* 410.20-410.69)	2%	2%	1.27	1.20	1.08	0.90
Chronic atherosclerosis (CC83-84)	84%	85%	1.02	**0.45**	**0.43**	0.96
Hypertension (CC89, 91)	87%	90%	1.03	**0.72**	**0.74**	1.02
Chronic obstructive pulmonary disease (CC108)	30%	33%	1.11	1.06	1.01	0.95
Diabetes mellitus or complications (CC15-19,120)	51%	52%	1.03	0.92	**0.88**	0.97
Protein-calorie malnutrition (CC21)	2%	3%	1.32	**1.56**	**1.35**	0.86
Dementia (CC49-50)	15%	17%	1.14	**1.49**	**1.42**	0.95
Hemiplegia, paraplegia, paralysis (CC67-69,100-102,177)	7%	8%	1.22	**1.46**	**1.36**	0.93
Metastatic cancer and acute leukemia (CC7-8)	5%	5%	1.07	**2.32**	**2.28**	0.98
Chronic liver disease (CC25-27)	2%	2%	1.09	**2.06**	**1.90**	0.93
Model Fit Indicators						
C statistic (95% CI)				0.743 (0.731- 0.755)	0.738 (0.726- 0.750)	
R^2				0.078	0.076	
Observed 30-day mortality (%) by predicted probability decile						
Lowest decile, predicted probability				1.67%	1.85%	
Highest decile, predicted probability				39.84%	36.94%	

AMI indicates acute myocardial infarction; CC, DxCG condition categories; *ICD-9-CM, International Classification of Diseases, Ninth Revision, Clinical Modification*; VA, Veterans Health Administration.
Odds ratios are estimates from hierarchical logistic regression models; covariates also included were age, sex, and fiscal year.
Odds ratios in bold indicate statistical significance at 5% level.

and second, the indirect effect on the risk weights associated with the risk factors. The direct effect increased the prevalence of all 25 risk factors, with 13 increasing by over 20%. The impact of the indirect effect of change in risk weights was mixed: 5 coefficients changed no more than 3%, 12 coefficients dropped by at least 4%, and 3 increased by at least 4%. Decreases in risk weights occurred more often than increases. This is not surprising: since, as noted, the sum of the expected equals the observed mortality rate, if disease prevalence increases, weights on

Table 3. Confounding of Model to Predict Mortality Following AMI Admission by Medicare Utilization

(N = 11,373 index AMI admissions in 104 VA hospitals)	OR (95% CI)		
Model to predict 30-day mortality with risk identified:	High Medicare Use Patients	Moderate Medicare Use Patients	Patients With No Medicare Use
1) Using VA data alone	**1.21** (1.07-1.38)	0.95 (0.82-1.09)	Reference
2) Using both VA & Medicare data	0.98 (0.85-1.11)	0.90 (0.78-1.03)	Reference

AMI indicates acute myocardial infarction; OR, odds ratio; VA, Veterans Health Administration.
Medicare utilization is the share of outpatient visits Medicare covered based on all outpatient physician visits during the 365 days prior to the index AMI admission. Share >25% is high, share greater than 0% and ≤25% is moderate, and the remaining patients had no Medicare use. Both models include risk factors for age, sex, and all comorbid conditions listed in Table 2, in addition to indicators for high and moderate Medicare–use patients. Odds ratio in bold indicates statistical significance at 5% level.

average"must decrease. Adding Medicare data did not improve the overall performance of the risk adjustment model, as measured by the C statistic, or the ability to distinguish differences in observed mortality across deciles of predicted risk (Table 2). Re-estimated model fit measures using the split-sample method described earlier revealed no significant decline in the C statistic from 0.74 (all sample) to 0.72 (split sample; see eAppendix Table 2).

Medicare Utilization and Risk of 30-Day Mortality

We included the extent of patient Medicare utilization as a covariate in a risk prediction model with other risk factors (Table 3). When we estimated this model with risk prevalence identified in VA-only data, there was higher risk of 30-day mortality for high Medicare–use patients (OR, 1.21; 95% CI, 1.07-1.38). When we re-estimated this model using risk factors whose prevalence was identified in either VA or Medicare data, the risk associated with high Medicare use was no longer statistically significant (OR, 0.98; 95% CI, 0.85-1.11).

RSMR Change From Adding Medicare Data

The impact of adding Medicare data was qualitatively similar for the 2 RSMR measures (Table 4). As expected, with about half of hospitals experiencing an increase, and the other half a decrease, there was virtually no overall change in O/E and P/E RSMRs. In the 53 hospitals for which O/E RSMR increased, the average change in the RSMR was 2.2% (95% CI, 1.6%-2.8%). Among the 51 hospitals with a decrease in O/E RSMR, the average change was –2.6% (95% CI, –3.3% to –1.9%); corresponding changes in P/E RSMR were smaller. The average change was 1.2% (95% CI, 0.0%-2.7%) and –1.3% (95% CI, –2.9% to –0.3%) among the 56 and 48 hospitals where P/E RSMRs increased and decreased, respectively.

After adding Medicare data, 4 hospitals changed outlier status based on O/E RSMR and no hospitals changed outlier status based on P/E RSMR (Table 4). Examination of the 4 hospitals with changed outlier status indicated that adding Medicare data shifted the RSMR 95% CI just enough to narrowly exclude the national VA mortality rate of 14.8%, thereby reclassifying each hospital from average to worse-than-average (eAppendix Table 1 and eAppendix Figure 1).

Table 5 reports the RSMR change for hospitals grouped by tertiles of Medicare-share of total outpatient care. For both RSMR measures, we found no significant differences across tertiles, separately among hospitals that experienced an RSMR increase or decrease.

Decomposition of the overall RSMR change into direct and indirect effects indicated similar trends between O/E RSMR and P/E RSMR. As expected, direct effect decreased the RSMR, while indirect effect increased the RSMR (eAppendix Figures 2a and 2b).

DISCUSSION

Veterans 66 years and older seeking care in VA hospitals differed considerably in their use of non-VA providers, leading to differential amounts of data fragmentation. To inform methods for improved hospital profiling, we compared profiles of VA hospitals, based on 30-day mortality for AMI admissions, and using VA-only versus combined VA/Medicare data. Results from 2 commonly used profiling measures, the traditional (O/E) and CMS Hospital Compare (P/E) measures of RSMRs, indicated modest RSMR change. Roughly equal numbers of hospitals experienced an increase or decrease in RSMR, with an average increase of more than 1.2% and an average decrease of more than –2.6% across both measures. The magnitude of RSMR change was not associated with hospital differences in the Medicare share of outpatient care. In terms of hospital outlier status, based on the O/E RSMR measure, only 4 out of the 104 hospitals experienced reclassification, all resulting from small RSMR changes for hospitals at the threshold borderline; none experienced reclassification based on the P/E RSMR. Thus, in our study of profiling using O/E or P/E RSMR measures, evaluating

Table 4. Impact of Adding Medicare Data on Hospital Risk Standardized Mortality Rate (RSMR)

	No. of Hospitals	Mean No. of discharges	Mean RSMR, VA-only data	Mean RSMR % Change			No. of Hospitals With Change in Outlier Status
				Mean % Change	95% CI Low	95% CI High	
O/E RSMR							
All hospitals	104	109	14.7	0.0%	–0.1%	0.1%	4
Hospitals with RSMR increase	53	115	15.0	2.2%	1.6%	2.8%	3
Hospitals with RSMR decrease	51	103	14.3	–2.6%	–3.3%	–1.9%	1
P/E RSMR							
All hospitals	104	109	14.8	0.1%	–0.9%	1.0%	0
Hospitals with RSMR increase	56	116	14.8	1.2%	0.0%	2.7%	0
Hospitals with RSMR decrease	48	101	14.8	–1.3%	–2.9%	–0.3%	0

O/E indicates observed mortality; P/E, predicted mortality; VA, Veterans Health Administration.
Mean RSMR % change equals percent difference between RSMR1 and RSMR2, where RSMR1 and RSMR2 are risk standardized mortality rates based on use of VA-only and VA/Medicare data, respectively.
Mean RSMR and RSMR % change are weighted averages using the number of hospital discharges as weights.
Top increasing/decreasing hospitals are based on RSMR % change. CIs are based on corresponding RSMR estimates from 1000 bootstrap samples.
A hospital's RSMR is considered to be an outlier if the RSMR 95% CI does does not contain the national average VA mortality rate. The last column above indicates the number of hospitals whose outlier status differs based on whether VA-only or VA/Medicare data are used. Additional information on the hospitals with status change is in the supplementary materials (eAppendix Table 2).

VA hospitals without using their patients' Medicare data to more fully specify their "risk" led to only modest differences in performance assessments.

To better understand how adding Medicare data affects profiling, we decomposed the final RSMR change into 2 components: first, the direct effect of higher-risk prevalence from comorbidities identified only in Medicare data; second, the indirect effect on risk weights from the reestimated risk adjustment model using newly identified risk factors. The traditional and Hospital Compare RSMR measures were similar in their sensitivity to both the direct and indirect effects, with the former lowering and the latter increasing RSMRs significantly across all hospitals.

Although profiling of VA hospitals based on patient outcomes among AMI patients is common, the effect of data fragmentation on these assessments has not been previously examined.[6,17,34] For instance, 2 recent studies estimated RSMR for elderly veterans using similar risk adjustment models, 1 using only VA data,[34] and the other using combined VA/Medicare data.[6] Findings from our study favor using VA/Medicare data, reinforcing a similar conclusion from other studies that found significant differences in the risk prevalence identified in the 2 data sources.[10,11,35]

We also examined whether elderly veterans with relatively higher use of Medicare-covered care had higher or lower risk than that captured in VA administrative data. Consistent with previous studies,[10,11] we found that veterans with higher use of Medicare-covered care were sicker. In quantifying this additional comorbidity, we estimated that high–Medicare-use veterans experienced 21% higher mortality (95% CI, 7% to 38%) compared with non–Medicare-using veterans after adjusting for risk identified in VA data. This difference disappeared once Medicare data were included. Therefore, hospital profiling without using Medicare data would result in this unobserved patient risk being wrongly characterized as higher mortality arising from relatively worse hospital quality.

We found that using combined VA/non-VA data adds substantial morbidity information, suggesting more favorable profiles for hospitals whose patients have higher Medicare use than those of other VA hospitals, although the observed size of this difference was modest and not statistically significant. Broadly, assessments based on complete data seem more fair, yet the time required to prepare combined files is a concern. Policy makers have to weigh the trade-off between completeness and timeliness.

With respect to generalizability of the study findings, we noted 2 issues. First, data fragmentation can arise in different contexts. As in this study, dual insurance coverage can lead to fragmentation of patient data among veterans, active military service members (TRICARE and commercial coverage), and low-income elderly dual Medicare and Medicaid coverage. Since receipt of care from multiple providers is common within and outside the VA, data fragmentation can also arise when all patient data are not consolidated within a given healthcare system or between health systems. Registry data relating to a disease or treatment is limited to patient data at participating hospitals. Additionally, individual hospitals or hospital networks evaluate performance metrics based only on in-house patient data.[36,37]

Second, gains from combining fragmented data could vary depending on the context. In this study, there was sig-

Table 5. Impact of Adding Medicare Data on Risk Standardized Mortality Rate (RSMR), by Medicare Utilization

	Mean Medicare Utilization (%)	No. of Hospitals	Mean No. of Discharges	Mean RSMR, VA-Only Data	Mean RSMR Change			Mean RSMR Change %			No. of Hospitals With Change in Significant Difference Status
					Mean Change	95% CI Low	95% CI High	Mean Change (%)	95% CI Low	95% CI High	
O/E RSMR											
Top Tertile Hospitals by Medicare Utilization %											
All hospitals	31%	30	82.4	15.7	–0.14	–0.35	0.06	–1.5	–2.6	–0.4	0
Hospitals with RSMR increase	31%	14	72.5	18.9	0.34	0.00	0.66	1.7	0.0	3.5	0
Hospitals with RSMR decrease	32%	16	91.1	13.4	–0.48	–0.74	–0.20	–3.8	–5.3	–2.0	0
Middle Tertile Hospitals by Medicare Utilization %											
All hospitals	23%	31	142.7	15.1	–0.02	–0.14	0.11	0.1	–0.5	0.9	2
Hospitals with RSMR increase	23%	17	150.6	13.9	0.33	0.17	0.49	2.3	1.2	3.5	1
Hospitals with RSMR decrease	23%	14	133.1	16.8	–0.50	–0.74	–0.23	–2.9	–4.2	–1.3	1
Lowest Tertile Hospitals by Medicare Utilization %											
All hospitals	17%	43	104.1	13.7	0.10	–0.02	0.21	0.6	–0.1	1.4	2
Hospitals with RSMR increase	16%	22	115.4	14.6	0.32	0.14	0.48	2.3	1.2	3.2	2
Hospitals with RSMR decrease	17%	21	92.3	12.5	–0.19	–0.36	–0.03	–1.6	–2.8	–0.2	0
P/E RSMR											
Top Tertile Hospitals by Medicare Utilization %											
All hospitals	31%	30	82.4	15.8	–0.08	–0.39	0.13	–0.6	–2.5	1.2	0
Hospitals with RSMR increase	31%	14	72.5	17.1	0.15	0.00	0.46	0.8	0.0	3.3	0
Hospitals with RSMR decrease	32%	16	91.1	14.9	–0.23	–0.54	–0.09	–1.6	–4.0	-0.7	0
Middle Tertile Hospitals by Medicare Utilization %											
All hospitals	23%	31	142.7	15.2	0.01	–0.13	0.16	0.2	–0.7	1.3	0
Hospitals with RSMR increase	23%	19	147.2	14.4	0.19	–0.07	0.34	1.4	–0.4	2.5	0
Hospitals with RSMR decrease	23%	12	135.6	16.6	–0.29	–0.40	–0.07	–1.8	–2.3	–0.3	0
Lowest Tertile Hospitals by Medicare Utilization %											
All hospitals	17%	43	104.1	13.9	0.06	–0.12	0.20	0.4	–0.7	1.4	0
Hospitals with RSMR increase	17%	23	117.9	14.3	0.15	–0.04	0.33	1.1	–0.3	2.3	0
Hospitals with RSMR decrease	17%	20	88.3	13.1	–0.09	–0.33	0.04	–0.7	–1.9	0.4	0

O/E indicates observed mortality; P/E, predicted mortality; VA, Veterans Health Administration.
Medicare utilization (%) is measured by the proportion of outpatient visits of a hospital's patients in the previous year that were covered by Medicare.
Mean RSMR change = RSMR2 – RSMR1, where RSMR1 and RSMR2 are risk standardized mortality rates based on use of VA-only or VA/Medicare data, respectively.
Mean RSMR % change = % difference between RSMR1 and RSMR2.
Mean RSMR, RSMR change, and RSMR change % are weighted averages using number of hospital discharges as weights.
Top increasing/decreasing hospitals are based on % change in RSMR.
CIs are based on corresponding RSMR estimates from 1000 bootstrap samples stratified by hospital.
A hospital's RSMR is considered to be an outlier if the RSMR 95% CI does not contain the national average VA mortality rate. The last column above indicates the number of hospitals whose outlier status differs based on whether VA-only or VA/Medicare data were used.

nificant change in risk prevalence, but not in risk-adjusted mortality. In practice, even a modest change in a metric can lead to a change in performance classification, with associated potential implications for incentive payments or penalties.[38] Gains for quality measurement from combining data can also be high when fragmented data captures important health service use, such as mental health services in Medicaid data or pharmacy use in VA data.

Limitations

First, we treated the healthcare system where care is received—VA or the private sector—as exogenous to patient mortality and hospital performance assessment.[39-41] For example, our combined model gives equal weight to diagnoses found either in the VA or Medicare, although that a veteran was seeking care outside the VA might indicate greater severity.[11] Second, because we only had access to Medicare data, besides VA data, we limited our study to the elderly (66 years or older); in practice, VA hospital profiling should be based on outcomes for all patients treated. Our intent was to quantify the impact of data fragmentation among patients for whom we have complete data. Further, our finding of modest impact indicates that if we had included all patients in profiling hospitals, then the impact of adding Medicare data would also be modest.

CONCLUSIONS

We found that Medicare data on care received by elderly veterans from the VA adds information on patient risk and that VA hospital profiling is modestly affected by whether administrative data from private sector care are included. These findings have salience for other dual-care settings, including Medicare and Medicaid, Medicare FFS and Managed Care, and the Department of Defense TRICARE and private sector.

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eAppendix

Table of Contents

1. Summary of findings in eAppendix

Additional findings from primary analysis

We identified 28,700 AMI discharges for patients aged 66 years or older from 138 Veterans Health Administration (VA) hospitals in the inpatient VA administrative records from 2006 to 2010. Of these, 17,327 were excluded for the reasons listed in the main manuscript, and the remaining 11,373 were in the study population. Note that the main reason for exclusion was that patients did not have continuous Medicare Fee for Service enrollment during the 12 months prior to the index date. **eAppendix Table 1** compares the included and excluded patients. We see that both in demographics and comorbidities, the 2 groups were very similar.

eAppendix Figures 1a and **1b** give the mean and 95% confidence interval for hospital RSMR. For most hospitals the change in RSMR and confidence intervals, after adding Medicare data, are modest. **eAppendix Table 2** lists the O/E RSMR change for the 4 hospitals that experienced outlier status change following the addition of Medicare data; no hospitals experienced outlier status change using the P/E RSMR measure. For 3 hospitals, O/E RSMR changed from above average to average, and for the fourth hospital the change was from below average to average. However, in all the 4 cases, the magnitude of RSMR was small; the change in outlier status was the result of O/E RSMR being on the threshold borderline.

eAppendix Figures 2a and **2b** present the decomposition of overall change into direct and indirect effects. eAppendix Figure 2a compares RSMR before and after data enhancement, while eAppendix Figure 2b performs Bland-Altman analysis. Both approaches indicate that direct effect decreased, and indirect effect increased, O/E and P/E RSMR across hospitals.

Sensitivity analysis: Using split sample for model prediction

We used the entire discharge dataset for both estimation of risk weights and making predictions on outcomes. Since this can lead to better indication of model fit than would be observed if predictions were made on different samples, we examined the extent of "over-fitting" by using a split-sample approach. Data on all discharges was randomly split, stratified by hospital, into 2 equal-sized subsamples. The first subsample, termed estimation subsample, was used for estimation of the risk adjustment model. Further, model fit estimates were also estimated on this subsample. To examine model fit on external samples, we applied risk weights estimated for the estimation subsample, on to the validation subsample. Results in **eAppendix Table 3** indicate

that model fit is smaller on cross-sample predictions than on estimation sample. For the VA-only model, the difference in c-statistic is 0.74 (estimation subsample) versus 0.72 (validation subsample), and for the VA+Medicare model the corresponding difference is 0.73 (estimation subsample) versus 0.71 (validation subsample).

2. Additional findings from primary analysis

eAppendix Table 1. Comparison of Included vs Excluded Patients

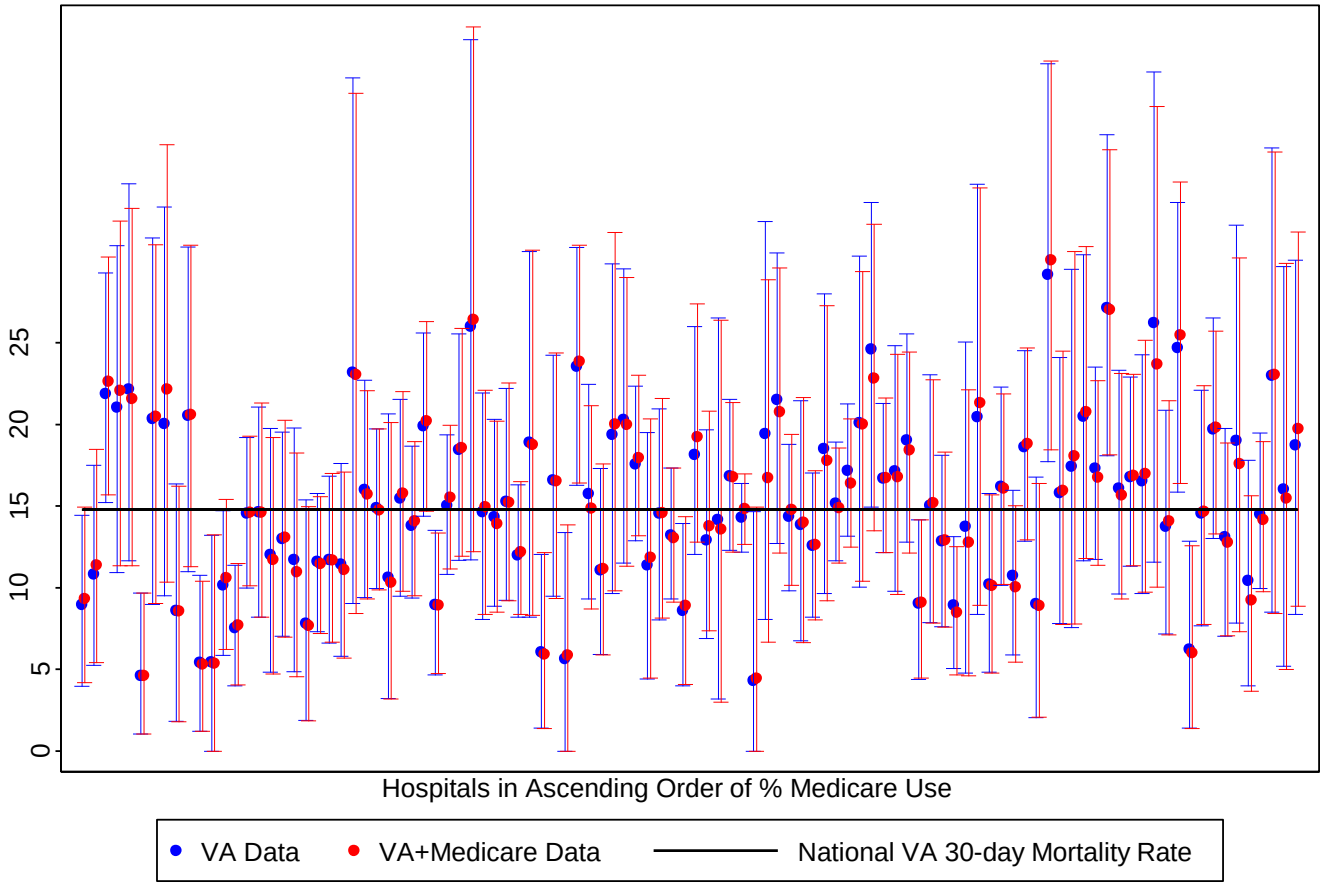
	Risk Prevalence	
	Included (N = 13,373)	Excluded (N = 17,327)
Years, mean (SD)	77.7 (7.1)	77.4 (6.9)
Female	2%	1%
Heart failure (CC80)	32%	31%
AMI (CC81)	22%	24%
Unstable angina (CC82)	21%	20%
Cardiopulmonary-respiratory failure and shock (CC79)	6%	6%
Valvular and rheumatic heart disease (CC86)	11%	11%
Stroke (CC95-96)	9%	9%
Cerebrovascular disease (CC97-99,103)	12%	12%
History of renal failure (CC131)	27%	26%
Pneumonia (CC111-113)	13%	12%
Peripheral vascular disease (CC104-105)	24%	23%
Trauma in last year (CC154-156,CC158-162)	17%	17%
Major psychiatric disorders (CC54-56)	8%	7%
Coronary artery bypass graft (*ICD-9-CM* 3610, 3611, 3612, 3613, 3614, 3615, 3616)	0.4%	0.5%
Percutaneous transluminal coronary angioplasty *(ICD-9-CM* 0066, 3601, 3602, 3605, 3606, 3607)	2%	2%
Anterior_MI (*ICD-9-CM* 410.00-410.19)	2%	2%
Other location MI (*ICD-9-CM* 410.20-410.69)	2%	2%
Chronic atherosclerosis (CC83-84)	84%	82%
Hypertension (CC89,91)	87%	86%
Chronic obstructive pulmonary disease (CC108)	30%	30%
Diabetes mellitus or complications (CC15-19,120)	51%	51%
Protein-calorie malnutrition (CC21)	2%	2%
Dementia (CC49-50)	15%	13%

Hemiplegia, paraplegia, paralysis (CC67-69,100-102,177)	7%	7%
Metastatic cancer and acute leukemia (CC7,8)	5%	4%
Chronic liver disease (CC25-27)	2%	2%

AMI indicates acute myocardial infarction; CC, DxCG condition categories; *ICD-9-CM, International Classification of Diseases, Ninth Revision, Clinical Modification*; MI, myocardial infarction.

2. Additional findings from primary analysis

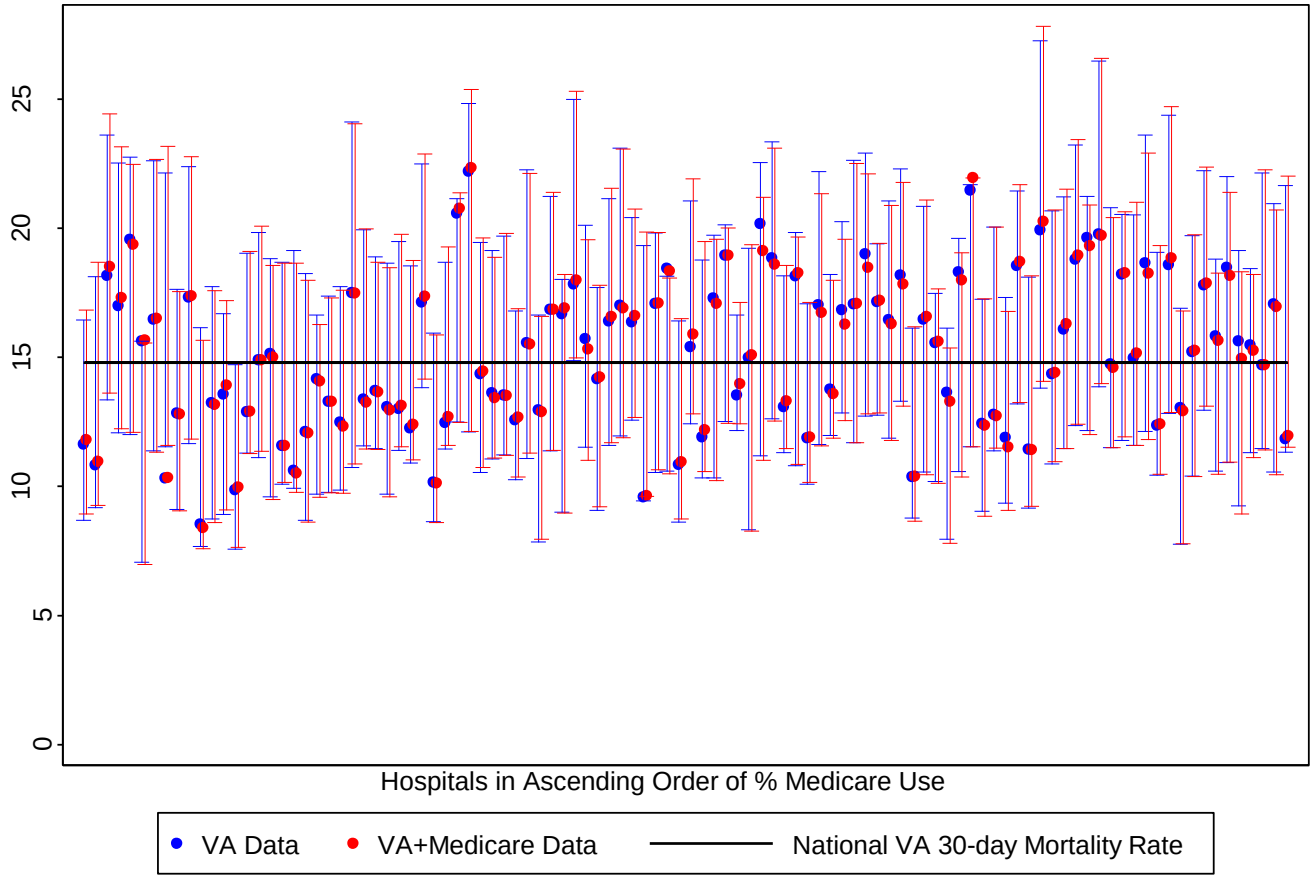
eAppendix Figure 1a. Hospital O/E RSMR with and without Medicare data: Mean and 95% Confidence Interval (N = 104 hospitals)



O/E indicates observed mortality; RSMR, risk standardized mortality rate.
Confidence interval based on bootstrap samples (N = 1000).
Hospitals are arranged on the x-axis in increasing order of the % Medicare use for hospitals, which ranges from 10% to 47% (Table 1).

2. Additional findings from primary analysis

eAppendix Figure 1b. Hospital P/E RSMR with and without Medicare data: Mean and 95% Confidence Interval (Validation Subsample N = 104 VA hospitals)



P/E indicates predicted mortality; RSMR, risk standardized mortality rate.
Confidence interval based on bootstrap samples (N = 1000).
Hospitals are arranged on the x-axis in increasing order of the % Medicare use for hospitals, which ranges from 10% to 47% (Table 1).

2. Additional findings from primary analysis

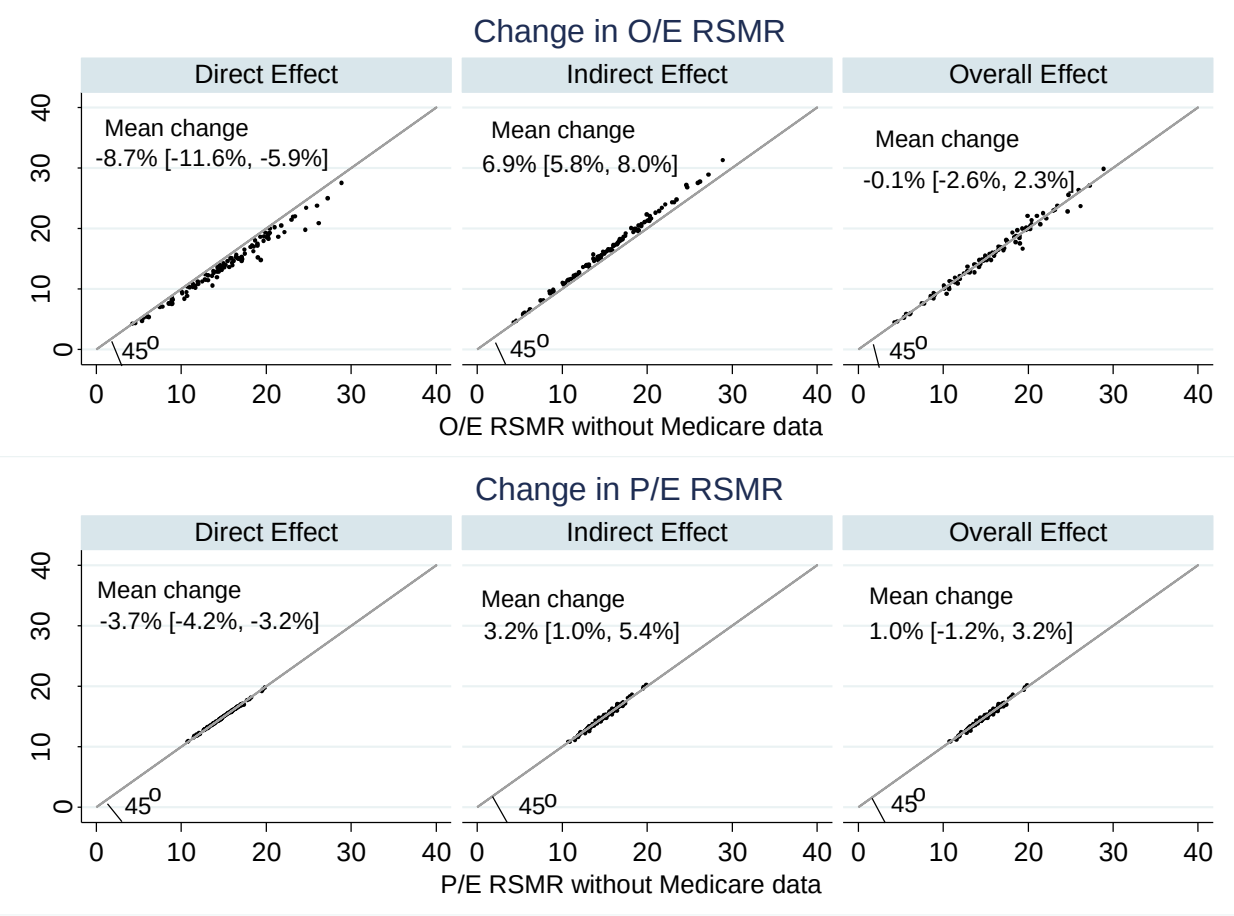
eAppendix Table 2. Change in O/E RSMR for Hospitals with Change in Outlier Status

Hospital identifier (encrypted)	Number of discharges	RSMR O/E: Base			RSMR O/E: Enhanced			RSMR O/E: % Change			Outlier Status: VA-Only	Outlier Status: VA+Medicare
			95% CI			95% CI			95% CI			
		Mean	Low	High	Mean	Low	High	Mean	Low	High		
10	191	10.2	5.9	14.7	10.6	6.2	15.4	4%	0%	9%	1	2
141	116	9.0	4.0	14.4	9.3	4.2	15.0	4%	0%	9%	1	2
24	26	4.3	0.0	14.7	4.5	0.0	15.0	3%	–2%	10%	1	2
59	30	24.6	15.0	33.6	22.8	13.5	32.3	–7%	–21%	6%	3	2

O/E indicates observed mortality; RSMR, risk standardized mortality rate.
Overall VA mortality rate is 14.8%.
Outlier Status: 1 = above average (95% CI <14.8); 2 = average (95% CI includes 14.8); 3 = below average (95% CI >14.8).

2. Additional findings from primary analysis

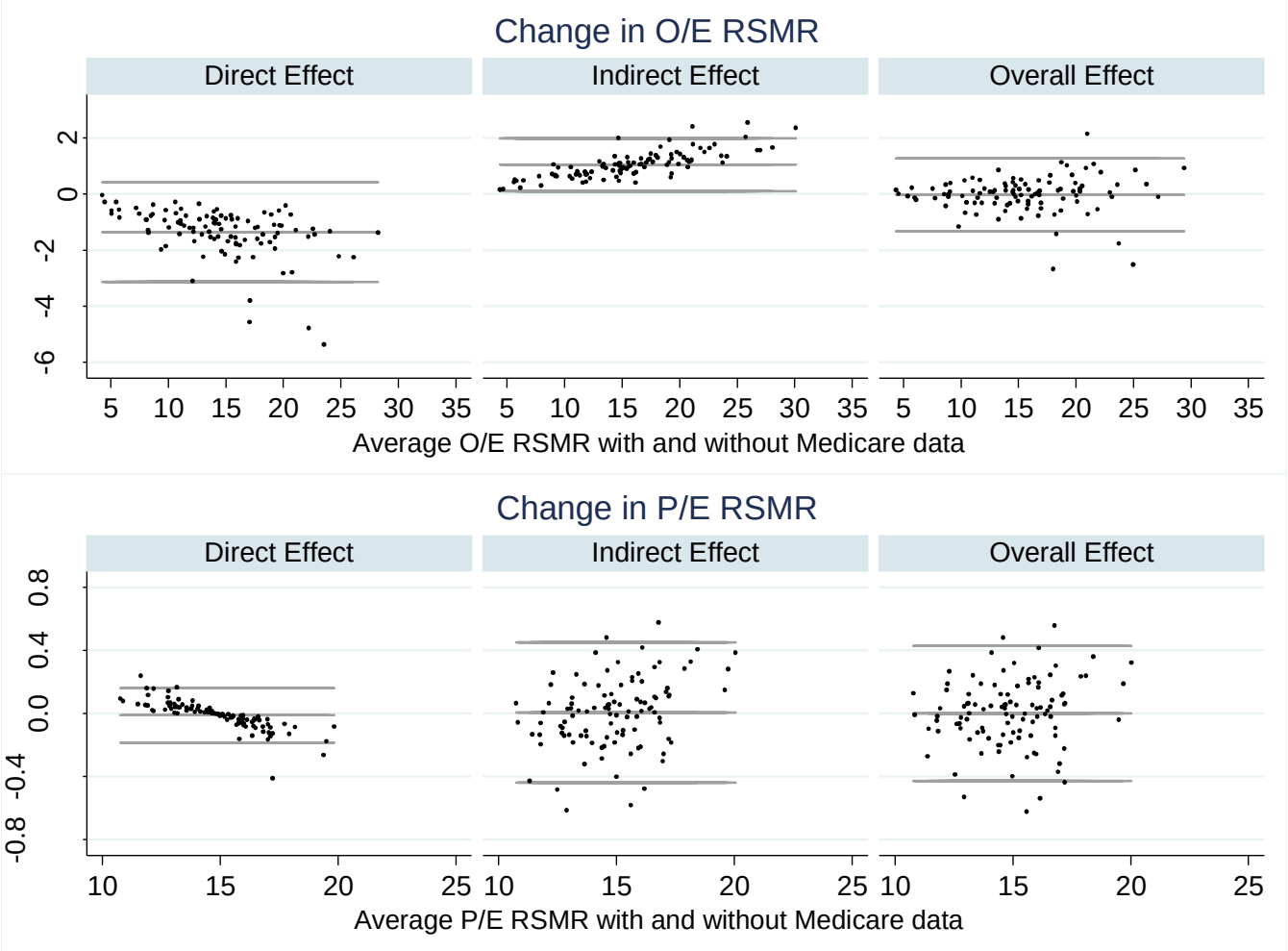
Appendix Figure 2a. Decomposition of Change in Hospital RSMR: Correlations
(N = 104 hospitals)



O/E indicates observed mortality; P/E, predicted mortality; RSMR, risk standardized mortality rate.
Mean change reported in each top panel graph indicates the % change in RSMR (along with 95% confidence interval) after pooling Medicare data.

2. Additional findings from primary analysis

eAppendix Figure 2b. Decomposition of Change in Hospital RSMR: Bland-Altman Analysis
(N = 104 hospitals)



O/E indicates observed mortality; P/E, predicted mortality; RSMR, risk standardized mortality rate.

3. Sensitivity analysis: Using split sample for prediction

Data on all discharges were randomly split and stratified by hospital into 2 equal-sized subsamples. The first subsample, termed estimation subsample, was used for estimation of the risk adjustment model. Further, model fit estimates were also estimated on this subsample. To examine model fit on external samples, we applied risk weights estimated for the estimation subsample to the validation subsample. eAppendix Table 3 reports the model fit estimates on both the estimation and validation subsamples. This is done for both VA-only and VA+Medicare models.

eAppendix Table 3. Sensitivity of Model Discrimination to Using Split (Estimation/Validation) Data

Model	Subsample	C statistic (95% CI)	R^2	Observed Mortality %	
				Decile 1	Decile 10
VA-Only	Estimation	0.735 (0.720, 0.750)	0.094	0.02	0.395
	Validation	0.718 (0.703, 0.731)	0.08	0.034	0.367
VA+Medicare	Estimation	0.732 (0.719, 0.751)	0.092	0.023	0.401
	Validation	0.709 (0.694, 0.724)	0.071	0.037	0.337