

Creating an Optimal Environment for Quality Healthcare for Individuals, Families, and Communities

Incremental Cost of Medicare Beneficiary Hospital Readmissions: Valuation via a Robust Machine Learning Approach

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CMS Quality Conference 2024 | Incremental Cost of Medicare Beneficiary Hospital Readmissions

Highlights

- Granular valuation of the incremental cost of Medicare beneficiary hospital readmissions (top 26 condition categories targeted in this study)
- Apply a previously unused approach (causal inference & machine learning) in the valuation
- Compare machine learning (ensemble models) in valuation to the traditional unadjusted or parametric model estimation methods
- We observe that the incremental cost of a schizophrenia readmission was undervalued by over \$3000 in the parametric model



Introduction

- Risk adjustment in health plan payment aims to redistribute funds according to the likely cost of enrollees
- Plans with costlier enrollees should receive larger payments than plans with less expensive enrollees (lezzoni, 1997)
- Similarly, readmission risk varies in the Medicare population (Jencks, 2009; Bradford, 2017; Joynt, 2011)
- However, valuation of the cost of hospital readmissions has largely been estimated in an "all-cause" manner
- Where they are by condition, they are unadjusted (Weiss & Jiang, 2021) or estimated from adjusted parametric models (Carey & Stefos, 2015)

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Introduction (continued)

- Hospital readmissions remains a major target in CMS's cost reduction agenda
- In CMS's 12th SOW, QIN-QIOs were required to report savings from 30-day readmissions and other measures
- All QIN-QIOs were presented with a single "all-cause" estimate as the cost of a hospital readmission
- This rate multiplied by number of *readmissions avoided (expected minus actual)* by the QIN-QIO yielded savings



Unadjusted estimates from Weiss & Jiang, 2021

Figure 1 a. Average readmission cost by payer b. Top 5 most expensive readmissions conditions



Table 3. Top five principal diagnoses with the h	nighest average cost of 30-o	lay all-ca	use adult hospital r	eadmissions, by expecte	d payer, 2018
		30-day	readmissions	-	
Principal diagnosis at index admission	admissions	Rank	Average cost, \$	Aggregate cost, \$ millions	readmission costs
Medicare	13,533,200	-	15,500	35,500	100.0
Chronic rheumatic heart disease	16,100	1	25,800	87	0.2
Complication of transplanted organs or tissue, initial encounter	27,100	2	24,200	180	0.5
Nonrheumatic and unspecified valve disorders	96,000	3	22,500	359	1.0
Diseases of white blood cells	13,100	4	21,800	79	0.2
Aortic; peripheral; and visceral artery aneurysms	45,000	5	21,300	121	0.3

Source: Weiss & Jiang (2021).

Adult hospital readmissions by expected payer. Analysis of Nationwide Readmissions Database (NRD), 2018.





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A Condition-Specific ML Framework (Rose, 2018)

- An experiment where one randomly samples a unit from the population and measure baseline features, medical conditions, and total payment from index and readmission periods
- We are interested in estimating how much more, on average, Medicare patients with 26 common index diagnoses cost when they are readmitted within 30 days of discharge (compared to similar not readmitted)
- Baseline controls include patient age, sex, race, state, length of stay, and up to 25 diagnoses (binary flags)
- The outcome variable is CMS's total payment to the provider during the index and readmission periods
 CMS 2024



Targeted Maximum Likelihood Estimation (TMLE) 1

- Targeted Maximum Likelihood Estimation (TMLE) is a causal inference framework used to estimate a statistical quantity of interest
- It allows the use of machine learning (ML) models in the process
- ML places minimal assumptions on the distribution of the data
- An ML approach known as "superlearning" is commonly used in TMLE
- Superlearning combines several models to make predictions, and is theoretically as-good-as or better than any of the individual models
- In this study, our ensemble models were <u>generalized linear model</u>, <u>boosting</u>, <u>lasso</u>, and <u>neural network</u>



Targeted Maximum Likelihood Estimation (TMLE) 2

- Let B denote baseline variables
- M is a vector of medical condition categories
- A denotes the current medical condition category under consideration
- M^- represents the vector M that excludes the variable A
- Y is the outcome, the total medical cost paid
- R is a binary readmission indicator (i.e., R = 1 implies readmitted, 0 otherwise)
- We assume a nonparametric model and define the parameter of interest as:

 $\emptyset = E_{W,M^{-}}[E(Y \setminus A = 1, R = 1, W, M^{-}) - E(Y \setminus A = 1, R = 0, W, M^{-})]$

This represents the effect of readmitted (R = 1) versus not readmitted (R = 0) for condition category A, adjusting for baseline variables and comorbidities

Incremental Cost of Medicare Beneficiary Hospital Readmissions

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Data

- Medicare FFS claims, 2021 2022
- All inpatient beneficiaries in Pennsylvania and West Virginia
- 933,255 observations (117,010 excluded)
- 18.7% readmission rate
- Median index length of stay of 4 days
- 9,971 unique primary diagnosis codes (recoded to 87 hierarchical condition categories (HCCs))



Readmission

 A 30-day readmission occurs when the beneficiary's "index" inpatient discharge is followed by an inpatient admission having an admission date within 30 days of the index inpatient discharge date

DENOMINATOR

 Medicare Fee-for-Service (FFS) Part A beneficiaries with Part A coverage for any days of the reporting time period

NUMERATOR

30-day readmissions among beneficiaries contributing to the denominator

- Inclusions
 - Readmissions within 30 days of index inpatient discharge that occurred during the period in short-term hospitals, critical access hospitals, and inpatient psychiatric hospitals and units
- Exclusions
 - Principal/first-listed diagnosis of COVID-19
 - Principal diagnosis of Sepsis or Transplant Complication with COVID-19 in any secondary position

Incremental Cost of Medicare Beneficiary Hospital Readmissions



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Figure 1. Characteristics of hospitalized beneficiaries (N = 816,245)



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Figure 2. Percent of hospitalized beneficiaries by hierarchical condition category (N = 434,665)



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Figure 3. TMLE estimates of incremental costs of hospital readmission for index condition categories 1 - 13

Incremental Costs

Machine learning effect estimates by index diagnosis category

Major Head Injury	15255.7
Acute Myocardial Infarction	14564.07
Metastatic Cancer and Acute Leukemia	13604.83
Specified Heart Arrhythmias	12784.22
Hip Fracture/Dislocation	12079.82
Colorectal, Bladder, and Other Cancers	12062.13
Cirrhosis of Liver	11796.47
Septicemia, Sepsis, SIRS/Shock	11601.61
Lung and Other Severe Cancers	11520.06
Vertebral Fractures without Spinal Cord Injury	11418.7
Vascular Disease with Complications	11163.18
Congestive Heart Failure	10838.19
Vascular Disease	10778.3
50 \$3,000 \$6,000 \$9	٥,000 \$12,000 \$15,000

Data Source: Medicare FFS claims, 2021-2022



Figure 4. TMLE estimates of incremental costs of hospital readmission for index condition categories 14 - 26

Incremental Costs

Machine learning effect estimates by index diagnosis category

Ischemic or Un	specified Stroke			10703.62	
Diabetes with	Chronic Complic	ations		10634.5	
Cardio-Respira	tory Failure and	Shock		10584.16	
Aspiration and	Specified Bacte	rial Pneumonias		10347.74	
Seizure Disord	ers and Convuls	ions		10296.69	
Pneumonia, un	nspecified organi	sm		10272.14	
Complications	of Specified Imp	lanted Device or	Graft	10202.15	
Acute Renal Fa	ilure			9815.58	
Intestinal Obst	ruction/Perforati	on		9391.84	
Major Depressi	ive, Bipolar, and	Paranoid Disorde	ers 8475		
Urinary Tract Ir	nfection		8149.63	L	
Chronic Obstru	uctive Pulmonary	v Disease	7520		
Schizophrenia			7275.22		
\$0	\$3,000	\$6,000	\$9,000	o \$12,0	00
Data Source: Medi	icare FFS claims, 20)21-2022			

\$15,000

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Figure 5. Difference in cost estimates from linear regression versus TMLE models

Linear Regression (LR) versus TMLE

Difference in effect estimates between LR and TMLE (LR minus TMLE)

Major Hoad Injury				860.35
				303.55
Acute Myocardial Infarction				//4./4
Metastatic Cancer and Acute Leukemia				395.93
Specified Heart Arrhythmias				
Hip Fracture/Dislocation				236.38
Colorectal, Bladder, and Other Cancers				
Cirrhosis of Liver				
Septicemia, Sepsis, SIRS/Shock				
Lung and Other Severe Cancers				
Vertebral Fractures without Spinal Cord Injury				17.86
Vascular Disease with Complications				5.5
Congestive Heart Failure			-3	.6
Vascular Disease			-26.22	2
Ischemic or Unspecified Stroke			-69.82	<u> </u>
Diabetes with Chronic Complications			-82.13	· · · · · · · · · · · · · · · · · · ·
Cardio-Respiratory Failure and Shock			-111.61	
Aspiration and Specified Bacterial Pneumonias			-164.71	
Seizure Disorders and Convulsions			-290.22	
Pneumonia, unspecified organism			-323	
Complications of Specified Implanted Device or Graft			-346.47	
Acute Renal Failure			-378.19	
Intestinal Obstruction/Perforation			-389.15	
Major Depressive Bipolar and Parapoid Disorders			-405	
Hajor Depressive, Dipolar, and Paranola Disorders			657.22	
Chronic Obstructive Pulmonany Discosso			770.96	
	2056.22		-770.80	
Schizophrenia	-3030.22	2000	1000	1000
	-3000	-2000	Cost Difference (\$)	0 1000

Data Source: Medicare FFS claims, 2021-2022



A General Approach to Return on Investment Valuation

Savings on avoiding <u>readmissions</u>:

$$\emptyset = E_{W,M^{-}}[E(Y \setminus A = 1, R = 1, W, M^{-}) - E(Y \setminus A = 1, R = 0, W, M^{-})]$$

Savings on avoiding <u>ED Superutilizers</u>

$$\emptyset = E_{W,M^-}[E(Y \setminus S = 1, W, M^-) - E(Y \setminus S = 0, W, M^-)]$$

Savings on avoiding <u>Adverse Drug Events</u>

$$\emptyset = E_{W,M^{-}}[E(Y \setminus E = 1, W, M^{-}) - E(Y \setminus E = 0, W, M^{-})]$$



Conclusion

- There appears to be a need for a more robust approaching to the valuation of the incremental cost of hospital readmissions
- Current methods may not be capturing the *true* estimate (i.e., unbiased)
- Thus cost or return on investment valuations related to hospital readmissions may be understated or overstated
- Perhaps unsurprisingly, we note that the average incremental cost of a schizophrenia readmission was undervalued by over \$3000 in the parametric model
- Previous literature demonstrated that mental health and substance use disorders are substantially undercompensated in the current Marketplace risk adjustment system (McGuire 2016; Montz et al. 2016)



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Appendix: ICD-10 to HCC classification

ICD-10-CM codes	HCC category description
B20, B97.35, Z21	HIV/AIDS
A02.1, A20.7, A22.7, A26.7, A32.7, A39.2-A39.4, A40, A41, A42.7, A48.3, A54.86, B00.7, B37.7, P36, R57.1, R57.8, R65.1-, R65.2-, T81.12XA	Septicemia, sepsis and systemic inflammatory response syndrome/shock
A07.2, A31.0, A31.2, B25, B37.1, B37.7, B37.81, B44.0-B44.7, B44.89, B44.9, B45, B46, B48.4, B48.8, B58.2, B58.3, B59	Opportunistic infections
C77.0-C77.2, C77.4-C77.8, C78, C79.00-C79.72, C79.89, C79.9, C7B, C80.0, C91.0-, C92.00-C92.02, C92.40-C92.A2, C93.0-, C94.00-C94.22, C94.40-C94.42, C95.0-	Metastatic cancer and acute leukemia
C15, C16, C17, C22, C23, C24, C25, C33, C34, C38.4, C45, C48, C90.00-C90.22, C92.10-C92.32, C92.9-, C92.Z-, C93.10-C93.92, C93.Z-, C94.30-C94.32, C94.80-C94.82	Lung and other severe cancers
C40, C41, C46, C47, C49, C56, C57.00-C57.4, C58, C70, C71, C72, C74, C75.1-C75.3, C77.3, C77.9, C79.2, C79.81, C79.82, C81, C82, C83, C84, C85, C86, C88.2-C88.9, C90.3-, C91, C95.10-C95.92, C96	Lymphoma and other cancers



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Engaging Partners and Communities

TMF Quality Innovation Network-Quality Improvement Organization



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Partnership for Community Health – El Paso, Texas Community



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Facilitated Conversation: Coordination of Care Barriers

Creative Brainstorming

- Discharge follow-up to ensure primary care physician follow-up
- Communication find the right contact
- Medication reconciliation
- Transfer of information between providers
- Downstream access to electronic medical records
- Streamline education and make it consistent
- Nurse-to-nurse handoff



Multi-Voting: Coordination of Care Barriers

Top results:

- Need nurse-to-nurse handoff
- Need transfer of information between providers

Identified transfer of information between providers as the main barrier



El Paso Nurse-to-Nurse Handoff Affinity Team: Leadership Organizing Actions

- WE, THE EL PASO NURSE-TO-NURSE HANDOFF AFFINITY TEAM...
- Are organizing with the El Paso community providers...
- To improve patient care coordination
- By having a nurse-to-nurse handoff report at transitions of care to improve the communication standard developed within this group of providers
- In order to reduce avoidable readmissions by 6% and adverse drug events by 2%
- By the end of December 2018

Resource: Originally adapted from a report by Ella Auchincloss, ReThink Health; modified by Kate B. Hilton, ReThink Health © Fannie E. Rippel Foundation, 2016. <u>https://tmfnetworks.org/link?u=39bf5f</u>





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Partnership for Community Health – El Paso, Texas Community Readmission Data



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El Paso Nurse-to-Nurse Handoff Affinity Team: Action Steps



Technical Assistance (TA) The TMF Quality Innovation Network provided TA to help the affinity team review care transition information and make needed updates.

Resources

- The affinity team created the Nurse-to-Nurse Handoff/Transfer Report.
- The Joint Commission released 8 Tips for Highquality Hand-offs. Scan the QR code to download it.





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Refining the Nurse-to-Nurse Handoff/Transfer Report





Nurse-to-Nurse Handoff/Transfer Report

Nurse to Nurse Handoff/Transfer Report

When transferring a patient, this checklist can be used between a patient's current and receiving caregiver. If the facility's process is to send information electronically, this sheet can be used as a checklist for the electronic form. Note: The essential items to send, according to The Joint Commission, are in red.

Handoff Report Nurse:	Reporting Nurse Contact Number:		
Situation Reason for admission to facility:	Patient Name: DOB: Date: Facility Name: Unit: Attending Physician: Consultants: Dates of Hospitalization: Influenza Vaccine Received: □ Yes □ No Date:	Patient Name:	DOB:
	Admitting Diagnoss:History of Present Riness: Discharge Diagnosis:Discharge Physician: Choose Mode of Discharge Transportation to Home/SNF/LTAC: \Cited Self Claregiver Clambulance	Assessment miness and Severity	Date of Most Recent V/S: Temp: BP HR: O2 Sat : D/C Weight: Pain Rating: □ Pain Site: □ Pain Med/Last Dose: Pain KX Sent? □ Yes □ No. Phermacy: Last Blood Sugar Results: Cardiac Rhythm: Current Eden Heinipigia: □ Yes □ No. Side Affected: Lung Sounds Bladder Incontinence: Follow: Free Tool Incontinence: D
Background	Age: C Male C Female Language: Communication Needs: Past Medical History: C Ansiety D Anticoagulant/Reason: C AriB C DVT/PE Mech Valve D Low EF: Current Coumadin Dose: Last PT INR Result: Next PT INR Due: Physician Ordering PT INR: C DVT/PE History of: C Arthritis D Asthma C VA D Alzheimer's D CAD C Cancer: Type: D CHF C Chronic Pain C COPD C CKD D Defibrillator D Dementis D Depression E Diabetes E fall Risk D GERD = Hypertension D Dialysis: D CHF C Arthyre: D Osteoporosis D Pacemaker D Seizures D Liver Disease Surgical Location: Surgeon: Advanced Directives: D Yes D No Code Status: D Full Code D DNR Bionact Diseasiar Contact:		Ostomy Date of Last BM: D Bowel Sounds D Normal D Hyper D Hypor Mental Status: D Alert D Disoriented D XI D X2 D X3 D Agitated D Forgetful D Comatose Diet Consistency: P Fund Restr Eats: D Self D With Assistance D Difficulty Swallowing D Aspiration Precautions Tube Feeding Product: Cc/every hours D Sale D G-Tube D J-Tube Date Inserted: * Free Water Bolus cc Infection: D MISA D E-Coli D C-Diff D VISA D Hep C D Steph D VRE D HIV D Other: Isolation Precautions: D Yes D No D PICC D PICC Measur D Ports Cath Accessed Date: C Heplock D CVL TPH D Yes D No D IP Drain D Penre Skin Care: D No Skin Breakdown D Pressure Ulcer Stage: Location: D V D Wound Vac Rate: mm/Hg D Intermittent D Continuous D Foam Color: Date Last Wound Care Orders D Sent Last Wound Care Note D Supples: D Scharge Condition: D V
		Recommendations To-Do Action List	DME Needed: D Hospital Bed □ Bariatric Bed □ W/C □ Walker □ Suction Setup □ Nebulizer □ Mode: □ AC □ IMV □ C-Pap Rate: TV Pi02: PS PEEP: □ □ Bi-Pap Settings: Oxygen Liters/Min:



2 Pressure Ulcer Stage:	Location:			- Wour	d Care Orders
C Wound Vac Rate:	mm/Hg I Int	ermittent Continuo	us 🗆 Foam Ci	olor:	
Date Last Wound Vac Dressing Changed		Dischi	arge Conditio	n:	
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Disent Wound Care Orders Disent Last	Wound Care /	eote Li supplies:			
			Kon unseren a	to the set	0200002002000
DME Needed: D Hospital Bed D Bariatric	Bed D W/C C	Walker © Suction Se	tup 🗆 Nebuli	ter D Ver	tilator Settings
Mode: © AC © IMV © C-Pap Rate:	TV:	FIO2		PS:	
					T Nacal Canoula
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C Pain Site: Pharmacy. Current Edema Status: Lung Sounds:

C Fluid Restriction

Other: D PICC Measurements:

hours 🗆 Salem Sump 🖾 Kaofeed cc every

E Bowel Incontinen

End Date

Source: TMF Quality Innovation Network, Nurse to Nurse Handoff/Transfer Request, retrieved online at https://tmfnetworks.org/link?u=fc977a on 2/7/2024

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Care Coordination during the Pandemic – El Paso Community



El Paso COVID-19 Capabilities Assessment

In an effort to support and help facilitate care coordination communication for our El Paso COVID-19 Care Coordination Collaborative, please complete the assessment in order to ensure the information is up-to-date and accurate.

TMF will collect these updates and distribute them to the members of the El Paso COVID-19 Care Coordination Collaborative.

Thank you!



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El Paso Nurse-to-Nurse Handoff Affinity Team: Next Steps



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Conclusion





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