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Modeling the Factors That Drive the Need for Inter-Facility Transfers to Downstream Services in US Emergency Departments:
The Case of Heart Attack Patients

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ABSTRACT

Improving emergency department (ED) care coordination requires analytics-based models that can integrate large patient-level and hospital databases to help formulate better transfer processes and policies across different hospital settings. This study develops a new empirical model to analyze over one million heart attack emergency department (ED) encounters between 2006-2014 to understand the factors that drive the need for inter-facility transfers (IFT) in different hospital settings. The resulting model has proven helpful for deriving public policy insights from this information. For instance, while we find that while healthcare IFT inequities and inconsistencies persist with ED discharge decisions because of some specific patient and hospital resource factors, these have been reduced significantly in the more recent post-reform period. We conclude by discussing the implications of using this empirical modeling approach for developing smarter policies and procedures for managing and benchmarking downstream healthcare operations practices in this disease area.

KEYWORDS

coordinated care, emergency department, healthcare models, healthcare operations, heart attack, Hospital data, patient data, smart care, standardized care, transfers

INTRODUCTION

Delivering equitable healthcare at sustainable costs is one of the most pressing economic challenges currently facing the US system. Consequently, leveraging big data with advanced computerized decision support and technology solutions provides a unique opportunity to assist medical professionals in delivering both intelligent and efficient patient-level decision-making policies. In this paper, we attempt to consider one such opportunity: US heart attack patients entering the hospital system via the emergency room. The failure to provide consistent treatment for different patient groups has

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long been a serious concern for those studying the US healthcare system. Accordingly, some of the primary motivations of the 2010 Affordable Care Act (ACA) legislation were to expand patient care and standardize healthcare delivery practices (US Department of Health & Human Services, 2018). One crucial area where procedural differences may be witnessed is in the emergency department (ED) discharge setting related to the inter-facility transfers (IFT) of heart attack patients. Acute myocardial infarction (AMI) – or a "heart attack" – is one of many high-transfer-rate medical conditions (Kindermann et al. 2015) where decisions at ED discharge can have important implications for health outcomes. During the patient encounter, providers must quickly gather and process information to determine if the ED heart attack patient requires admission to the hospital or if the patient (or hospital) would be better served by an inter-facility transfer (IFT) between hospitals, dedicated nursing facilities, and/or primary or secondary support centers for different types of downstream cardiac care (Joseph et al. 2020). Because heart-attack cases often involve multiple care decisions at both the time of admission and after ED discharge, the procedures involved in coordinating heart attack care have been considered extensively by both healthcare (e.g., Currie et al. 2016; Ward et al. 2016; Kindermann et al. 2015) and operations management scholars (e.g., Youn et al. 2022, Lu and Lu, 2017; Theokary and Ren, 2011). Yet, empirical analysis of the discharge decision-making process and the impact of recent government and industry reform on ongoing coordination of care in the ED remains unclear (Dobrzykowski 2019).

Given the complexity of diagnosis and multi-step treatment required in EDs for heart attack cases, it is expected that modeling the decision-making processes in this area would rarely conform to a fixed array of treatment guidelines and procedures and would be highly prone to process workarounds depending on the surrounding environment (Tucker et al. 2014). This fact has also been clear from both the data and resulting analyses. For instance, some non-clinical factors such as the time of patient arrival at a hospital (Anderson et al. 2014), patient payer status with insurance (Ward et al. 2016; Kindermann et al. 2015; Spencer et al. 2013), hospital ownership status (Ding, 2014), government regulations (Ho et al. 2017), local population density (Jarman et al. 2016), and patient income (Hisam et al. 2016) have been found to affect healthcare clinical processes, outcomes, and costs in different ways for different groups of patients. Recent healthcare research studying operations has advocated for standardizing process routines to avoid workarounds, emphasizing the need for metrics to manage the multiple dimensions of conformance and experiential quality (e.g., Smith et al. 2022; Senot et al. 2016). Yet, wide differences observed in the discharge practices for patients facing similar medical conditions, particularly within similar ED settings, would appear to undermine these efforts.

Heart attack care and treatment will also involve intrinsically time-sensitive procedures for the ED provider. Policies for a heart attack patient IFT can vary widely because of resource availability and specialist access, so healthcare providers may not have the available resources (technology) or ED capacity to care adequately for some patients. In such cases, the patient may be transferred to another acute care hospital (Kindermann et al. 2015) or a focused rehabilitation facility for follow-up (or downstream) care (Dobrzykowski 2019). Yet, the effective coordination of downstream care (involving IFTs) has many benefits for heart attack patients – including better patient outcomes and lower long-term hospital costs (Jacobs, 2016; Sandhoff et al. 2008). Among 266 patients transferred to a cardiac rehabilitation facility (Sandoff et al. 2008), ED annual readmission rates were 30% below the benchmark, netting an effective annual hospital network cost savings of approximately $12M. Heart attack research studies suggest that more proactive follow-up and aggressive cardiac care treatment after discharge can also lead to better patient outcomes and cost savings (e.g., Currie et al. 2016; McClellan, 2011; Sandhoff et al. 2008), but it also notes that ED decision-making in this area is prone to inconsistent practices because of extensive patient and hospital heterogeneity.

At the same time, US healthcare policy reform has introduced many incentives for hospitals to reduce readmission rates and related costs. For example, the ACA has driven a significant increase in the number of insured patients and, perhaps more significantly, the number of ED patients insured under the Medicaid program. Medicaid and Medicare reimburse hospitals at a lower payment-to-cost ratio than private insurance (American Hospital Association, 2016). However, the ACA introduced additional financial incentives in 2013 for hospitals to reduce readmission rates through the Center for Medicare and Medicaid Services (CMS) Hospital Readmissions Reduction Program (HRRP). This program ties reimbursement rates to the patient populations served and clinical and experiential quality measures. Even though this type of reform should provide an incentive to coordinate downstream care, penalties for poor performance are capped, and as many as two-thirds of hospitals still incur a penalty for readmission under the program. Presumably, this is because they find HRRP noncompliance to be in their best short-term economic interest (Zhang et al. 2016).

This large-scale, exploratory study aims to develop and test a predictive model for downstream patient transfers in the ED that incorporates individual patient clinical and non-clinical data as well as surrounding environmental data from when and where the patient encounter takes place. As such, the model will include broad factors such as patient payer status, individual patient health conditions, and the ED/hospital resource setting. This model is then used to examine over 1 million AMI-related ED encounters culled from the National Emergency Department Sample (NEDS) across two periods of healthcare policy reform. Finally, we discuss the implications of these initial findings for using the model and data to develop smarter healthcare policies and clinical process designs.

PATIENT AND RESOURCE FACTORS PROMOTING DIFFERENT IFT DECISIONS

One decision providers must make with each AMI-related patient arriving at an ED is admitting, discharging, or initiating an IFT. Three potential drivers of this decision for each patient are the patient's health at arrival, the hospital status and capabilities of the ED accessed by the patient, and the patient's ability to pay for follow-up services. While patient health, hospital capability, and remuneration for services may all affect healthcare decision-making related to an IFT, there are few empirical models that simultaneously consider the interpretation of these different dimensions when examining an AMI discharge decision.

Individual Patient Payer Status Factors

Patient payer status in a fee-for-service (FFS) refers to the primary insurance source (if any) that each ED heart attack patient uses to pay for healthcare services. Studies of healthcare practices in FFS environments (Ellimoottil et al. 2014; McClellan, 2011) show that incentives for and against specific courses of treatment in the US healthcare system (in our case, the decision to admit or transfer an AMI patient) constitute a unique principal-agent problem for service reimbursement. Most patients do not understand the complex payment system for US hospitals with both government (Medicare and Medicaid) and private insurance (Reinhardt, 2006), which introduces additional uncertainty around coverage for downstream treatment options that may be available to them both during and after the initial ED service encounter.

For healthcare providers, patient resource constraints may increase the variability and complexity of determining downstream treatments. These challenges include ever-expanding medical procedures, equipment, technology, and information processing requirements. Perhaps this complexity is best demonstrated by diagnosing, treatment planning, coding, billing, payment, and collection processes based on the specific care provided to patients. Most extant health economics literature focuses on medical tasks and outcomes with far less attention paid to the institutional environment that may create "varied and complex reimbursement processes that drive divergent stakeholder incentives, varying use of healthcare protocols and processes, and differing patient outcomes" (Lee et al. 2016, p. 47). In the ideal setting, more efficient procedures should resource the more complex cases, while it would conserve resources when they are not well-used (McClellan, 2011). The reality is that ED decision-making procedures, including those related to IFTs, are not resource-efficient and may be swayed by the financial incentives and insurance attached to each patient (Grant, 2009; Gruber et al. 1999). Uninsured patients, for example, are known for using the ED for primary care (in place of

PCP services). As such, the services they receive often require lower acuity care and likely can be transferred to downstream care facilities. In their cross-sectional study of IFTs in various high-transfer rate conditions, Kindermann et al. (2015) show that patients using private insurance tend to receive IFTs for downstream coordination of care more often than other patients. Powell et al. (2012) similarly warn that the institutional environment (reimbursement structure) can alter the process of physician treatment choices, indirectly affecting how patients are evaluated and treated – leading to additional complexity and revenue management uncertainty. Consequently, payer status may drive both the incentives and resulting variation in hospital caregivers' and administrators' discharge practice data.

Individual Patient Health Factors

Patient health (also referred to as comorbidity) refers to two or more disorders/illnesses co-occurring in the same person, and higher comorbidities are found to be associated with worse health outcomes, more complex clinical management, and increased healthcare costs (Valderas et al. 2009). A key challenge in emergency healthcare is dealing with patients that suffer from multimorbidity issues because ED systems are primarily designed under a "single disease" framework for handling different treatment and discharge options (Doessing and Burau, 2015). This additional complexity would make procedures for single disease treatment in a rehabilitation facility less likely and should tend to favor hospital admission over an IFT for a heart attack patient.

Patient comorbidity scores are tightly linked with patient frailty and severity of condition, reflecting complicating risk factors associated with a heart attack patient's complete health profile (Housley et al. 2015), and these "frail" patients will require a higher level of acute services, so they will be less likely to be transferred to facilities that offer lower levels of care. Complete patient health profiles can best be constructed from measurement models incorporating a full range of patient risk factors, including age, gender, and comprehensive comorbidity scores. Nevertheless, interpretation of these profiles is not always straightforward for heart attack patient ED encounters and discharge dispositions. In the case of gender, for example, men are more likely than women to have a first-time heart attack, but women are more likely to have more severe consequences or complicating risk factors from those heart attacks than men (Becker, 2005). This would presumably make them more likely to be admitted than discharged to a lower-level condition-specific facility. Patients with more complicated health conditions are more likely to have complications requiring them to be admitted directly to the hospital rather than receive an IFT. For example, Canto et al. (2011) find that older patients or those with higher comorbidity scores from complicating factors are at greater risk of having more severe or repeat heart attacks. Because several risk factors help determine heart attack severity and ongoing health problems, it is uncommon for even first-time AMI to occur without other patient health issues (Canto et al. 2011). Given the research on heart attack care practices and health, patient comorbidity would be negatively associated with heart attack patient IFTs in these cases, so it would need to be directly incorporated into any analytics-based model.

ED or Hospital Resource Access Factors

Resource munificence (versus scarcity) refers to the service resource bundle available in the hospital setting (system) where a heart attack patient ED encounter takes place. Trauma and Teaching facilities are less likely to transfer (IFT) because they have the resources to coordinate care internally. These characteristics determine the hospital resources available to patients, including the hospital's trauma-level status, teaching status, and the ED and hospital location (e.g., rural location).

Hospitals operate with heavy institutional pressures that originate from external forces (e.g., regulatory agencies, competition, high levels of environmental uncertainty) and internal forces (e.g., the hospital's stakeholders, its professional staff, and service providers) to manage their available resources. The pressure of complying with the competing demands of stakeholders, regulation, and the government may result in different "hospitals implementing workarounds that may have detrimental effects on the overall quality of care offered to the patients" (Bhakoo and Choi, 2013, p.446). While the cost of doing business for EDs is increasing as hospitals spend more on compliance-related technology and specialized physician equipment (Ding et al. 2020, Brown et al. 2012), primary acute care facilities may have fewer available resources to treat patients. Alternatively, highly-rated trauma care EDs (e.g., Trauma 1-3) have higher patient volumes but tend to be specialized and resourced in specific procedures (Ding et al. 2020, Nathens et al. 2004). Consequently, these hospitals should be less likely to IFT heart attack patients to another ED because the resource bundles that they need to coordinate downstream care effectively are already in place.

In addition, EDs in teaching hospitals may offer a more specialized service mix that makes them capable of providing more aggressive and effective ongoing treatment options internally (Ding et al. 2020). Currie et al. (2016) find that hospitals offering the most aggressive and clinically responsive practice styles were staffed by younger doctors who had graduated from "top-20" medical schools (p.72). These hospitals may also offer greater clinical flexibility in their treatment options, which has been shown to benefit cardiac patients positively (Nair et al. 2013). These hospitals may also just be more effective at optimizing their internal resources. For example, Doyle et al. (2010) find that physicians working in more highly-ranked medical institutions achieve the exact medical outcomes, on average, but at 15-20% lower cost because they are more effective at diagnostic testing and avoid ordering unnecessary services. Since teaching and research hospitals also tend to be more specialized and have better-trained physicians, EDs will be less likely to seek out a provider outside the hospital to provide ongoing care for their patients.

Finally, data from the Centers for Disease Control suggest that regional and location factors may affect the differences in care seen in the ED decision-making process for heart attack patients (www.cdc.gov/heartdisease/facts.htm, accessed 2/11/2023). Rural patients have less access to local medical care resources overall, which should favor IFTs over facilities with more resources available to handle such patients. Studies also show less concentration on hospitals and healthcare services in less-populated parts of the US, so there may be fewer local options for patients to receive IFTs in these areas (e.g., Cutler et al. 2013).

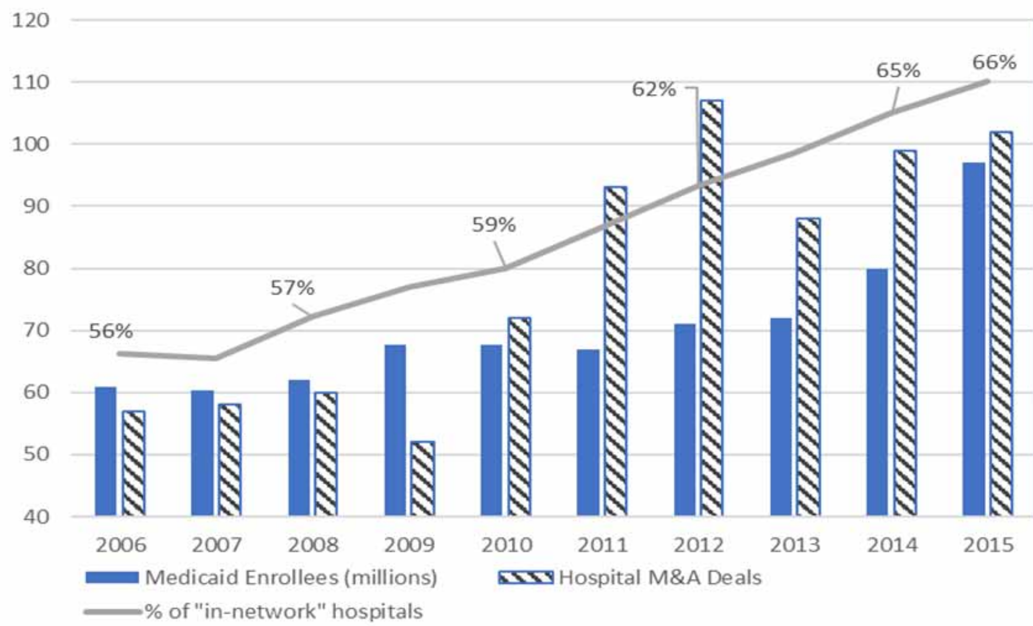
Industry and Policy Reform Factors

Healthcare reforms in the US under the ACA have affected hospitals in essential areas that may relate to ED IFTs for different patient groups, and these must be incorporated into any health model to derive meaningful analysis. While aggregate payment-to-cost ratios for both Medicare and Medicaid pay types have remained relatively flat at 90%, there has been a substantial increase in the number of total patients receiving Medicaid under the ACA (AHA Chartbook 2016, Chart 4.6 and 4.7). This has increased a hospital's cost of doing business and indirectly encouraged consolidation by forcing hospitals to find new ways to reduce costs and their negotiating clout (Brown et al. 2012). At the same time, the accountable care organization (ACO) model embedded in these reforms has simultaneously encouraged a great deal of consolidation into different hospital network formations that may help facilitate the coordination of varying levels of care. As Figure 1 shows, hospitals have consolidated recently into more extensive hospital networks during the study time period, as the overall proportion of Medicaid patients has expanded.

More recent trends towards consolidated and in-network structures should have made hospitals more efficient and integrated with their operational procedures for heart attack patients. The consolidation and rise in the number of in-network hospitals triggered by government policy may also profoundly impact the role that financial incentives, patient health profiles, and hospital capabilities have historically had for heart attack patient care. By increasing the transparency of payments and insurance, along with a new emphasis on standardized care procedures, these ACA reforms and hospital consolidations may have influenced ED care transitions. The ACA was passed in 2010, but most provisions of the reform, including penalties for readmission and Medicaid expansion, were not implemented fully until the 2013-2014 period in our study analysis. While a great deal of this research has focused on the impact of reforms on the cost structure of the US hospital industry, our

Figure 1. Simultaneous Growth Trends in Medicaid Enrollees (in millions), M&A Deals, and Percentage of Hospitals within a Larger Hospital Network (2006-2015)

Data Source(s) for Figure: Centers for Medicare & Medicaid Services (CMS), Office of the Actuary 2015 and American Hospital Association Chartbook 2016, Supplementary Data Appendices 1 & 2.



model examines if these reforms have had a material effect on ED IFT practices for different groups of heart attack patients.

The increase in hospital consolidations triggered by regulation and reform may also provide some benefits concerning offering follow-up care for a more significant number of heart attack patients. For example, Birkmeyer et al. (2002) find that consolidation can improve surgical outcomes because the higher patient volume increases the need for specialization. There has been a trend for many health systems to create a "hub and spoke" system between community and specialized centers of care to reduce costs through additional scale and provide improved access to different types of care (Weeks, 2015; Cutler and Scott Morton, 2013). Overall, research suggests that the structure of external markets and internal hospital capabilities all influence IFTs for heart attack patients in different settings. Considering the rising proportion of Medicaid and Medicare heart attack patients, some hospitals may neither have the resources nor the cost structure to support the ongoing treatment of these patients effectively. Likewise, stand-alone and rural hospitals have increasingly become part of multi-hospital systems in recent years (AHA 2022, https://www.aha.org/research/rc/stat-studies/fast-facts.shtml, accessed 2/12/2023).

DATA AND MODEL VARIABLES

The data used to construct and validate our model comes from the Nationwide Emergency Department Sample (NEDS), which is part of the Healthcare Cost and Utilization Project (HCUP) sponsored by the Agency for Healthcare Research and Quality (AHRQ). NEDS is the largest all-payer ED database that is publicly available in the United States and offers comprehensive data on approximately 30 million annual emergency department (ED) visits from approximately 945 separate hospitals in 33 states and the District of Columbia for each year between 2006 and 2014. The patient file contains demographic and health information on individual patients, diagnosis and treatment codes, charges, and expected payment source. The hospital file contains information on the trauma level, urban-rural location status, teaching status, ownership, and region of each ED's hospital affiliation.

Using diagnosis codes from the International Statistical Classification of Diseases and Related Health Problems (ICD-9) that provide the reasons for ED visits and hospitalizations, we limited specific ED patient observations to those having a first-listed (DX1) diagnosis code beginning with "410" which indicates that the primary patient diagnosis is for an acute myocardial infarction (AMI), commonly referred to as a heart attack. Using this technique and R software, we captured 10,085,441 initial AMI-related observations over the nine-year study period, which contain patient-level information, including discharge codes related to individual patient admissions and transfers.

The outcome measure of interest is a *transfer,* a dichotomous variable indicating that the patient received an IFT to another intermediate care facility, skilled nursing facility, cardiac-specific care center, or rehabilitation facility (short-term hospital) at discharge. Several patient discharge codes are captured in the NEDS database (including admission to the same hospital as the ED visit, being transferred to another hospital, patient dying in the ED, patient being treated and released, patient leaving against medical advice, patient being assigned to home healthcare, and destination unknown for patient) so that only those patient discharge codes pertaining to an IFT or hospital admission are considered in our analysis. The resulting final sample size identifies 1,038,298 total individual heart attack patient-level observations used in this analysis. For each identified patient, we can capture complete descriptive data on payer status (patient payment source file) and from the attending hospitals for each ED encounter (hospital file), as well as clinical data about each individual patient (patient health file).

The consolidated patient file containing insurance status for each patient was categorized into four distinct groups identified for each ED patient encounter – Private-pay insurance (including HMOs), Medicaid, Medicare, and Uninsured or "Self-pay" (which includes uninsured or patients who choose to pay out-of-pocket). ED patients listed as "other" or unknown insurance status are typically excluded from any calculation involving payer status (Ward et al. 2016). The *comorbidity* measure is developed using the "medicalrisk" package in R (McCormick and Joseph, 2016) to generate a measure for each patient based on the ICD-9-CM codes captured in our dataset using the revised Charlson weights developed by Schneeweiss (Schneeweiss et al. 2003) to generate a final comorbidity index number for each patient for each year. We then linked the data from the patient files to the corresponding ED organizational file to construct our transfer model. Additional details on the definition, transformation, and operationalization of the model variables are documented in Table 1, and descriptive statistics of each model variable are reported in Table 2a-b.

MODELING APPROACH AND RESULTING EMPIRICAL ANALYSES

One concern with the IFT decision modeling was eliminating any endogenous, confounding, or omitted factors that could contribute to the variation in patient IFTs observed in the ED discharge decision. Because the dependent variable transfer in this model is binary and represents less than 20% of the total volume of AMI patients, we apply an odds-ratio logic to interpret all the empirical analyses (e.g., Joseph et al. 2020; Ward et al. 2016). Therefore, we fit our basic model using the logistic maximum likelihood function in summary form:

$$\eta_{ikt} = \ln\left(\frac{p_i}{1-p_i}\right) = \beta_1 payer_i + \beta_2 health_i + \beta_{(3..5)} access_{ik} + \gamma_1 Z_{ikt} + \gamma_2 T_t^{yr} + \gamma_2 T_t^{qtr} + \varepsilon_{ikt}$$

Table 1. NEDS database transformations and model variables

Variable	Definition	Operationalization, *NEDS database source file.*	Units
Outcome			
Transfer (IFT)	Indicator of a ED inter-facility transfer (IFT) to an external provider –non-acute care hospital, dedicated nursing facility, and/ or primary or secondary support center	Removed observations with ED outcomes labeled as routine, home health care, against medical advice, died in ED, discharged/transferred to court/law enforcement, and not admitted to this hospital, destination unknown. Outcomes identified as transfer to short-term hospital and transfer other: includes skilled nursing facility (SNF), intermediate care facility (ICF), and another type of facility were considered 1 and those admitted labeled 0. *Patient file.*	Admit=0; Transfer=1
Patient payer status			
Paytype	Insurance coverage of patient (categorical variable)	Observations labeled "NA," and "Other" were replaced with missing values. *Patient file.*	Private (including HMO), Medicaid, Medicare, Self-pay (Uninsured)
Patient health			
Comorbidity	Measure of the overall health indicator for patient using the Charlson comorbidity index scoring system	ICD codes are presented as a string where the first letter is "P" or "D" depending on whether the code is Procedure or Diagnosis. The rest of the code is present as a string of numbers. Diagnostic codes (up to 15 per patient) are assigned to categories of diseases/conditions with "weights" assigned to each, and the score is the sum of these weights. *Patient file.*	Index ranges from a score of 1 (single disease) to 20 (very sick, 20 other multimorbidity codes)
ED or affiliated hospital resource setting			
Trauma	Indicator of ED's status as a trauma center (I,II,III)	Selected all ED's from NEDS variable [hosp_trauma] having indication as a Trauma I, II, or III level center. *Hospital file.*	[0,1=trauma I, II, III]
Teaching	Indicator of ED's hospital teaching status	NEDS indicator [hosp_ur_teaching] transformed into single variable indicating hospital teaching status, regardless of metro/non-metro classification. *Hospital file.*	[0,1=teaching]
Rural	Indicator of hospital location (rural) status	NEDS indicator [ur_cat4]; Collapse all categories not designated as "micro" as value=0, then linked "micro" indicator to "non-metro" indicator in variable [hosp_ur_teach] to indicate ED was in "rural" area. *Hospital file.*	[0,1=rural]
Control variables			
Age	Patient age	NEDS code = [age]; changed misspecifications of age (e.g., -66; -99) to missing values. *Patient file.*	Age in years 0-121
Gender	Patient gender	NEDS code = [female]; changed "NA" to missing values. *Patient file.*	[0=Male; 1=Female]
Income	Patient income as indicated by zip code	Reverse coded quartile indicator [v15] to create a (1-4) variable indicator for patient income. *Patient file.*	1-bottom quartile household income zip codes….4-top quartile of household income zip codes
Charges	Total charges incurred for patient ED visit until discharge	NEDS code = [charges], *Patient file.*	Dollars ($)
Offtime	Indicator of whether the patient arrived at the ED during weekday hours or weekend hours	NEDS indicator [aweekend] transformed into a dichotomous variable to indicate "offtime," *Patient file.*	[0=weekday;1=weekend]
Ownership_ private	Indicator of hospital ownership	Transformed variable [hosp_control]; collapsed all private hospital indicators into a single indicator variable "private-ownership." *Hospital file.*	[0=public/govt; 1=private/nonprofit]
Region	Indicator of the region where the patient visit took place	Dummy code for hospital region; NEDS code = [hosp_region]. *Hospital file.*	Midwest, South, Northeast, West
Quarter	Indicator of which time of year ED visit took place	Dummy code for time of year (quarter); NEDS code = [dqtr]. *Hospital file.*	QTR 1, QTR 2, QTR 3, QTR 4
Year	Indicator of the year in which ED visit took place	Dummy code for year; NEDS code = [year.x], *Hospital file.*	2006-2014

Table 2a. Tables showing ED AMI-related patient ED visits, transfers, and paytypes (2006-2014)

	2006	2007	2008	2009	2010	2011	2012	2013	2014	Total
AMI-related ED visits	112,387	112,103	119,481	113,300	114,615	113,429	116,809	116,329	119,845	**1,038,298**
Transfers (IFTs)	12,982	14,429	15,018	14,612	14,875	16,821	16,042	16,230	17,532	**138,541**
Payer Status Total	*108,698*	*108,341*	*115,722*	*109,545*	*110,625*	*109,216*	*112,323*	*111,683*	*115,687*	***1,001,842***
Private	31,681	31,102	33,175	30,775	29,610	28,910	28,271	28,343	29,802	**271,669**
	29.2%	*28.7%*	*28.7%*	*28.1%*	*26.8%*	*26.5%*	*25.2%*	*25.4%*	*25.8%*	
Medicaid	5,261	5,917	6,591	6,909	7,571	7,187	8,072	7,700	11,306	**66,514**
	4.8%	*5.5%*	*5.5%*	*6.3%*	*6.8%*	*6.6%*	*7.2%*	*6.9%*	*9.8%*	
Medicare	65,339	64,278	68,535	64,486	64,977	65,603	67,467	67,122	68,378	**596,185**
	60.1%	*59.3%*	*59.3%*	*58.9%*	*58.7%*	*60.0%*	*60.1%*	*60.1%*	*59.1%*	
Uninsured	6,417	7,044	7,421	7,375	8,467	7,516	8,515	8,518	6,201	**67,474**
	5.9%	*6.5%*	*6.4%*	*6.7%*	*7.6%*	*6.8%*	*6.9%*	*7.6%*	*5.3%*	

Source: National Emergency Department Sample (NEDS) Patient File Database
Note: Paytype group "other" is excluded from analysis

Table 2b. Tables showing ED AMI-related patient ED visits, transfers, and paytypes (2006-2014)

	Obs	Mean	Std. Dev.	<25%	>75%
Comorbidity	1,038,298	11.07	7	2	17
Age	1,038,051	67.6	14.6	57	80
Charges	1,038,298	$34,929	$17,314	$16,538	$51,410
(0,1) variables		***nontrauma***	***trauma***		
Trauma	1,038,298	696,824	341,474		
		67.1%	32.9%		
		non-teaching	***teaching***		
Teaching	1,038,298	636,964	401,334		
		61.4%	38.7%		
		more urban	***rural***		
Rural	1,038,298	925,237	113,061		
		89.1%	10.9%		
		male	***female***		
Gender	1,038,011	625,594	412,417		
		60.3%	39.7%		
		hrs-(wk)	***Hrs-(wkend)***		
Offtime	1,038,298	746,607	291,691		
		71.9%	28.1%		

Source: National Emergency Department Sample (NEDS) Database – Patient and Hospital Files

Since individual patient encounters in the NEDS database are nested within unidentified EDs across annual time periods, our modeling approach uses the procedure that Thompson (2011) developed for computing two-way clustered standard error estimates that are robust to potential simultaneous correlation across both firms (EDs) and time. These robust standard errors, in our case, are clustered by ED (*hosp_ed*) and *year* using the *VCE(cluster)* commands in STATA v15, which allows us to generate valid estimates of coefficient terms when the error terms involving both dimensions may not be identically and independently distributed. Since individual patients may be nested within the same ED (*hosp_ed*), standard errors were estimated for each model accounting for all the different ED-year group clusters (ε_{ikt}). While this method does not fully guard against endogeneity or autocorrelation of patient observations within EDs and across time periods, it can be "generalized to any two-dimensional panel data setting," particularly when the clusters of data within the dataset are sufficiently large to conduct this type of estimation (Thompson, 2012, p.2). While endogeneity concerns cannot be completely ruled out, this provides some evidence that the findings have measurement validity. Finally, the results were validated through multiple alternative model specifications, which included probit analysis, classification analysis, and cross-sectional multi-level modeling analysis, which offered similar results to the main logistic analysis (the results of these analyses can be shared upon request).

INITIAL MODEL FINDINGS

We first examine the drivers of discharge IFTs accounting for the control variables of *age*, *gender*, *income*, ED *charges*, *offtime*, *owner_private*, *region*, *quarter*, and *year* and then consider the independent variables pertaining to patient payer status, health, and the hospital ED setting where the patient encounter had occurred. Table 3 reports the odds ratios, chi-squared probabilities, and pseudo R^2 values for the five separate logistic models M1-M5. M1 is the controls-only model, where all individual control factors are statistically significant at the p<0.001 level. M2 is the relative contribution of different *paytype* categories where *Private* insurance is the reference value (payer status); M3 is the relative contribution of comorbidity (patient health); and M4 the relative contribution of the hospital variables for the ED associated with each patient observation (hospital ED setting). M5 is the complete model in which we use all variables to test our hypotheses.

Model 1 (see M1, table 3) is comprised solely of the control variables. The results suggest that *age*, *gender*, *income*, and ED *charges* are all statistically significant at less than p <.001%. Next, we find evidence in M2 and M5 that patient-payer status does seem to influence IFT decisions. For example, compared to the reference *Private*-insured patient group, the odds of a *Medicaid* or *Medicare* patient receiving an IFT decreases by 10.5% ($e^{-0.105}$=0.899, p<.0.001) and merely 3.7% ($e^{-0.037}$=0.963, P<0.10) respectively (M5), even after controlling for patient health, hospital access, and other patient demographic information. One reason for these differences is that heart attack patients with *Private* insurance may be able to take advantage of specialized centers and more comprehensive follow-up treatment after discharge in line with programs designed to improve coordinated care (e.g., Sandoff et al. 2008). For *Uninsured* patients, the odds of being transferred increase by 24.2% ($e^{0.216}$=1.242, p<0.001) versus a patient with *Private* insurance. Compared to all other payer-status patient groups, *Uninsured* ED patients are more likely to receive an IFT than any other payer-status group.

The presence of *comorbidity* – one or more additional diseases/disorders co-occurring with a primary disease/disorder also adds complexity to a diagnosing and treatment position, as it complicates the operational analysis of corresponding procedures. Our analysis in M4 and M5 suggests that patients in poor health (higher comorbidity) increases the odds of being admitted to the hospital. Each point of increase in the patient *comorbidity* index would decrease the odds of an IFT by about 9.5% ($e^{-0.099}$=0.905, p<0.001), regardless of whether all other model variables are included as control variables. As such, *comorbidity* is found to be an independent patient-level clinical variable that is quite insensitive to the impact of other model variables, as patients in poorer health tend always to have lower odds of receiving an IFT, and these odds decrease with higher individual comorbidity scores as expected.

Next, the analysis considers the ED-setting and hospital access factors that may impact the IFT decision for heart attack patients. Specifically, we examine whether an ED patient encounter occurs in a hospital that offers a high-level trauma center, is a teaching hospital, or is in a rural location. The odds of a heart attack patient receiving an IFT decrease significantly if the ED is a higher-level *trauma* center ($e^{-1.346}$=0.260 or ~74%, p<0.001) or a *teaching* hospital ($e^{-2.029}$=0.131 or ~87%, p<0.001). On the other hand, the odds of IFT increase by more than 2 to 1 if the ED is in a rural area ($e^{0.704}$=2.023 over 100%). The results suggest that EDs in areas with less access to some types of care will be more likely to IFT patients to more resource-capable facilities in more urban areas.

Table 3. Impact of Payer status, health condition and ED hospital access variable indicators for emergency department IFTs (2006-2014)

DV=transfer	M1	M2	M3	M4	M5
	Odds ratios	Odds ratios	Odds ratios	Odds ratios	Odds ratios
Payer status indicators					
Private (reference group)					
v. Medicaid		0.665***			0.899***
v. Medicare		0.798***			0.963†
v. Uninsured		1.194***			1.242***
Health condition indicators					
Comorbidity			0.905***		0.905***
Hospital access indicators					
Trauma				0.261***	0.260***
Teaching				0.131***	0.132***
Rural				2.026***	2.023***
Controls					
Age	0.978***	0.982***	0.989***	0.972***	0.984***
Gender	0.880***	0.898***	0.945***	0.857***	0.922***
Income	1.242***	1.267***	1.299***	1.112***	1.557***
Charges	0.999***	0.999*	0.999	0.999***	0.999**
Offtime	1.027***	1.023**	1.020*	1.024**	1.017†
Owner_private	1.528***	1.526***	1.532***	0.464***	0.486***
Regional, qtly, and yrly dummies	Y	Y	Y	Y	Y
Constant	0.431***	0.358**	0.413***	2.106***	1.848***
Prob. > $\chi 2$	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.032	0.036	0.096	0.174	0.230
Obs.	1,014,419	979,388	1,014,419	1,014,419	979,388

†p<0.1; *p<0.05; **p<0.01; ***p<0.001; Robust Standard Errors adjusted 2,696 hosp_ed and 9 year clusters

SAMPLE MODEL APPLICATION: EFFECT OF RECENT INDUSTRY REFORM EFFORTS ON OBSERVED IFT PRACTICES

Using the same procedures and sample used for constructing Model 5 (M5; Table 3), we separated our data set into two distinct groups for analysis based on the specified reform periods (Group 1: pre-ACA reform = 2006-2010) and (Group 2: post-ACA reforms = 2013-2014) to show any effects of government policy and industry reform may have had on heart attack patient IFTs (Table 4). Model 6 in Table 4 reports both the odds ratios and z-scores for the study variables from 2006-2010 (pre-reform) encounters, while Model 7 reports the same results in the years that incorporated most changes in CMS reimbursement policy, Medicaid expansion, and accountable care reforms (2013-2014). Although the odds ratios were generated independently, we also compared significant differences between predictor variables using the 'suest' and 'test' command in STATA v15 to simultaneously compare the parameter coefficients across both model sets (M6 and M7). The simultaneous estimation technique combines the estimation results of two regressions by taking the individual parameter estimates and associated covariance matrices from both model groups, then stores this information into a single parameter vector and simultaneous covariance matrix for the combined dataset (Stata v15 help file, p2651, www.stata.com). When comparing the two reform periods, we find statistically significant differences across *payer* and *rural* location status types (χ^2_{diff}, $p<.05$). Indeed, in M7 (post-reform), we found no statistically significant differences in IFTs between any payment source and *Private* except for *Uninsured* heart attack patients. Moreover, patients arriving at EDs in *rural* locations appear to be less likely to receive an IFT post-reform (χ^2_{diff}, $p<.05$). Overall, our results seem to provide significant evidence that government policy and industry reform have significantly standardized treatment at the point of discharge, at least for heart attack-related patient IFTs. Alternative model robustness checks and a model sensitivity summary are available upon request.

DISCUSSION AND CONCLUSION

The empirical modeling in the paper may be considered within the broader issue of how healthcare information technology can be used to better inform and benchmark field-level healthcare delivery decision-making practices and policy. While patient treatment differences and access to quality care are likely to be present in EDs as they are in the broader US healthcare system (O'Connor and Haley, 2003), a smarter healthcare system should identify new models to benchmark and target these gaps in care to deliver better care at lower costs for a more significant number of patients.

Our basic empirical model and analysis generally confirm earlier findings that non-clinical factors such as payer status incentivize specific IFT decisions. In the case of heart attack patients, for example, the persistent discharge focus on financial over patient health risk seen across different study time periods is a concerning finding since heart attack patient encounters often require multi-step treatments and ongoing coordinated care or rehabilitation to reduce long-term readmission rates (Sandhoff et al. 2008). Moreover, delivering smarter forms of care may require recognizing and tailoring specialized treatment practices using external sources of patient and hospital data that are not always consistent for different hospital types (Ding et al. 2020, Jollis et al. 2016). The data reveals that a driver of some of the IFT differences for this disease population appears to be patient payment source. This result generally validates earlier healthcare research results using cross-sectional data from prior to 2010 (e.g., Ward et al. 2016; Kindermann et al. 2015). However, it also reveals that some inequities persist within the post-ACA healthcare market as payment source differences still have a meaningful predictive impact on driving IFT practices for downstream care in our model.

In addition to patient payment source differences, we find evidence that the ED hospital setting of the initial patient encounter is a primary driver of many IFT decisions. The model reveals how teaching, trauma, and rural status are resource availability indicators that affect the odds of an IFT and further shows potential gaps in follow-up treatment across the healthcare landscape. For example,

Table 4. Pre/Post models showing the potential impact of policy and industry reforms on IFTs for heart attack patients

DV=transfer	M5 [2006-2014] BASELINE	M6 [2006-2010] PRE_REF		M7 [2013-2014] POST_REF	
	Odds Ratios	**Odds ratios**	**z**	**Odds ratios**	**z**
Private (reference)					
v. Medicaid	0.899***	0.863***	-4.31	0.966 +	-0.69
v.Medicare	0.963†	0.926**	-3.11	1.034 +	0.91
v. Uninsured	1.242***	1.296***	6.81	1.229***	4.66
Comorbidity	0.905***	0.906***	-56.24	0.899***	-49.17
Trauma	0.260***	0.277***	-7.88	0.237***	-7.34
Teaching	0.132***	0.136***	-11.29	0.112***	-11.68
Rural	2.023***	2.204***	7.18	1.972*** +	4.47
Age	0.984***	0.981**	-22.46	0.988***	-9.78
Gender	0.922***	0.833**	-9.80	1.004 +	0.36
Income	1.557***	1.133**	4.33	1.156***	3.34
Charges	0.999**	0.999**	-5.60	0.000**	13.96
Offtime	1.017†	1.013	1.19	1.035**	2.08
Owner_private	0.486***	0.529***	-4.54	0.346***	-5.68
Regional, qtly, and yrly dummies	Y	Y	Y	Y	Y
Constant	1.848***	3.075***	6.89	1.908**	2.68
Prob. > $\chi2$	0.000	0.000		0.000	
Pseudo R^2	0.230	0.225		0.261	
Obs.	979,388	540,227		222,171	

†p<0.1; *p<0.05; **p<0.01; ***p<0.001; Robust standard errors adjustment for hosp_ed and year clusters
+ significant difference in underlying model coefficient based on simultaneous estimation "test" comparisons of χ^2 differences (p<.05)

patients arriving at high-level trauma centers or teaching hospitals are far more likely to have access to the resources they need to coordinate their treatment internally, making an IFT less likely overall. Moreover, additional iterations of the model revealed that government-insured (Medicaid or Medicare) patients are likely to receive the same discharge disposition as privately-insured patients across these hospital types. On the other hand, insurance status appears to matter more when the ED encounter occurs in a non-teaching or low-level trauma care hospital, since these facilities may not have the specialization or service mix to coordinate ongoing patient care internally (Ding et al. 2020). Across all the model iterations, we find that the odds that uninsured patients will receive an IFT are about the same across all different ED settings (this additional analysis is available upon request).

Our model identifies a potential opportunity for new research related to rural hospitals and overall patient access to care. Not surprisingly, IFTs are most common in rural locations. However, we have noted that Medicare patients are more likely to be admitted to rural hospitals from the ED than privately insured patients with the same underlying health conditions. Overall, this research suggests that ED discharge practices in rural hospital settings may be motivated by several non-clinical economic, competitive, and location-distance factors that may provide for different structural incentives for many IFT decisions.

Despite these more structural incentives, ACA government healthcare policy and industry efforts appear to have had an impact on the IFT practices for heart attack patients observed in US emergency departments. While healthcare reform efforts have increased the proportion of US heart attack patients using both Medicaid and Medicare, this change has not sufficiently mitigated the degree to which payer status influences discharge practices for this large group of patients. However, a major model finding is that there is a statistically significant reduction based on the payer resource factors used by the model to predict IFTs in the more recent time periods (after most reforms from ACA legislation actually went into practice). This fact, coupled with the rise in the overall number of Medicaid patients, and the corresponding decrease in the number of uninsured patients in the sample in later time periods, is an encouraging sign for better and more consistent follow-up care. Moreover, we find in our robustness checks using classification analysis that our empirical models are more predictive of IFTs in post-reform implementation (2013-14) periods, which provides some additional empirical evidence that there has been increasing standardization in IFT practices across the different patient groups in our study. As such, the empirical models to benchmark and predict IFTs may become a more practical means to evaluate emergency department practices and performance.

Due to reform efforts, hospitals have increasingly been moving towards an accountable care organization (ACO) and value-based purchasing model that has encouraged consolidation and network formation (Figure 1). In the case of heart attack IFTs, healthcare law and hospital network formation may have created significant second-order effects on patient care and ongoing treatment planning. For instance, heart attack patients arriving at EDs with less specialization or volume (e.g., rural EDs) still have higher odds of being transferred, but the odds have significantly reduced post-reform (Table 4). Related studies have argued that changes to patient mix and payment-to-cost structure are the primary motivation for this trend toward hospital network consolidation (e.g., Weeks, 2015). This research offers some empirical support for that conclusion.

There may be little general competition for downstream skilled healthcare services in many geographical areas, and it is hard to envision any organization or system always having the necessary resources to provide the best follow-up care in all cases. Yet, our findings generally support the proposition from other studies of heart attack care that EDs may tend to develop their own practice styles or routines that are motivated by factors outside of patient health (Currie et al. 2016). Nevertheless, introducing a more extended evaluation period or process friction in the ED may lead to preferred cost outcomes while not sacrificing speed, quality, and standardization (Smith et al. 2022, Berry Jaeker and Tucker 2020). As such, we believe a relevant contribution of our study is providing an analytical means for hospital EDs and hospital networks to benchmark how they make underlying operational decisions for managing IFTs in specific disease management areas (e.g., such as for heart attacks).

Several broad operational policy implications are suggested based on the findings of this paper. Arguably one of the triumphs of recent reform efforts, and found in our analyses, is that more Americans are getting access to insurance-funded heart attack treatment than before the reforms were implemented. This payer access is a net positive for providing more consistent care, for more patients, with fewer treatment gaps and disparities in care. To create more of an accountable performance model for the US healthcare system, we agree with research suggesting that signals and incentives may be too weak in the case of third-party healthcare system reforms in the US (Zhang et al. 2016). The fact that two-thirds of hospitals pay the penalty under HRRP, suggests that the drive for operational efficiencies may be providing incentives for healthcare providers to minimize and manage the wrong risks. Instead of focusing on developing a healthcare system that will maximize healthcare outcomes, we fear the return to a more fee-for-service (FFS) based system based on attracting and providing value and convenience for only patients with preferred payer status. As growth in specialized treatment areas and hospital consolidation continues, there will be a greater need for analyses investigating the IFT procedures for better care coordination between facilities. For example, the increased coordinated care in specialized areas may further drive the need for more IFTs for different disease management and treatment areas. Models like ours that are used to benchmark and monitor the ED's performance in this area should incorporate the heterogeneity in patient health and hospital access conditions, as well as understand the impact that payer status has on the resulting discharge decisions to coordinate and improve the coordination of downstream care. It might also be interesting to see how these models hold up in the post-Covid period, which was a disruptive event to ED processes and operations.

Reform efforts appear to have also led to second-order positive effects towards long-term treatment options that may be difficult to measure and incorporate into models intended to promote care accountability. A movement towards a pay-for-performance care reimbursement system, which may include strategies such as "Bundled Payments" where healthcare providers have flexibility in selecting conditions to bundle and make more flexible the integrated care delivery structure would seem to be a good development for promoting more integrated heart attack treatment across multiple sites.

Since the US healthcare system appears to be experiencing significant regulatory changes and uncertainties regarding the future of reform (Youn et al. 2022; Dobrzykowski 2019), it would be interesting to study how recent policy modifications have influenced care decisions and planning in different disease areas or for different hospital status types. For instance, while we do not consider the differences between private and publicly-owned hospitals associated with the ED, examining how ownership structure reflects coordinated disease management choices would be interesting for future research. Moreover, our findings on IFTs at rural hospital motivates several questions about the long-term profit model and the competitive dynamics underlying decision-making processes for patients in those ED settings. Finally, studying the impact of value-based payment structures on IFT and downstream care performance models, including those for capitated payments and treatments, would be of great interest and value.

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Additional analyses and a statistical appendix for this manuscript are available upon request

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