Title

Condition-Specific Variations in 30-Day Episode Cost and Admission Rates among All-Payer Beneficiaries in Emergency Department

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Condition-Specific Variations in 30-Day Episode Cost and Admission Rates among All-Payer Beneficiaries in Emergency Department

A dissertation submitted in partial satisfaction of the

requirements for the degree of Doctor of Philosophy

in Health Policy and Management

by

Bo Kang

2023

ABSTRACT OF THE DISSERTATION

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by

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Doctor of Philosophy in Health Policy and Management

University of California, Los Angeles, 2023

Professor Jack Needleman, Chair

Introduction: Emergency Department (ED) is an important component of the US healthcare system, but it lacks appropriate usage. To incentivize high value care in ED, transparency of ED utilization is critical as it offers comparability across providers.

Data Source & Study Population: Data sources include the 2018 All-Payer Claims Database in Colorado and American Hospital Association Annual Survey. Study population contains eligible beneficiaries who have received 30-day episodes of care for condition-specific cohorts in 2018.

Methods: We construct the 30-day window and standardize price to estimate ED-level, unadjusted variation in episode cost and hospitalization. We design risk-adjustment model and measures of

expected-to-predicted ratios to capture ED-level variation in cost and hospitalization, which reflects ED practice difference. We conduct an improved signal-to-noise analysis for measures' reliability assessment. ED's pattern consistency and correlation among risk-adjusted measures are examined in descriptive and factor analyses. Lastly, we evaluated the effect of systemic factors on risk-adjusted measures using regression analysis.

Results: For ED-level episode cost and hospitalization, unadjusted variations range from $675 to $4,589 and 1.85% to 32.54% across condition-specific cohorts respectively. Adjusted variations in RAPRs and RAARs range from 11% to 18%, and 15% to 48% respectively. Risk adjustment models explain 20% variations on average in episode cost and hospitalization. Average signal-to-noise ratios of episode cost and hospitalization both surpassed 0.7, indicating good reliability. 43 out of 55 EDs exhibit coherent patterns of care of ED utilization, 12 EDs demonstrate mixed patterns, and the rest do not show explicit patterns. Higher variation in episode cost is associated with freestanding EDs, urban location. Higher hospitalizations are observed for not-for-profit hospital-based EDs, minor teaching responsibilities, and urban location.

Conclusion: Sizeable ED-level variations in episode cost and hospitalization are captured. Patient and systemic factors are partial contributors of these variations. Coherent pattern found in majority of EDs and strong correlation in measures illustrate that EDs incline to maintain similar levels of cost or hospitalization across conditions. This study expands the design of the risk-adjustment measures to all-payer beneficiaries, facilitates the profiling of hospital value in ED care, and provides information enabling hospitals to optimize and coordinate care.

The dissertation of Bo Kang is approved.

Russell G. Buhr

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2023

Dedication

For my grandfather Hongjun Kang, for instilling the value of pursuing ology beyond higher education. For my parents Xiangrong Du and Le Kang for ingraining the belief on the importance of good education, the value of persistence, and resilient attitude when facing life's adversities. For my senior fellow and my dear friend, Dr. Dahai Yue, for being the most helpful academic consultant. For my fiancée , Lulu Chen, for selflessly supporting me all the time and encouraging me every day to become the best version of myself.

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I want to thank the financial support from my university and public-private entities. I am receiving tuition support from the UCLA Dissertation Year Fellowship Program. The study was made possible by publicly available data from the Center For Improving Value In Health Care (CIVHC), who offered the Colorado All-Payer Claim Database at a discounted price. Specifically, I want to acknowledge Peter Sheehan and David Dale, who facilitated the data application and release process. I also bring my sincere thankfulness to the rest of the staff of CIVHC. A complete list of personnel furnishing data for the project is available at https://civhc.org/about-civhc/who-we-are/staff/.

Thanks for the data analysis support from Institute for Digital Research and Education (IDRE), UCLA. Due to the hierarchical structure of data nature and the study's complexity, the data

cleaning, management, and analyzing process consumes a great deal of time and requires advanced technical skills. I greatly appreciate Andy Lin, an experienced supervisor and consultant, who shared his knowledge and strategies to manage datasets and conducted analysis efficiently. His generous assistance encouraged me to enhance my data-analyzing skills to a higher level. I also would like to thank Raffaella D'Auria, a computational scientist from IDRE, who guided me on using Hoffman2 cluster to array my heavy data workload, to solve the challenge of massive calculation.

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Chapter 1 Scope of Dissertation

1.1 Introduction

Emergency Departments (EDs) are significant components of US healthcare. In 2011, there were 136 million visits to Hospital-Based Emergency Departments (HBEDs). It is the most common route to admission; 14% (about 19 million) of patients seen in EDs were admitted (Pines et al., 2016). EDs are also the most prevalent healthcare resources for patients. Nearly 1 in 5 US residents visit the emergency department (ED) annually (Lin et al., 2020). ED also plays a significant share in healthcare expenditure. All stakeholders cite ED care as a vital cost driver, including physicians, policymakers, and the mainstream media. Aggregate ED visit costs totaled $76.3 billion in the United States in 2017, encompassing 144.8 million ED visits with an average cost per visit of $530 (HCUP, 2017).

As a result, skyrocketing costs and large number of ED volume and admissions created the huge economic burden on emergency care. Although ED's are critical providers in the healthcare system, they are often used inappropriately. In general, ED only treat some life-threatening conditions, such as syncope, chest pain, severe bleeding, or dehydration (Conley et al., 2016) and provide unscheduled acute care when primary care physicians are experiencing out-of-work hours or staffing shortage. Nonetheless, past research found that at least 30% of all ED visits in the US are non-urgent (Uscher-Pines et al., 2013). Another study proves visiting the ED instead of another care site for a non-urgent condition may lead to wasteful healthcare spending, unnecessary testing and treatment, and represent a missed opportunity to promote better coordinate care with primary care physicians (Carret et al., 2007). 4.4 billion USD would be saved if non-urgent ED visits were cared for in retail clinics or urgent care centers during the hours these facilities are open. In addition,

44% to 92% admission through ED were avoidable that could be substitute with immediate discharge or transferring to nursing home.

Although emergency physicians discourage non-urgent visits, ensuring appropriate use of emergency care is a challenge for them. They often hesitate to admit ED patients to the hospital, with variations in clinical judgment of the severity and progression of the patient's condition. Variations in clinical decisions results in considerable variations in services patients receive in the ED and subsequent care (Simkins et al., 2021). ED variations also highlight the overuse, underuse, or misuse of ED care. Moreover, EDs are often the priority contact for recently discharged patients presenting for complications or follow-up care from their first admission. Treatment in the EDs will determine if patients are to be readmitted or not. The presentation of a patient at the EDs may also signal weaknesses in the discharge planning at the end of the admission, or breakdown, or weakness in post-discharge services (Vernon et al., 2019). Post-discharge outcomes, such as subsequent visits and return visits to an ED or hospital after an index ED visit, can strain already overburdened EDs and the broader healthcare system. The care patterns may be planned for follow-ups, including monitoring, and evaluating symptoms or disease progression. Still, it may also reflect the barriers to ambulatory services or poor-quality care in the ED. Poor quality outcomes have led policymakers to reconsider prioritizing ED care resources and reducing preventable repeat visits. Accordingly, reducing emergency care for non-urgent condition and correction of judgment on admitted/non-admitted is a critical step for physician to provide high-value ED care. However, there is a prerequisite that ED physicians admit patients for hospitalization or discharge patients to home or other less costly service places only when appropriate follow-up care is established.

In summary, differences in ED patterns may lead to variations in cost and hospitalization rates among EDs when treating the same disease. What factors contribute to variation in ED utilization remain answered. To better understand the ED patterns on cost and admission rate and towards high-value care, a critical step is to provide transparency of cost and admission of care that is comparable across providers, and to track the potential contributors of variation in cost and admission from patient and provider perspectives.

1.2 Background

1.2.1 ED Utilization: Visits, Hospitalization, and Cost

Emergency departments (EDs) are a significant source of medical care in the United States. Medical resources, including over 57,000 ED physicians, 18,000 ED nurses, and 15,276 ambulatory services, served over 130 million ED visits in 2011(Weiss et al., 2006). ED utilization is increasing yearly. National Hospital Ambulatory Medical Care Survey (NHMACS) found that the total ED visits rose from 136.9 million in 2015 to 145.6 million in 2016 and reached 150 million in 2017 (Simon et al., 2019; Venkatesh et al., 2017). One major factor contributing to ED volumes is the growing number of admissions originating in EDs. From 1993 to 2006, the proportion of hospitalization beginning in EDs increased from 33.5% to 43.8%, with more than 17 million admissions annually (Leyenaar et al., 2016). Consequently, the ED-related cost increased with the rising trend of hospitalization originating in EDs. Center for Medicare and Medicaid Service (CMS) also reports that ED admission has become the largest share of healthcare expenditure, accounting for 30% of 2.7 trillion in US healthcare spending from 2011(Studnicki et al., 2012).

1.2.2 Evidence of Variation in ED

The rising trend in variation of ED admission rate has gradually become hospitals' major concern. The proportion of hospitalized patients admitted through the ED increased from 38.6% in 1999 to 49.7% in 2009 (Venkatesh et al., 2017). The cross-sectional study by Moore & Liang (2006) used data from three EDs within the same health system to estimate their variations in hospitalization. It is found that the hospital and physician-level admission rates vary from 27% to 41%, respectively(Moore & Liang, 2006). Similar patterns of variation were also observed in ED cost. In an analysis using Medicare administrative data from 2,707 US hospitals, the HBEDs cost varied between 1.0 and 12.6 times (Moore & Liang, 2006). This finding illustrated that patients visiting different EDs can receive varying charges for similar care. Moreover, ED charges could vary within each acuity level (99281-5) that is classified by intensity of service required for treatment. Huan et al.(2020) found that charges for each ED level visit varied extensively. They found charges of level 2 ED visits ranged from $156 to $1,422; level 3, from $266 to $3,130; and level 4, from $275 to $6,662. This huge difference in charges observed for each ED-level is likely due to the role organizational factors played in incurring cost.

Sizeable variations in ED utilization were observed in certain conditions. An official report documented by the American College of Emergency Physicians (Moore & Liang, 2006) described twofold to threefold overall rates of ED admission variations in chest pain, trauma, and pneumonia visits. Sabbatini et al.(2014) measured variation of admission rates using interquartile range (IQR) ranging from 1.03 for sepsis to 6.55 times for chest pain across EDs from 964 hospitals. Condition-specific variations were detected even in observation medicine. AUCM found significant variability (IQR) in observation rates for syncope (36.4%, 68.1 %), chest pain (37.9%, 69.1%),

abdominal pain (14.3%, 35.7%), and altered mental status (53.3%, 85.1%) (Pines et al., 2016). Although these variations were reduced to around 15% with risk adjustment methodology, the remaining variations reflect substantial difference in ED treatment decisions and the patterns of care for the same condition(Pines et al., 2016).

The manifestation of wide variation not only revealed differences in the pattern of care but also helped stakeholders identify the clinical conditions with significant variation in emergency care. With growing academic interest in ED variation, current research has expanded the scope of interest and concentrated on variations in targeted condition-specific diseases. Smulowitz et al.(2021), using a national sample of US hospitals, found broad hospital-level variation for mood disorders, chest pain, skin and subcutaneous infections, urinary tract infections, and chronic obstructive pulmonary disease. Venkatesh et.al (2015) analyzed the national emergency dataset (NDED) using clinical classification software to identify 15 commonly admitted diseases in 964 hospitals with the five highest variations in mood disorders (5.8%, 51.8%), nonspecific chest pain (10.7%, 30.1%), skin subcutaneous tissue infections (8.6%, 20.8%), urinary tract infection (11.8%, 23.6%), and chronic obstructive pulmonary (COPD) (22.4%, 46.0%) (Venkatesh et al., 2015). A newer study found the variation of ED admission was higher for patients with cerebrovascular disease, congestive heart failure, and gastrointestinal bleeding than their counterparts with skin and subcutaneous infections, abdominal pain, and other external injuries (Khojah et al., 2017).

As mentioned above, patients with less acute, life-threatening conditions appeared to have a broader ED variation than those admitted for time-sensitive, more severe illnesses. This phenomenon may reflect physicians' uncertainty about appropriate admission decisions, especially

when patients' conditions are less intense and urgent than conditions that satisfy the requirement of hospitalizations. Extensive variations in EDs revealed the inappropriate use of healthcare delivery in emergency service. Therefore, recognizing the cause of variations in ED utilization for specific conditions will improve the efficiency of healthcare assignments and reduce unnecessary costs.

1.2.3 Sources of Variation in ED

1.2.3.1 Patient Factors

In the past two decades, a considerable body of literature has described the association between ED usage and patients' differences in age, gender, insurance status, race/ethnicity, and comorbidities. Duseja et.al(2015) found that female patients, infants younger than one year, seniors at least 85 years old, or uninsured beneficiaries are the majority who frequently visit ED and are admitted to hospital. Insurance status is a critical patient factor that is well-discussed by previous literature. Alexander & Dark(2019), Baehr et al.(2020), and Ballard et.al (2010) found more comorbidities in Medicare beneficiaries, which will increase inpatient resource consumption. On the other hand, the uninsured population could also exhibit high inpatient rates since hospitalization may be associated with lack of timely outpatient follow-up care. Insurance status of Medicare and uninsured were associated with higher admission rates in EDs.

New studies have been using more extensive, systematic datasets with advanced approaches to illustrate that patient factors alone cannot interpret wide variation without considering community resources. Boggs et.al (2022) found that race, ethnicity, and poverty are only associated with high emergency department use in urban regions. In suburban and rural areas, fewer elderly residents and shorter distances to the nearest ED are correlated with increased emergency department use.

1.2.3.2 Hospital Factors

National studies found variations could be driven by the hospitals' locations and surrounding community resources. Many communities only have access to one ED. Hence, the low admission rate could reflect a lack of social or ambulatory services in those communities (Muelleman et al., 2010). A series of studies led by Venkatesh et al. (2015) and Hsuan et al. (Hsuan et al., 2020) documented that hospital-operation factors influence admission decisions from ED more than patients' factors. These factors consist of property type (teaching status, ownership, hospital level), capacity level during the peak times (bed size, observation units, size, and composition of the hospital staffing), expertise (triage, clinical decision-making process, access to technologies for advanced diagnostic and treatment procedures), post-acute care pattern (length of stay, discharge pattern), and physician's treatment preference (risk-aversion, fearing of malpractice, and shift schedule).

Organization variables such as teaching status and ownership, contributed to variations in ED utilization. Pines et al. (2013) found admission rate from teaching, hospital-based ED is 2.5 times in non-teaching. Hospital-Based ED. For-profit hospitals' admission rate is higher than not-for-profit hospitals by a similar ratio. Hospitals with teaching responsibilities usually receive more patients because they have more comprehensive healthcare resources, including but not limited to inpatient beds and other ancillary services that are unavailable in smaller, not-for-profit, non-teaching hospitals (Capp et al., 2014; Pines et al., 2013). For for-profit hospitals, their pursuit of profitability goals will limit or preclude them from serving patients who are unable to pay or from offering needed services that cannot be provided at a profit. Nonetheless, for ED visit and

hospitalization rate originating in ED, there is no statistical difference between for-profit and not-for-profit hospitals (National Academies PressPress, 1986).

Previous studies have found physicians' characteristics associated with variation in healthcare delivery. Pavlova et al. found that physician differences in of experience, gender, language ability were related to variation in ED spending (Chen et al., 2022; Pavlova et al., 2022; Valiuddin et al., 2020). Physicians' preference is also a part of physicians' characteristics. Physicians tend to select patients by preferences in primary care (Baehr et al., 2020; Baker et al., 1994; Joseph & White, 2020; Warner et al., 2018). For example, primary care physicians may choose to see younger, healthier (with fewer comorbidities), with lower acuity measures, and have more defined chief concerns at the end of a shift to simplify patient handoff operation or leave a shift on time (Chang & Obermeyer, 2020). However, this preference in selecting patients will be eliminated in ED where all patients are randomly assigned to on-duty physicians (Chang & Obermeyer, 2020). Therefore, physicians' characteristics are unlikely to influence the variation in ED utilization than systemic factors. Physicians' age is another factor that could influence the ED utilization and outcomes. Patients treated by younger emergency physicians had lower mortality rates compared with those treated by older physicians (Miyawaki et al., 2023).

1.2.4 The Relationship between Hospital-Based Emergency Departments and Freestanding Emergency Departments

While most Emergency Departments are physically part of hospitals and owned and operated by the hospital, some EDs are freestanding, separate physically from a hospital structure, and may be independently owned. The American College of Emergency Physicians (ACEP) defines a

freestanding emergency department (FSED) as a structurally separate facility distinct from an HBED and providing emergency care (Herscovici et al., 2020). Unlike a traditional HBED, this facility provides emergency services to patients who cannot access the hospital. Freestanding emergency departments (FSEDs) have grown rapidly over the past decade. Depending on the state, FSEDs can be operated independently or as part of a hospital system (Gutierrez et al., 2016).

There is a debate over the appropriateness of FSEDs even as their share of ED visits rises. Previous research was concerned that patients could misuse FSEDs as an alternative for cheaper urgent care, or misunderstand FSEDs' insurance network status, thus increasing overall medical cost or patient liability for payment. Such concern motivated researchers and healthcare organizations to seek justification for commonly accepted standards of FSEDs worldwide. Dark et.al (2017) identified 360 FSEDs in 30 US states in 2015. The Medicare Payment Advisory Commissionary reported between 550~600 operating FSEDs as of 2017 (Pines et al., 2018). ACEP, who used 11 national datasets from the National Emergency Department Inventory (NEDI), proposed a more precise, universal definition of FSEDs and successfully identified 669 FSEDs at the end of 2017 (Burke et al., 2019; Simon et al., 2019). The previous literature acknowledges the validity of NEDI-USA definition due to its up-to-date inventory and power to differentiate satellite versus autonomous FSEDs. Among All states in the US, Texas, Ohio, and Colorado account for the largest share of FSEDS (Burke et al., 2019; Pines et al., 2018; Xu & Ho, 2020).

There is a preconception documented by a body of literature that FSEDs could alleviate crowding in HBEDs because they are alternative venues when long waiting is endemic. However, Alexander & Dark(Alexander & Dark, 2019) argued that FSEDs generally treated relatively low-acuity

patients, and those discharged patients have only a minor effect on length of stay and wait times. Previous literature documents patients sometimes prefer FSEDs due to prolonged wait times at HBEDs(Shen & Lee, 2018). FSEDs treat patients faster than HBEDs for all the categories, and the price for care was nearly identical. Therefore, the primary motivations driving patients to FSEDs over HBEDs are door-to-needle time and the distance from home rather than financial reasons.

Comparison analyses between HBEDs and FSEDs have previously been conducted regarding patient characteristics and associated healthcare outcomes. Pines et.al (2018) found significant variation in patients visiting HBEDs and FSEDs in gender, acuity levels, diagnosis, and the number of visits. FSEDs usually have lower admission rates while providing higher patient satisfaction than HBEDs. Moreover, the hospital admission rate was 37% lower overall in FSEDs than in HBEDs. Simon et al.(Simon et al., 2019; G. E. Simon et al., 2018) conducted two studies and found similar results: The odds ratio of admission rates was 20%-30% higher in HBEDs than in FSEDs. Nonetheless, the difference was no longer statistically significant after adjusting confounders of patients' age, gender, health condition types, and acuity level. The impact of comorbidities on ED-utilization between HBEDs and FSEDs remained controversial. The prevalence of patients with high comorbidities admitted from FSEDs was significantly lower than those admitted from HBEDs (Dark et al., 2020; Simon et al., 2019). It is not uncommon that HBEDs have a higher capacity of beds, staffing, and advanced services that cater to the demand for treating more complex diseases. This conclusion gave rise to the assumption that patients being admitted from FSEDs have fewer comorbidities than those being admitted from HBEDs. However, this hypothesis has been challenged by Simon et al.(2018). They found critically ill patients being

treated at FSEDs manifested more complications in diseases than those being treated at HBEDs (E. L. Simon et al., 2018).

1.2.5 Value-Based Payment in ED Utilization

The value-based payment (VBP) model rewards healthcare providers with incentive payments for providing good quality care. It aims to encourage more preventive care and cost-efficient care and reduce rehospitalization(Teisberg et al., 2020). These models often include incentives for providers to have lower costs or lower admission or readmission rates for specific conditions or types of patients. VBP models also include Accountable Care Organizations (ACOs), Alternative Payment Models (APM), also known as Bundled Payment Models, and Hospital readmission reduction programs (HRRP)(Halpern et al., 2017; Medford-Davis et al., 2017). Episode Payment Model (EPM) is a bundled payment model that bundles all services provided within a specific time frame (e.g., 30-day, 60-day., 90-day, etc.) for a single health condition or medical event. It is typically initiated with a referral or admission and ends with a discharge. Under the episodes of care, patient outcomes improvement and cost reduction are achieved simultaneously. Episodes of care offer financial incentives that motivate the entire healthcare process to be more efficient at a lower cost. Meanwhile, by having a single price for all phases of medical services, clinicians can align their work efforts to focus on achieving long-term results, not just aiming for the completion of a single aspect of care (Waddle et al., 2020).

Although the VBP model has been extensively used in primary care and for hospital inpatient care, models suitable for emergency care are limited. ACEP documented two proposals which facilitate the development of VBP applications in emergency medicine. First is the Merit-based Incentive

Payment System Value Pathway (MVP). It is intended to improve patient outcomes and promote value-based care by allowing clinicians to concentrate on existing medicine-specific quality measurements of wide variation in ED utilization and associated cost outcomes(Gettel et al., 2022). Second, ACEP proposed the Acute Unscheduled Care Model (AUCM) framework to embrace the value-based arrangements in Emergency medicine. AUCM provides incentives to safely discharge Medicare beneficiaries from the emergency department (ED), reducing avoidable inpatient admission to the ED and rewarding post-discharge care coordination to drive patient-centric care transformations within the ED. (Luke, 2016). This model was built on episodes of unscheduled acute care provided by emergency physicians. AUCM filled the knowledge gap in ED physicians' contribution to care quality during initial diagnosis, stabilization, and treatment prior to hospitalization.

Existing study on VBP models in emergency medicine is not comprehensive. Analysis of both the MVP proposal and AUCM proposal had strengths and weaknesses. The former evaluated five possible emergency medicine-specific MVPs that address thirty conditions. However, it is focused more on preventive services than an episode of care. The latter used episode-based methodology to assess condition-specific variation in admissions (to inpatient or observation) and cost, whereas it only examined four conditions(Pines et al., 2016). Moreover, whether VBP models could effectively reduce the admission rate originating in ED remains unclear. Robinson et al.(2020) pointed out that MVPs are more sensitive to primary care practice than other specialty practices. ED physicians still face limited opportunities to engage in episode payment models and be rewarded for their efforts to improve quality and efficiency within care episodes. Several studies illustrate that the only motivation for physicians to participate in bundled payment programs is to

avoid financial penalties (Engelman, 2017; Rosenkrantz et al., 2017; Self & Coffin, 2016; Self & Coffin, 2017). Such phenomena revealed ED physicians would like to care for fewer patients but with more expensive charges to compensate for the program's administrative burden. Such adverse selection could further restrict the space for the continuum and expansion of the value-based payment program in the emergency care field.

In conclusion, previous literature discussed the burden of variations and its potential contributors in emergency medicine. This reference-based evidence helps us to conceptualize a framework that explains how contributors affect ED utilization from various aspects. It also supports us to discover our study interests, thus raising specific research questions and associated hypotheses.

1.3 Conceptual Framework

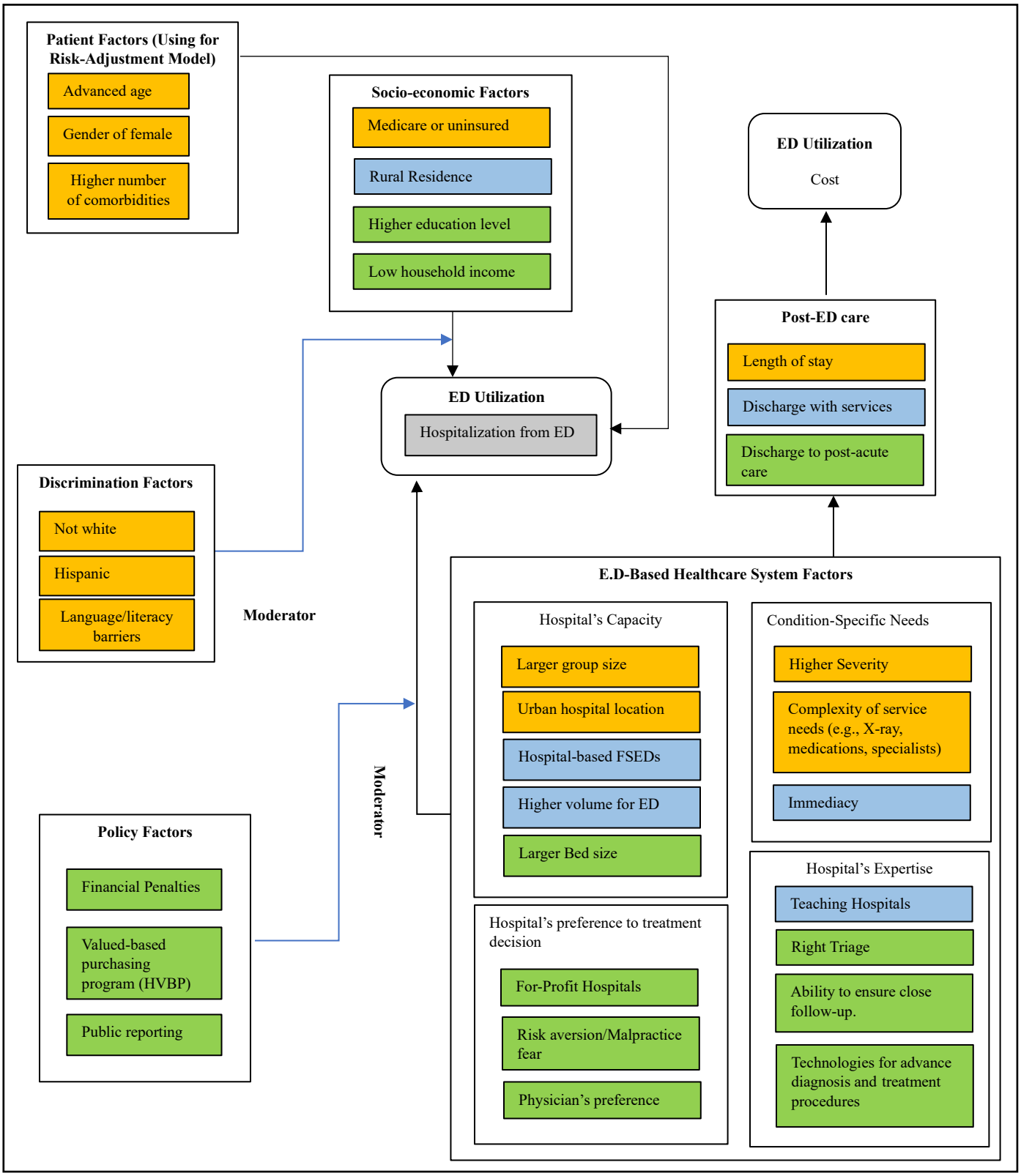

Figure 1.1 Conceptual Framework of ED Utilization

Based on literature review, the conceptual model[1] is designed to capture significant associations between ED utilization and related contributors. As suggested in the literature, contributors in the orange boxes could increase the hospitalization rate and costs. Contributors in blue boxes could decrease ED utilization. Boxes in green are unmeasured characteristics due to data limitation, but they can potentially affect overall ED utilization. Patients' essential attributes including age, gender, and comorbidities influence ED utilization. These are risk-adjusted factors suggested by the CMS-HCC model. Patients' socioeconomic factors, such as insurance status, education, and household income level, also affect individuals' ED utilization. Discrimination factors are less mentioned in the literature, but the cited studies described an increasing tendency of ED admission rates among Blacks, Native Americans, Hispanics or patients who have difficulty communicating with physicians (Begley et al., 2011; Hong et al., 2007; Parast et al., 2022).

Healthcare system factors involved four aspects: hospital capacity, expertise, physician preference, and condition-specific needs. Previous findings suggested that four aspects are associated with ED utilization. Condition-specific needs could affect the disease severity, choice of treatment, and post-ED pattern, thus influencing ED cost. Some hospital-related factors (boxes in green) cannot be measured or controlled, for example, policy factors. Prior literature found that value-based purchasing programs (VBP), public reporting, and financial penalties vastly improved the reimbursement system by reducing unnecessary costs and avoidable admission from ED healthcare (Farmer & Brown, 2017; Luke, 2016; Medford-Davis et al., 2017). Lastly, after patients' initial

[1] Note: Boxes in orange and blue denote the factors that are expected to increase and decrease ED admission rate and expenses respectively. Green boxes are unmeasured factors but could influence overall ED utilization. The gray boxes refer to outcome interests. We decided not to include association arrows from patient, policy, discrimination, and socioeconomic factors to post-ED acute care to keep the conceptual model less cluttered.

ED visit, their subsequent care is an essential component of condition-specific episodes of care, and they could either decrease or increase the overall hospitalization and costs.

1.4 Study Objective & Dissertation Outline

The previous literature and the conceptual model above document the many factors that contribute to ED-level utilization. They raise the question of the extent to which variations in admission originating in the ED and in post-ED spending reflect practice patterns that vary across EDs. Our study objective is to capture the difference in care provided by ED for patients with specific conditions.

The dissertation is divided into seven chapters. This chapter, Chapter 1, describes the research background and current studies' limitations on ED utilization and value-based payment models, which gives rise to our research questions. Chapter 2 discusses our data sources, data cleaning and processing, and measure construction for sample selection. Chapters 3, 4, 5 and 6 focus on statistical analyses of our study results, which incorporate four aims for three main research questions and corresponding hypotheses. The four aims assess the difference in ED performance on admission rates and cost from unadjusted, model construction, risk-adjusted, and systemic perspectives. Chapter 7 summarized our study results and discussed its meaning on health policy and the current Value-Based Payment system. Four aims with research questions and hypotheses are demonstrated below.

1.5 Research Questions (RQ) & Hypotheses (HA)

AIM 1: Examined variation in patient-level and ED-level, condition-specific unadjusted cost, and admission rates.

RQ1: Is there variation in cost and admission possibilities across EDs when patients present themselves in the EDs?

HA1: Substantial differences inpatient admissions and episode costs exist when these are aggregated to the ED level.

AIM 2: Construct condition-specific, risk-adjustment models and evaluate overall models' performance.

HA2: Risk adjustment models will explain a substantial portion of variation in admission and episode costs and are thus necessary for any analysis comparing ED performance.

AIM 3: AIM 3: Examined variation in ED-level, condition-specific adjusted cost ratio and admission ratio, which is calculated by random-effect regression model that includes ED-level variables prediction divided by Risk Adjustment Model (RAM) prediction outcome (which excludes ED-level variables) respectively. Ranked EDs' performance based on cost ratios and admission ratios and explored patterns of care consistency among EDs across conditions.

RQ2: Are the differences sufficiently reliable for measurement to compare episode cost and admission across patients and EDs?

HA3: Risk adjusted measures of admission and episode cost aggregated to the ED level will show sufficient between ED variation (relative to within ED variability) that they are reliable measures of ED performance i.e., it is feasible to construct reliable measures for comparing ED performance.

AIM 4: Examined the association between risk-adjusted ED performance and hospital systemic characteristics.

RQ3: Are some differences in ED performance associated with systemic characteristics such as ownership, the volume of the ED, location, and teaching status?

HA3: If there is any association, we hypothesized that part of the differences in ED performance were associated with systemic characteristics.

Chapter 2 Data Extraction and Management

2.1 Data Sources

2.1.1 All-Payer Claim Database, Colorado (CO-APCD)

Data from the Colorado All-Payer Claims Database (CO-APCD) will be used for this analysis. This state-level data warehouse has claim data from all third-party payers in Colorado, including medical, dental, pharmacies, providers, and product data. The APCD data set has inpatient and outpatient claims incorporating data elements from the electronic CMS-1500 and UB-04 claim forms. Each claim includes identifiers for the patient, provider, insurer, service date, charges, diagnosis codes, and Current Procedural Terminology (CPT) and Healthcare Common Procedure Coding System (HCPCS) II codes for medical procedures, services, and supplies. The pharmacy claims data follows the National Council for Prescription Drug Programs (NCPDP) standard format. It consists of ID for the patient, provider, insurers, allowed amount, National Drug Code (NDC), and drug name.

It has been shown in the literature (Diaz-Perez et al., 2019; Finison et al., 2017; Hashibe et al., 2019; Kim et al., 2017; Raifman et al., 2020) that all-payer claims data sets can be used to analyze and compare healthcare performance across providers to inform regional and organizational healthcare policies. We initially applied for APCD from CO, MA, and VA. However, the quote price and timeline proposed by the health department-regulated APCD in MA and VA are unsuitable for our project. The Colorado Health Department not only approved our application request, including multiple years (2017-2018) and de-identifiable data elements (patient's zip code), but also agreed to provide the dataset with an economically discounted price. According to previous documented literature, Colorado is one of three states in the US with the most FSEDs.

The other two are Texas and Ohio, but they do not have All-payers administrative data, which justifies choosing Colorado as it is the only option due to their roles and potential capacity of FSEDs in the US. Moreover, among the three states, Colorado is the only state documented official list distinguishing hospitals and FSEDs, which are the focus of our dissertation aim. We were initially concerned about the small population in a single-state dataset. Fortunately, CO-APCD, one of the most robust APCDs in the nation, contains over one billion claims. As a result, we only acquired APCD from Colorado. This study sample is only generalizable to the region sharing similar geographic characteristics of Colorado.

2.1.2 American Hospital Association (AHA) Survey

American Hospital Association (AHA) annual survey is one of the commonly used data to facilitate essential health services research about emergency care. This database is commercially available annually and contains hundreds of data elements, including ED-related variables. It collects data directly from over 6,000 US hospitals via the voluntary AHA Annual Survey, with an average response rate of 75% each year (Boggs et al., 2022). This database includes many details about hospital and ED characteristics and can easily be linked with other databases to investigate associations between facility characteristics and patient outcomes.

AHA survey has several limitations. It usually grouped EDs within the same health system under a single identification number (Medicare ID), and it is challenging to attribute facility characteristics to individual EDs. This grouping methodology made non-hospital-affiliated FSEDs unavailable from the AHA survey.

In our case, we extracted Hospital-based ED information about its ownership type, teaching status, urban/rural classification, address, county, and zip code. The rationale for choosing AHA over other ED databases, i.e., National Emergency Department Inventory (NEDI)-USA), is because of its data strength on generalizability and validity, economy, and enabled linkage to CO-APCD. Although we have identified limitations of the AHA data set, our main question interest was mainly focused on hospital-based EDs, thus including little classification bias in study results. On the other hand, we encourage caution when investigating ED characteristics that may not be well represented in the AHA, such as FSED status. When using AHA data, we also cross-checked the hospital urban-rural classification, as a single data point in the AHA may represent multiple hospitals or ED locations.

2.2 Measure Construction

2.2.1 Identification of ED Providers

1. The initial task was identifying claims by hospitals or freestanding EDs (a distinct feature of the Colorado health system) for either EDs services or hospitalization from ED. Therefore, the identified ED claims are bills only from hospitals and FSEDs in Colorado.
2. We downloaded the list of hospitals and FSED from the Colorado Department of Public Health & Environment (CDPHE) (https://cdphe.colorado.gov/health-facilities).
3. We investigated the Colorado Department of Public Health and Environment website (https://cdphe.colorado.gov/health-facilities) using keywords from the list (including but not limited to *hospital name*, *phone number*, *facility address*, etc.) to obtain National Provider Identifier (NPI) for each Colorado hospital and FSED. We cross-checked the identified facility by downloading all the identifying information for each NPI in the multiple, creditable NPI Registries (https://npidb.org; https://nppes.cms.hhs.gov/#/).

4. In our dataset, we used the NPI, a unique identifier of each hospital-based ED and FSED, to find facility-related claims. We found a few hospitals/FSED NPI in the NPPES NPI Registry with no claims in the dataset or records in the provider files associated with the claims data set. Some facilities may have experienced business combination or termination of operations during the period of this study (2017-2018). Some hospitals might have updated or replaced their NPI for unknown reasons. We contacted these facilities via phone or e-mail to verify their previous NPI.
5. Some FSEDs are independent facilities in our dataset, and some are owned by hospitals and use the hospital NPI for billing. By confirming with the billings department of hospitals, we confirmed that those dependent freestanding departments that share the same NPI with their hospitals. Under this circumstance, we treated their NPI as one hospital instead of freestanding emergency departments.
6. For each ED with unique NPI, we created an abbreviated ED identifier using the combination of belonging counties and order number alphabetically by ED's name. The NPI numbers of hospitals-based ED and FSEDs with reflected abbreviation of ED identifier were contained in the Tabel A- 1 (Appendix A).

2.2.2 Condition Selection

This research study focuses on understanding the variation in the likelihood of admission and total costs across ED for similar patients. The overall sample needs to be analyzed by presenting conditions. Our particular interest is conditions with common cases for ED and that may result in hospitalization or immediate discharge depending on the ED's performance and physician's judgment. Conditions with almost a hundred percent of inpatient admission rates or nearly zero percent of inpatient admission rates are not meaningful in this research. We therefore limited

conditions considered for this study to those with between 5% to 50% admission rates, based on CDC data and previous work (Capp et al., 2014; Sabbatini et al., 2014). The preliminary analysis started with identifying condition-specific diseases using previous peer-reviewed literature and government proposals supported with statistical evidence. We acquired the diagnosis code regulated by the *International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10-CM)* corresponding to each condition.

Twenty-five ED-related diagnoses were frequently mentioned in the last 5-10 years peer-reviewed journal, AUCM approach and HCUP annually reported as the most common, severe conditions (Duseja et al., 2015; Khojah et al., 2017; Kocher et al., 2014; Pines et al., 2013; Scherer et al., 2017; Venkatesh et al., 2015; Weiss et al., 2006; Wharam et al., 2007). Our preliminary list from the research included (1). The strain of muscle, fascia, and tendon of the lower back, initial encounter; (2). Abdominal pain; (3). Contusion;(4). Chest pain; (5). Back pain; (6). Open wound of extremities; (7). Headache; (8). Skin and subcutaneous tissue infections; (9) Urinary tract infections; (10). Pneumonia; (11). Congestive heart failure; (12). COPD; (13). Cardiac dysthymias; (14). Acute cerebrovascular; (15). Acute myocardial infarctions; (15). Altered mental problems; (16). Diabetic Mellitus; (17). Atherosclerotic heart disease of the native coronary artery without angina pectoris; (18). Fluid and electrolyte disorders; (19). Biliary tract disease; (20). Syncope; (21). Hemolytic jaundice and perinatal jaundice; (22). Asthma; (23). Malaise; (24). Gastroenteritis; (25). External injury.

Among these twenty-five conditions, we further restricted our study interest to those that meet both requirements of 1) at least presenting 30 ED visits per year and 2) having admission as the

principal diagnosis over 3,000 cases as recommended by CDC (CDC,2009). In other words, we restricted our list by excluding certain conditions that do not provide a large enough ED utilization for further data analysis. As a result, we selected eleven condition-specific diseases that satisfied our defined inclusion and exclusion criteria.

ICD-10-CM codes defining the selected conditions are presented in Table 2.1. We listed eleven disease description, Clinical Classifications Software Refined (CCSR), ICD-10-CM codes, and literature cited.

Table 2.1 Condition-Specific Cohort Inclusions

Description	CCSR	ICD-10-CM	Literature Citation
Biliary tract disease (BTD)	DIG017	K83.01,K83.09,K83.1,K83.2,K83.3 K83.4,K83.5,K83.8,K83.9	(Venkatesh et al., 2015) (Weiss et al., 2006) (Scherer et al., 2017)
Cardiac dysthymias (CD)	CIR017	I49.01,I49.02,I49.1,I49.2,I49.3,I49.40,I49.49, I49.5,I49.8,I49.9	(Venkatesh et al., 2015) (Weiss et al., 2006)
Chest pain	CIR012	R07.9,R07.2,R07.82,R07.89	(Duseja et al., 2015) (Khojah et al., 2017) (Weiss et al., 2006) (Wharam et al., 2007)
Congestive heart failure (CHF)	CIR019	I50.20,I50.21,I50.22,I50.23,I50.30,I50.31, I50.32,I50.33,I50.40,I50.41,I50.42,I50.43, I50.9	(Duseja et al., 2015) (Khojah et al., 2017) (Weiss et al., 2006) (Pines et al., 2013)
COPD	RSP008	J42,J44.0,J44.1,J44.9,J47.0,J47.1,J47.9	(Duseja et al., 2015) (Khojah et al., 2017) (Weiss et al., 2006)
Diabetic mellitus (DM)	END003	E10.10,E10.11,E10.21,E10.22,E10.29,E10.311,E10.319,E10.3211, E10.3212,E10.3213,E10.3219,E10.3291,E10.3292,E10.3293,E10.3299,E10.3311,E10.3312,E10.3313,E10.3319,E10.3391,E10.3392,E10.3393,E10.3399,E10.3411,E10.3412,E10.3413,E10.3419,E10.3491,E10.3492,E10.3493,E10.3499,E10.3511,E10.3512,E10.3513,E10.3519, E10.3521,E10.3522,E10.3533,E10.3539,E10.3541,E10.3542,E10.3543,E10.3549,E10.3551,E10.3552,E10.3553,E10.3559,E10.3591,E10.3592,E10.3593,E10.3599,E10.37X1,E10.37X2,E10.37X3,E10.37X9,	(Venkatesh et al., 2015) (Weiss et al., 2006) (Kocher et al., 2014; Scherer et al., 2017)

		E10.40,E10.41,E10.42,E10.43,E10.44,E10.49,E10.51,E10.52,E10.59, E10.610,E10.618,E10.620,E10.621,E10.622,E10.628,E10.630, E10.638,E10.641,E10.649,E10.65,E10.69,E10.8,E10.9,E11.00,E11.01,E11 .10,E11.11,E11.21,E11.22,E11.29,E11.311,E11.319,E11.3211, E11.3212,E11.3213,E11.3219,E11.3291,E11.3292,E11.3293,E11.3299,E1 1.3311,E11.3312,E11.3313,E11.3319,E11.3391,E11.3392, E11.3393,E11.3399,E11.3411,E11.3412,E11.3413,E11.3419,E11.3491,E1 1.3492,E11.3493,E11.3499,E11.3511,E11.3512,E11.3513, E11.3519,E11.3521,E11.3522,E11.3523,E11.3529,E11.3531,E11.3532,E1 1.3533,E11.3539,E11.3541,E11.3542,E11.3543,E11.3549, E11.3551,E11.3552,E11.3553,E11.3559,E11.3591,E11.3592,E11.3593,E1 1.3599,E11.36,E11.37X1,E11.37X2,E11.37X3,E11.37X9,E11.40, E11.41,E11.42,E11.43,E11.44,E11.49,E11.51,E11.52,E11.59,E11.610,E11 .618,E11.620,E11.621,E11.622,E11.628,E11.630,E11.638, E11.641,E11.649,E11.65,E11.69,E11.8,E11.9	
Fluid and electrolyte disorders	END011	E87.0,E87.1,E87.2,E87.3,E87.4,E87.5, E87.6,E87.70,E87.71,E87.79,E87.8	(Duseja et al., 2015) (Khojah et al., 2017)
Gastroenteritis	DIG021	K5701,K272,K2101,K2931,K2971,K2091,K5731,K51511,K2941 ,K5741,K5751,K920,K5521,K2081,K625,K280,K284,K274,K5753, K5791,K922,K2901,K50011,K266,K31811,K254,K921,K5733,K286,K28 2,I8501,K51411,K2921,K5713,K252,K5793,K270,K50911,K5711,K5121 1,K262,I8511,K2951,K5781,K264,K51811,K2961,K260,K256,K50111,K 51011,K250,K276,K50811,K2981,K51311,K2991,K5721, K51911	(Duseja et al., 2015) (Khojah et al., 2017) (Weiss et al., 2006) (Kocher et al., 2014)
Pneumonia	RSP002	J15.9,J16.0,J16.8,J17,J18.0, J18.1,J18.2,J18.8,J18.9	(Venkatesh et al., 2015) (Weiss et al., 2006)
Skin and subcutaneous tissue infections(SSTI)	SKN001	L0592,A363,L03116,L03811,L02532,A201,L02512,L03321,L02211, L0882,L0109,A46,A431,L02519,L03314,L03324,L03031,L03326, L02411,L0591,L03898,L02429,L03316,L02426,L03317,L011,L02235,L0 2221,A311,L02231,L0102,L02435,L03019,L0231,L03122,L03125,L00,L0 2531,L02239,L03039,L0201,L02425,L03222,L03325,L03327,L02629,L05 01,L03319,L043,L02436,L048,L02229,L02632,L0203 ,L02818,L0502,L0202,L02529,L0291,L02828,L0213,L03126,L041, A5139,L081,L03021,L03111,L02621,L049,L02631,L02234,L02611 ,L02219,L0100,L02225,L02511,A210,L02439,L03123,L03041, L02424,L02421,L03323,L03322,A220,H05013,L03313,L03121, L0101,L042,L02223,L03124,L03329,L089,L0293,L02416,L03029, L03115,L02522,L02431,H05011,L02222,L02831,L03221,L0292, L02821,L02414,L03022,H05012,L0211,L02232,L02224,L03114, H05019,L02622,L02419,L03213,L02811,L02639,L03112,L03113, L0391,L02212,L02415,L0390,L03032,L03315,L02233,L303,L02214,L03 211,L02433,L0103,L03312,L02432,L03311,L03011,L0232, L02521,L02838,L02612,L03049,L02216,L0212,L0881,L02434, L03818,L0889,L080,L02539,L03212,L03042,L03891,L03012, L02422,L02213,L02423,L040,L02412,L02619,L02413,L02226, L0233,L03119,L02215,L03129,L02236,	(Duseja et al., 2015) (Venkatesh et al., 2015) (Weiss et al., 2006)
Urinary tract infections(UTI)	GEN004	N39.0,O86.20,O08.83,O03.38,O04.88,O03.88, O07.38,O23.30,O23.31,O23.32,O23.33,O23.40, O23.41,O23.42,O23.43,	(Duseja et al., 2015) (Khojah et al., 2017) (Weiss et al., 2006) (Pines et al., 2013)

Table 2.2 display the count of inpatient and outpatient claims grouped by conditions. The conditions are identified by documented ICD-10-CM codes, based on principal diagnosis or both principal and secondary diagnosis of specific conditions. (Claims in which one of the condition codes only appeared as a secondary diagnosis are not considered condition-specific claims). We determined if a patient has a selected condition by examining the principal diagnosis in the APCD data.

Table 2.2 Condition-specific related claims of outpatient ED and hospitalization from the ED

1. Biliary Tract Disease(BTD)

Biliary	Outpatient	Inpatient	Total
Principal only	3,098	416	3,514
Principal +Secondary	9,285	2,359	11,644
Total	12,383	2,359	15,158

2. Cardiac Dysthymias(CD)

Cardiac	Outpatient	Inpatient	Total
Principal only	8,191	383	8,574
Principal +Secondary	23,949	3,838	27,787
Total	32,140	4,221	36,361

3. Chest Pain

Chest Pain	Outpatient	Inpatient	Total
Principal only	17,555	26	17,581
Principal +Secondary	47,255	752	48,007
Total	64,810	778	65,588

4. Congestive Heart Failure (CHF)

CHF	Outpatient	Inpatient	Total
Principal only	2,630	450	3,080
Principal +Secondary	12,000	8,504	20,504
Total	14,630	8,954	23,584

5. Chronic Obstructive Pulmonary Disease (COPD)

COPD	Outpatient	Inpatient	Total
Principal only	11,727	553	12,280
Principal +Secondary	32,617	5,396	38,013
Total	44,344	5,949	50,293

6. Diabetic Mellitus (DM)

Diabetes	Outpatient	Inpatient	Total
Principal only	4,732	224	4,956
Principal +Secondary	31,457	4 ,883	36 ,340
Total	36,189	5,107	41,296

7. Fluid and Electrolyte Disorders

Fluid	Outpatient	Inpatient	Total
Principal only	3,223	175	3,398
Principal +Secondary	11,762	4,850	16,612
Total	14,985	5,025	20,010

8. Gastroenteritis

Gastro	Outpatient	Inpatient	Total
Principal only	2,365	271	2,636
Principal +Secondary	7,524	3,553	11,077
Total	9,889	3,824	13,713

9. Pneumonia

Pneumonia	Outpatient	Inpatient	Total
Principal only	4,340	980	5,320
Principal +Secondary	10,325	5,719	16,044
Total	14,655	6,699	21,364

10. Skin and Subcutaneous Tissue Infections (SSTI)

Skin	Outpatient	Inpatient	Total
Principal only	6,903	200	7,103
Principal +Secondary	27,756	3,251	31,007
Total	34,659	3,451	38,110

11. Urinary Tract Infections(UTI)

Urinary	Outpatient	Inpatient	Total
Principal only	10,138	446	10,584
Principal +Secondary	38,194	3,063	41,257
Total	48,332	3,509	51,841

2.3 Data Management

2.3.1 Matching

The data structure of CO-APCD is hierarchical. Each claim has multiple medical records. Each patient and their providers could submit multiple claims and reimbursed patients can be treated by multiple healthcare providers. Therefore, data was merged to identify claims by providers, patients, and by ED-related claims. The medical claim-level file included multiple lines per claim with information on each procedure, i.e., claim number, ED flag, claims type, diagnosis, and relevant billing amounts. The patient-level claims file consisted of the patient's identifier, age, and gender. The provider-level claims files contained provider’s information, including several types of provider identifiers, provider name, phone number, address, and zip code. To construct unified, systematic data, we first merged the multiple medical lines into the corresponding claims, then merged the patient- and provider-level information into medical claims.

2.3.2 Cleaning

Following the creation of the intermediate analysis files above, we used the following steps to clean our combined dataset.

1. **Unifying Claims-level Analysis.** As mentioned above, one claim had multiple records, with unique diagnoses or procedures presented in each record of the claim. Claims were sorted using claim identifying numbers, and one record for each claim was identified as the record for claim-level analyses.

2. **Fill-in and Unify National Provider Identifier (NPI).** The National Provider Identifier (NPI) is a unique,10-position, numeric identifier for covered health care providers. We used the NPI to identify ED claims for patients with ED visits, outpatient visit in ED or inpatient admission (admitted) through the ED. Our merged Medical Claims data contained four potential provider identifiers: provider ID and provider's composite ID for billing and services purposes. In this study, we constructed a single NPI for use by merging NPI numbers into the data set for each provider ID. Initially, we created NPI variables for each provider ID type in the dataset. These four NPIs could either be the same, different, or missing. A single NPI was generated for each claim using the billing provider composite ID for each claim. For the cases where provider composite ID is unavailable, the billing provider ID is used for NPI as an alternative. In the cases where both are not available, NPI is generated using the service provider composite ID. Subsequently, if those mentioned above are unavailable, the service provider ID is used to create NPI. At the end of the process, we still have some claims that do not have NPI associated with them. Those are saved for later analysis.

3. **Identifying ED-related Claims.** The data has a precise ED flag variable to identify all ED-related Claims, where yes indicates ED-related claims and otherwise no. We cross-checked the ED flag with Current Procedural Terminology (CPT) codes 99281-99285, all ED visits for the Evaluation and Management (E/M) of a patient in the ED, excluding critical care services.

4. **Identifying Hospital and FSED Claims.** As we mentioned, we used the created flag variable of the hospital-based ED and FSED to identify all hospital-based EDs and FSEDs claims.

5. **Identifying outpatient and inpatient claims**. To find this study's inpatient bills, we used EB-04 bill codes, a uniform billing form for institutional providers. Bills from providers identified as from hospitals or FSED based on their NPI were classified as admissions through the ED if billing code was 111 (complete bill) or 117 (replacement bill) and the ER flag was "yes." Bills from hospitals or FSED were identified as ER visits if the billing code was 131 or 137 and the ER flag was "yes." Information on the billing code system used in institutional billing is available on CMS website (CMS, N.A.).

6. **Capturing Claims Result in Selected Conditions with Principal and Secondary Diagnosis.** Based on a review of the literature (Duseja et al., 2015; Khojah et al., 2017; Venkatesh et al., 2017; Weiss et al., 2006), we identified 11 potential conditions that were often presented in ED, which may result in admission from the ED. For each broadly defined condition, drawing from the literature, a specific set of ICD-10-CM diagnostic codes were identified and associated with each condition. Analysis was done at the claim-level to determine if the ICD-10-CM was coded in a diagnosis field and whether it was coded as a primary or secondary diagnosis, and this information was summarized at the claim level. The conditions and this process are described in more detail below.

7. **Identifying index visits.** An index visit was defined as the first ED visit (regardless of disposition) for a unique patient or any successive visits in which the patient had no prior visit or hospitalization during the preceding 30 days. Index visits are necessary tools that help us to construct the 30-day episode of care for the following analysis in Chapters 3, 4 and 5.

8. **Cleaning Unnecessary Variables and Missing Values.** We deleted any observations with missing NPI and missing negative payment value.

2.4 Sampling and Condition-Specific Sampling

The process of how we created sample size and allocated by condition-specific were described in the flow chart (Figure 2.1). Details of processing are:

- There was a total of 140,834,058 records in the claim database consisting of 58,340,962 claims. These claims were narrowed down to institutional claims from Hospitals or FSEDs, with a total of 6,533,331 claims. 51,807,631 claims from physicians, labs, and SNF are deleted.
- Restricted the institutional claims for ED use, based on the ER flag: 1,997,526 remained, 4,535,805 excluded.
- Restricted sample to inpatient admission or discharge from the ED: 1,828,735 claims remained; 168,791 claims excluded.
- Restricted sample to condition-specific ED-related visits only, based on the condition code: 820,937 claims remained, 1,007,798 excluded.

Our final sample includes 820,937 ED claims or hospitalizations through 87 Hospital-Based EDs or 48 Freestanding Emergency Departments (FSEDs) identified. Among the 48 FSEDs, 9 FSEDs shared hospital NPIs and are identified as satellite FSEDs from their affiliated hospitals. The other

39 FSEDs are identified as autonomous FSEDs because of its independence of operation (Herscovici et al., 2020). As a result, total 135 EDs were enrolled in 30-day episode of care window (Appendix A).

Before assigning to individual conditions, the final sample comprises 711,580 outpatient ED claims and 109,357 inpatient claims. In the following steps, we constructed 30-day episodes for conditions:

- Created eleven condition-specific samples by allocating 820,937 claims to each condition and identified patients' indexed visits using a 30-day interval.
- Previously excluded claims related to 11 conditions were retrieved based on the principal only and principal plus secondary diagnosis code of the patient. 24,770,399 condition-related claims were allocated to each condition and merged with individual condition-specific samples. These merged condition-specific datasets were sorted by ED, patient, claims, and services start date.
- In each merged condition-specific sample, created a 30-day episode for each index visit and enrolled all claims that matched the patient ID and its service date occurred on the same day or later but within 30-day windows of index visits.

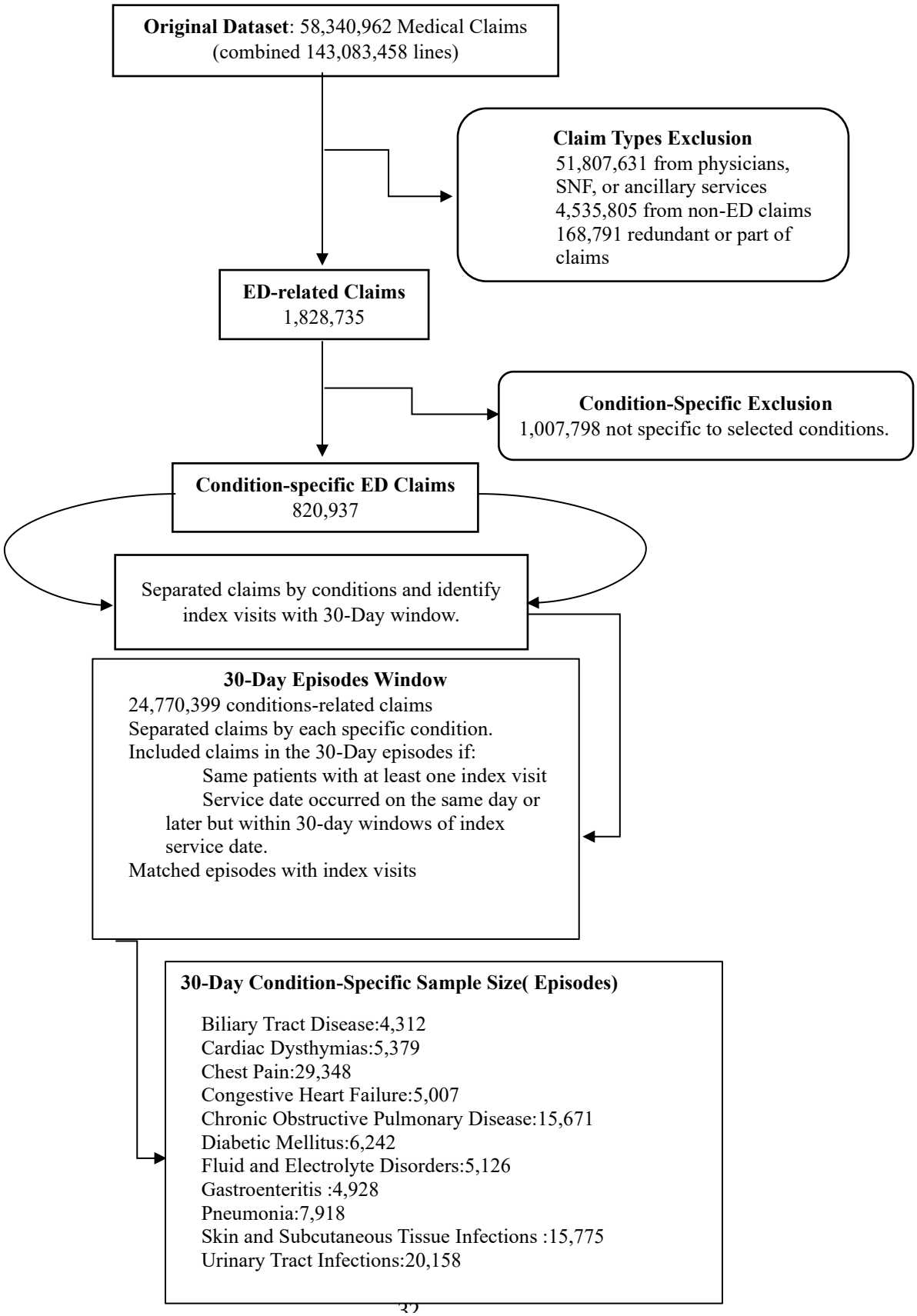

Figure 2.1 Condition-specific episodes sample selection

Chapter 3 Unadjusted Analysis

Aim 1: Examined variation in patient-level and ED-level, condition-specific unadjusted cost, and admission ratio.

3.1 Analysis Overview

Prior literature has found wide ED-level variations in cost and admission rates among Medicare beneficiaries. However, the extent of variations in other payers has never been researched. As private insurance and out-of-pocket spending have been increasing on an annual basis in national health expenditure, it is essential to assess the variation in cost and admission rates more accurately by including patients of all-payer types. By constructing 30-day timeframes, Aim 1 calculated condition-specific patient-level and ED-level variations in episode cost and admission. Variations for both levels were studied with a range of selected percentiles.

3.2 Methods

3.2.1 Sample size

Using administrative data from CO-APCD, we measured condition-specific unadjusted cost and admission rate for each episode of care. The condition–specific sample size of episodes, patients, and EDs is described in Table 3.1.

Table 3.1 Condition-Specific Sample size by No. episodes, patients, and EDs

Condition	**Final Sample Size**		
	No. of episodes	**No. of patients**	**No. of EDs**
Biliary Tract Disease	4,312	4,225	91
Cardiac Dysrhythmias	5,379	5,016	87

Chest Pain	29,348	28,054	97
CHF	5,007	4,540	71
COPD	15,671	14,745	97
DM	6,242	5,399	86
Fluid and Electrolyte Disorders	5,126	4,953	93
Gastroenteritis	4,928	4,796	85
Pneumonia	7,918	7,772	94
Skin and Subcutaneous Tissue Infections	15,775	15,009	95
Urinary Tract Infections	20,158	19,052	97

CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus

3.2.2 Construction of 30-Day Episode

A 30-day episode was counted from an index visit and is defined to end 30 days after the episode index visit. Condition-specific samples were first restricted to hospitalization claims from ED or ED visits in 2017 and 2018 and were sorted by patient and claim start and end dates. Claims in 2018 were identified as valid index visits only if there was no claim with a service end date less than 30 days earlier than the claim's start date. We also excluded ED index visits of those patients who presented inconsistent gender information, died, left against medical advice, received ED care out-of-state, or whose index visits occurred in January and December 2018. The 30-day episodes included all claims from all providers with a start date of the valid index visit or within 30 days of the end date of the index visits. As a result, the episodes matched the number of index visits. Patients may have multiple index visits, thus creating multiple episodes available for the analysis. We justified constructing a 30-day episode instead of another time frame based on recommendations and empirical evidence of similar risk-adjustment condition-specific model studies from CMS and Yale New Haven Health Service Corporation/Center for Outcomes Research & Evaluation's (YNHHSC/CORE) measure reports (Anderson et al., 2020; Horwitz et

al., 2014; Keenan et al., 2008; Krumholz et al., 2011; Krumholz et al., 2013; Lindenauer et al., 2011).

We selected 30 days for an episode of care for several reasons. A 30-day condition-specific measure aligned with many current CMS's publicly reported payment and admission/readmission measures, which is reported 30 days after admission(Krumholz et al., 2019). Aa 30-day window provides a standard observation period by which to compare all hospitals. In addition, decisions made at the treating ED, whether there is an admission or not, can affect decisions on follow-on care during the immediate post-visit or post-discharge period. Assigning payments for a continuous episode of care to hospitals reveals practice variations in the full care of the illness experienced by patients that can result in increased payments.

3.2.3 Cost Standardization

The 30-day episode cost measure is intended to capture variation in expenditures that reflect difference in ED care provided for patients rather than difference based on geography, reimbursement rate, or policy adjustments. To remove the payment adjustment unrelated to clinical care, we used three steps to standardize condition-specific 30-day episode cost. The first step is establishing a standardized index price index for each service included in the 30-day episode. Charges are the billed amount, but payers and patients rarely pay billed charges. Allowed costs, included in the billing data, is the sum of the member liability amount and the plan reimbursed amounts. This amount captures variations in payment by insurer and any incentive inherent in payment differences (Dworsky, 2017). Compared to total charges, the allowable amount is more reasonable as representative of price for episode of care. The allowed amount is an appropriate cost index unless different payers have different allowable amounts for treating the same conditions.

The second step is to create standardized prices for each type of service reimbursed by claims. To create a standardized cost per episode, three categories of claims were constructed and calculated separately:

- For claims that were paid based on CPT4 codes, such as physician billings and laboratory tests, the average allowed amount across all claims per CPT4 code were constructed by and merged into each claim with that CPT4 code. The standardized price per CPT4 was equal to the sum of allowed amount with COT4 divided by total number of corresponding claims.
- For hospital inpatient claims, claims for which DRGs were available in the data set, we constructed the average allowed amount across all claims per DRG and these were merged into each inpatient claim with that DRG. The standardized price per DRG was equal to the sum of allowed amount with DRG divided by total number of corresponding claims.
- For the remaining claims, largely institutional claims without standard pricing, such as ED visits not resulting in admission, skilled nursing facility admissions and hospice, we used the average allowed amount as the standardized claims price.

The third step is cost winsorization. Winsorization is a transformation that limits extreme values in the statistical data to reduce the effect of possibly spurious outliers. The observed standardized episode cost still has several extreme outliers that may influence the higher-level episode cost. By winsorizing the episode cost, we changed extreme episode cost to fewer extreme values without losing any samples. We choose the winsorizing level at 99% based on recommendations from YNHHSC/CORE (Krumholz et al., 2011; Krumholz et al., 2013). A 99% winsorization sets all condition-specific episode costs greater than the 99.5th percentile equal to the episode cost at the 99.5th percentile and all those less than the 0.5^{th} percentile equal to the value at the 0.5^{th} percentile. As a result, the final episode cost is the standardized episode cost after 99% winsorization.

3.2.4 Statistical Analysis

We examined the extent of variation in condition-specific 30-day episode cost and admission rate at the patient-level and ED-level. After 30-day episode construction and cost standardizing, we computed the episode cost and admission rate of mean, median, interquartile range (IQR), and standard error at the patient level and ED-level, respectively. Consistent with the previous literature, we focus on the 25^{th} to 75^{th} percentile range to measure variations in episode cost and admission (Anderson et al., 2020). Specifically, we judged there to be a wide variation in admission if the absolute difference between 25^{th} and 75^{th} percentile was greater than 15% (Pines et al., 2016).

3.3 Results

3.3.1 Patient-level Extent of Variation

Part A: Patient-level, 30-Day Unadjusted Episode Cost

Table 3.2 Distribution of Patient-level, condition-specific, unadjusted(standardized) 30-day episode cost

Condition	# Of Patients	Cost per episode of care after winsorization (99.5^{th} percentile)								
		Mean	S.E	Range including percentile						
				Min	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	Max
Biliary Tract Disease	4225	$7,690	5730.51	$1,017	$1,424	$3,302	$6,570	$9,871	$15,732	$23,468
Cardiac Dysrhythmias	5016	$6,445	7148.04	$912	$1,201	$1,868	$3,506	$7,462	$17,570	$27,870
Chest Pain	28054	$2,551	2128.69	$605	$807	$1,121	$1,771	$3,074	$5,706	$8,902
CHF	4540	$10,168	10450.95	$1,367	$1,991	$3,597	$6,226	$1,2133	$2,4518	$4,2811
COPD	14745	$2,551	2679.10	$389	$530	$799	$1,440	$3,175	$6,471	$10,704
DM	5,399	$5,445	6123.79	$652	$866	$1,438	$2,847	$6,642	$15,468	$23,111
Fluid and Electrolyte Disorders	4953	$4,968	5662.38	$640	$787	$1,327	$2,517	$6,095	$13,404	$22,105
Gastroenteritis	4796	$6,002	7032.27	$539	$708	$1,431	$3,502	$7,119	$15,850	$28,289
Pneumonia	7772	$5,058	6020.72	$577	$734	$1,230	$2,608	$5,989	$13,616	$23,891

Skin and Subcutaneous Tissue Infections	15,009	$2,174	2635.18	$342	$389	$593	$1,080	$2,378	$5,928	$10,569
Urinary Tract Infections	19,052	$2,695	3002.66	$389	$510	$804	$1,527	$3,044	$7,155	$12,022

CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus
S.E: standard error

Table 3.2 summarized the statistics of patient-level, condition-specific, 30-day episode cost after standardization and winsorization (0.5^{th} percentiles are lower bound and 99.5^{th} percentile are upper bounds) with the number of patients. We computed the episode cost's mean, S.E, range (min, max), and selected percentile level (10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th}).

For each condition-specific disease, the key statistical results for patient-level, unadjusted cost associated with a 30-day episode of care are presented below:

- The patient-level average episode cost was relatively close to its median (50^{th} percentile), which suggested that the mean value of episode cost is a desired measure of central tendency.
- The mean episode cost for all conditions ranged from $2,174 to 10,168. The standard error of mean episode cost went from 2128.69 to 7148,04, indicating a widely distributed episode cost at the patient-level.
- On average, conditions with the most and least expensive episode cost at the patient level were CHF and skin & subcutaneous tissue infections.
- The variation (25^{th}, 75^{th}) of episode cost ranged from $1,785 to $8,536. According to the absolute value of variations, CHF ranked 1^{st} with the highest variation, and skin & subcutaneous tissue infections ranked 11^{th} with the lowest variation. In other words, patients with CHF have various spending for episodes of care, whereas the episode cost for patients with skin and soft tissue infection has a similar spending scope.

- Conditions with minor variations (<$4,000) in cost were chest pain, COPD, Skin and subcutaneous tissue infections, and urinary tract infections. There were slight differences in episode cost between the patients for these conditions. Patients with those conditions had similar costs during the episode of care.
- The rest of conditions presented wide variation (>=$4,000) among patients. High variation indicates that the episode cost for those conditions varies among patients even after winsorizing.
- Except for CHF and skin, the rest of the nine conditions cost around $2,174~$7,690, implying the general price range of episode care for the most common severe diseases among patients.

Part B. Patient-Level, Unadjusted Admission Rates

Table 3.3 Patient-level, condition-specific, unadjusted admission rates

Condition	Admission Probability	
	Rates (%)	Std.dev
Biliary Tract Disease	29.48	0.46
Cardiac Dysrhythmias	31.23	0.46
Chest Pain	1.21	0.11
CHF	75.55	0.42
COPD	13.20	0.33
DM	31.27	0.38
Fluid and Electrolyte Disorders	21.13	0.40
Gastroenteritis	35.37	0.48
Pneumonia	33.59	0.47
Skin and Subcutaneous Tissue Infections	8.62	0.28
Urinary Tract Infections	7.16	0.25

CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus
Std.dev: standard deviation

Statistics of patient-level condition-specific admission rates were summarized in Table 3.3. Based on the absolute value of 15% difference rules, we ranked the variation level of admission rate at three levels: High (40%+), Medium (15%-40%) and Low (15%-). For all conditions, admission

rates were 0 from the 25th to 75th percentile. Standard deviation that indicates the distance of each value from the mean can be used to measure admission rate variations.

For each condition-specific disease, the key statistical results for patient-level unadjusted admission rates associated with a 30-day episode of care are presented below:

- Conditions with substantially high and low admission rates were CHF and chest pain, respectively. On average, about three-fourths of patients admitted with CHF were hospitalized from ED visits. Over 90% of patients seen chest pain were directly discharged from ED.
- Variations in admission rate were not observed in patients admitted with chest pain.
- Gastroenteritis condition has the highest variation in admission rates based on standard deviation value. Urinary tract infections condition has the lowest variation in admission rate.
- Except for CHF and chest pain, the average admission rates ranged from 7% to 36% for the other nine conditions, indicating the general admission rate range for the most common severe diseases admitted from ED.

3.3.2 ED-level Extent of Variation

Part A: ED-Level, 30-Day Unadjusted Episode Cost

Table 3.4 Distribution of ED-level, condition-specific, unadjusted 30-day episode payment

Condition	# Of EDs	Unadjusted cost per episode of care after winsorization (99.5th percentile)								
		Mean	S. E	Range including percentile						
				Min	10th	25th	50th	75th	90th	Max
Biliary Tract Disease	91	$7,225	2763.81	$1,017	$3,929	$5787	$7308	$8737	$10,337	$15,822
Cardiac Dysrhythmias	87	$6,101	3365.97	$935	$2,275	$4,069	$5,831	$7,321	$8,755	$18,911
Chest Pain	97	$2,513	698.84	$1,244	$1,662	$2,091	$2,485	$2,766	$3278	$5,622
CHF	71	$9,954	4915.27	$1,517	$3,352	$7,618	$10,129	$12,207	$14,198	$26,800
COPD	97	$2,304	897.51	$421	$1,198	$1,665	$2,358	$2,880	$3,265	$6,516
DM	86	$4,789	2234.52	$652	$1,449	$3,479	$4,946	$6,008	$7,316	$11,882

Fluid and Electrolyte Disorders	93	$4,534	3359.99	$640	$1,491	$2,355	$4,080	$5,433	$6,668	$21,105
Gastroenteritis	85	$5,545	3749.77	$539	$1,780	$3,345	$5,408	$6,683	$8,362	$21,672
Pneumonia	94	$5,137	3094.12	$562	$2,071	$3,409	$4,872	$6,136	$8,201	$23,891
Skin and Subcutaneous Tissue Infections	95	$2,043	793.93	$663	$1,180	$1,443	$1,902	$2,432	$2,964	$5,237
Urinary Tract Infections	97	$2,449	1019.89	$407	$1,267	$1,847	$2,357	$2,818	$3,654	$7,240

CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus
S.E: standard error

The ED-level condition-specific unadjusted cost after 99% winsorization and its selected percentile level were illustrated in Table 3.4. The ranking of variation in condition-specific episode cost was similar to the ranking at patient-level. Given that the ED-level cost is the average of the sum of episode costs within the ED, we would expect that the average unadjusted cost should have less variation than those at the patient-level.

For each condition-specific disease, key statistical results for ED-level episode cost associated with a 30-day episode of care are presented below:

- The ED-level average episode cost is an approximate measure of central tendency as there is negligible difference between mean and median.
- The mean episode cost for all conditions ranged from $2,043 to $9,954. The standard error of mean episode cost varies from $698.84 to $4,915.27, indicating a less widely distributed episode cost at ED-level than at patient-level.
- Conditions of CHF and skin have the most expensive and cheapest episode costs, respectively.
- The variation of episode cost ranged from $675 to $4,589. CHF ranked 1st with the highest variation, and chest pain ranked 11th with the lowest variation. The variation range across conditions has been roughly reduced by half compared with the variation at patient-level.

- Conditions with minor variations are consistent between ED-level (<$2,000) and patient-level (<$4,000). The rest of the condition's episode cost varied among EDs.
- The average episode cost for the other nine conditions (CHF and skin excluded) varied from $2,449 to $7,225. For the most common severe diseases, the general price range had a slight decrease at ED-level when compared to patient-level price range.

Part B: ED-level Unadjusted Admission Rates

Table 3.5 Distribution of ED-level, condition-specific, unadjusted admission rates

Condition	# Of EDs	Unadjusted Admission Rates								
		Mean (%)	S. E	Range including percentile (%)						
				Min	10th	25th	50th	75th	90th	Max
Biliary Tract Disease	91	14.09	0.16	0	0	0	9.10	27.27	36.43	53.06
Cardiac Dysrhythmias	87	14.90	0.17	0	0	0	8.00	31.11	40.54	50.00
Chest Pain	97	0.52	0.01	0	0	0	0	0.95	1.85	4.42
CHF	71	48.85	0.34	0	0	8.33	57.14	77.27	85.33	1
COPD	97	7.83	0.08	0	0	0	6.58	11.77	20.00	31.96
DM	86	18.83	0.18	0	0	0	20.00	32.35	36.80	1
Fluid and Electrolyte Disorders	93	9.47	0.12	0	0	0	2.86	17.95	26.58	61.51
Gastroenteritis	85	17.84	0.19	0	0	0	11.29	35.82	41.43	62.32
Pneumonia	94	21.57	0.21	0	0	0	20.00	34.38	43.29	1
Skin and Subcutaneous Tissue Infections	95	5.10	0.07	0	0	0	2.40	7.92	13.25	33.33
Urinary Tract Infections	97	5.31	0.08	0	0	0	3.88	7.73	15.38	50.00

CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus
S.E: standard error

Table 3.5 presented the ED-level condition-specific average admission rate, standard error, and its selected percentile level. We used the 50th to 90th percentile to measure variation in admission because for all conditions, the admission rate is 0 from the min to 25th percentile. We would expect less admission variation than those at patient-level. Furthermore, as is typical with data for healthcare admission, some conditions may present either 0 or 1 ED admission rate due to small number of episodes.

For each condition-specific disease, the key statistics results for patient-level unadjusted admission rates associated with a 30-day episode of care are presented below:

- Three conditions, CHF, diabetes (D.M.) and pneumonia, had a substantial (≥15%) variation at the ED level.
- Conditions with substantially high and low admission rate were CHF and chest pain respectively. On average, about half of patients with CHF were admitted to the ED. Almost all patients seen with chest pain were discharged from EDs.
- Variations in admission from chest pain were not observed due to low probability of hospitalization across EDs.
- The variation in admission for the other ten conditions ranged from 5.10% (Skin and Subcutaneous Tissue Infections) to 48.85% (Cardiac Dysrhythmias). Most patients seen with Skin soft tissue infections were immediately discharged from EDs. Patients seen with Cardiac Dysrhythmias have roughly equal chances of being discharged or hospitalized by EDs.
- Measured against a standard of 15% absolute value difference, large variations were observed in cardiac dysrhythmias, gastroenteritis, CHF, biliary tract diseases, fluid and electrolyte disorders, pneumonia, and diabetes.

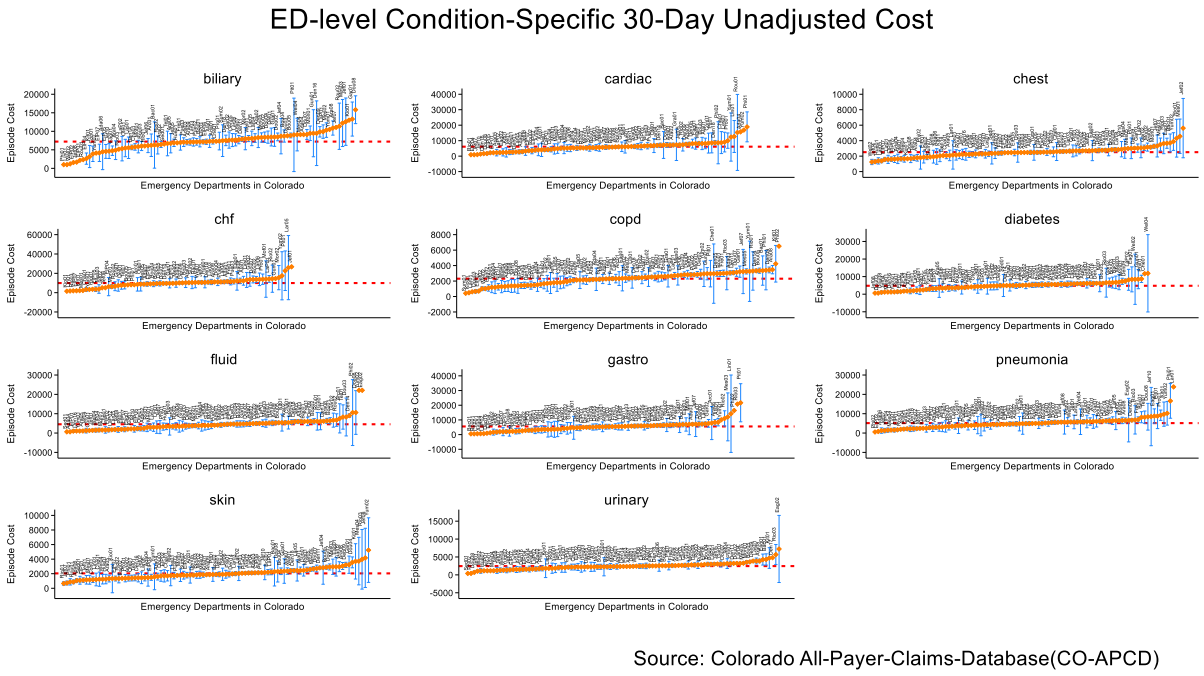

Figure 3.1 .ED-level,Condition-specific, unadjusted 30-day episode payment pooling each ED

Figure 3.1 shows the distribution of condition-specific 30-day episode cost (orange red diamond) for each ED with a confidence interval plot (blue vertical bar). The purpose is to visualize explained variation in episode cost across EDs when they provide episode of care for the same conditions. Hospital-based EDs or FSEDs in Colorado were in ascending order on x-axis by average unadjusted episode. Some confidence intervals have wide variation, reflecting large standard errors and often low volumes. For each condition, EDs with only one episode are noted on the graph by orange red diamonds without a blue interval plot.

In evaluating plots like these, it has become customary to characterize providers as having low admission rates or episode costs if the upper confidence interval is below the average cost, high admission rates or costs if the lower bound is higher than the average, and neither high nor low if the confidence interval includes the average.

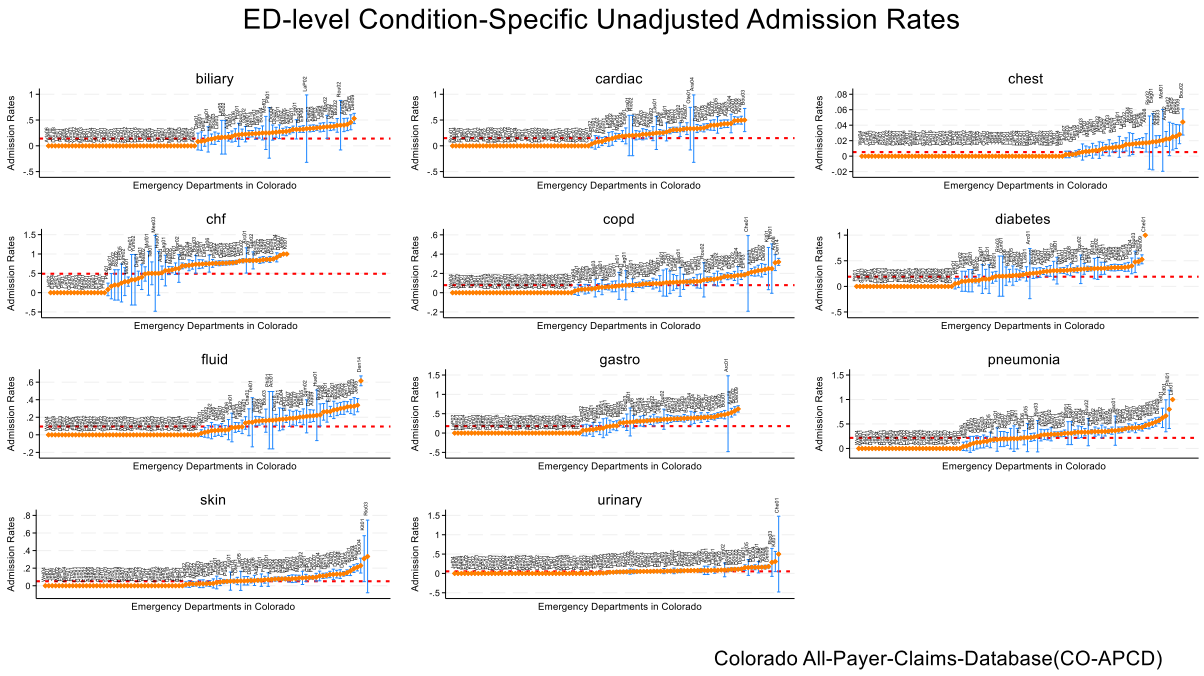

Figure 3.2 ED-level, condition-specific, average admission rates pooling each ED.

The distribution and confidence interval of condition-specific admission rates for each ED is presented in Figure 3.2. In sub-graphs of each condition, certain EDs' admission rate was observed without interval plot, indicating only one case admitted or discharged from the ED. Because of the intrinsic nature of binary data for admission cases, we observed many EDs had an average 0 or 1 admission rate for each condition. Such all-or-none hospitalization results from a limited number of episodes provided by EDs. For those EDs admitted 0% or 100%, their average number of episodes ranged from 2 to 47. We should disregard such EDs in the analysis because it does not provide any information on variation in admission rate. More importantly, the general range of 30-day episode condition-specific admission rates may have been over- or underestimated by EDs presenting only a small number of episodes.

The admission rate varied across EDs. By noting the width of interval and the distance from interval plot (upper or lower bound) to reference line, high degrees of variation, both within-ED and between-ED, in admission rate was detected in conditions of cardiac dysrhythmias, gastroenteritis, CHF, biliary tract diseases, fluid and electrolyte disorders, pneumonia, and diabetes.

3.4 Discussion

In this chapter, both variations in ED-level unadjusted episode cost and admission rate were observed. For each specific condition, variations between EDs were somewhat biased by the inclusion of EDs presenting a limited number of episodes. As shown in Figure 3.1 and Figure 3.2, relatively higher variations in unadjusted cost and admission within the ED, compared to between EDs, were observed from wide interval plots.

The subgraph of condition-specific unadjusted episode cost and admission rates in EDs from Colorado are included in Appendix B.

Chapter 4 Construction of Risk Adjustment Model for Episode Cost and Admission

AIM2: Constructed condition-specific risk adjustment models and evaluated overall models' performance.

4.1 Analysis Overview

In Chapter 3, we estimated and graphed ED-level variations in 30-day, unadjusted condition-specific episode cost and admission rate. In Aim 1, we raised questions about the extent of variations contributed by patient factors. In further analysis (Aim 2) to answer this question, we developed separate risk adjustment models for each of the eleven conditions for two outcomes, episode cost and admission. Our risk adjustment models referenced the Yale New Haven Health Services Corporation (YNHHSC) approach in risk variables selection and measure construction under the National Quality Forum (NQF) guideline. In this chapter, we identified associated patient characteristics, constructed 22 risk adjustment models, reviewed the degree of variation explained and calibrated the prediction with observed outcomes. In the last section, the dropping or keeping of any condition(s) is discussed.

4.2 Methods

4.2.1 Sample Size

The same samples used in Chapter 3 for the unadjusted analysis was used to construct condition-specific risk-adjustment models. Sample episodes have at least one of eleven condition-specific diseases admission records. Sub-sample size for each condition is described in Table 4.1.

Table 4.1 Condition-specific, Risk-Adjustment Model sample

Condition	Final Sample Size		
	No. of episodes	**No. of patients**	**No. of EDs**
Biliary Tract Disease	4,312	4,225	91
Cardiac Dysrhythmias	5,379	5,016	87
Chest Pain	29,348	28,054	97
CHF	5,007	4,540	71
COPD	15,671	14,745	97
DM	6,242	5,399	86
Fluid and Electrolyte Disorders	5,126	4,953	93
Gastroenteritis	4,928	4,796	85
Pneumonia	7,918	7,772	94
Skin and Subcutaneous Tissue Infections	15,775	15,009	95
Urinary Tract Infections	20158	19052	97

CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus

4.2.2 Risk Factors Exclusion Criteria

To be consistent with NQF guidelines and CMS practice, our risk adjustment models (RAMs) did not adjust for the patients' source of admission or discharge disposition. In addition, socioeconomic status (SES), race, or ethnicity are also not adjusted in our RAMs. While there is substantial debate about whether SES factors should be included in the risk-adjustment, at the time this research was begun, the consensus was to exclude them from risk adjustment models. The rationale of exclusion is that the standard of emergency care should not be differentiated based on the demographics of patients. To the extent of variation in payments and admission rates are associated with these characteristics, the argument goes, they potentially reveal the disparity in episode care provided to vulnerable populations. Adjusting for these factors would obscure such inequality. The model also did not adjust for systemic traits such as ownership, teaching status, and location. Systemic associated variations in ED performance will be analyzed in a later chapter. The data structure is hierarchical, meaning that medical claims in 30-day episodes are nested

within patients and patients are nested within healthcare providers. ED-level systemic factors may provide an association to the outcomes instead of existing as confounders.

4.2.3 Grouping Hierarchical Condition Categories (HCCs)

RAMs aim to characterize differences across EDs in patient demographics (age, gender, etc.) and clinical factors that are potentially related to the outcome measures but unrelated to the pattern of episodes of care. By extracting the ICD-10-CM diagnosis code, we recognized patient comorbidities for inclusion in the RAMs, starting from condition-specific indexed visits and tracing 12-month medical history. We used an ICD-10-CM to CMS-HCC assignment map to categorize 9,700 diagnosis codes into 86 Hierarchical Condition Categories (HCCs) (ICD-10 mapping,2023).

4.2.4 Candidate Variables Selection

Age and gender information are pre-determined risk variables based on the CMS-HCC risk adjustment model recommendation. The HCCs for each patient were coded from claims of 12 months before the indexed visits and aggregated to the episode level. We started with age, gender, and all 86 HCCs as candidate variables.

To inform the HCC variables selection, we conducted 1,000 stepwise bootstrap regressions with all candidate variables. The percentage of times each candidate variable was significantly associated with outcomes at the $p<0.05$ level in the 1,000-bootstrap sample is summarized. A candidate variable was selected if it was significant at $p<0.05$ in at least 900 out of 1,000 bootstrap samples. We also assessed the direction and magnitude of the regression coefficients. As a result, HCC variables above the 90% cutoff were kept as candidate variables. Although this technique is

not universally accepted, CMS measures with risk adjusters selected in this manner have been routinely endorsed by NQF. Variables above the 90% threshold provided robust, relevant associations with outcomes. The form of bootstrap regression used is dependent on the choice of function determined in Chapter 4.2.5.

Committee members also reviewed 86 HCCs and removed those not clinically related to each condition-specific disease in each RAM. Hence, the set of candidate variables not only provided statistical but also clinical relevance to RAM construction. Lists of final risk candidate variables of condition-specific RAMs are included in Appendix C and Appendix D.

4.2.5 Choice of function form

Part A: Function to Episode Cost

We winsorized payment (lower bound of 0.5th percentile and upper bound of 99.5th percentile) to improve model performance and prevent drastically altering hospital performance which may result from an unrepresentative, suspiciously cheap, or expensive outlier payment. As is typical with data for healthcare payment, the condition-specific, winsorized 30-day episode cost was both right-skewed and leptokurtic. The skewness ranges from 1.36 (biliary tract disease) to 1.96 (skin and subcutaneous tissue infections), and kurtosis ranges from 4.10 (biliary tract disease) to 5.96 (skin and subcutaneous tissue infections). We utilized the algorithm suggested by NQF to address the concern of estimation caused by non-normally distributed data. Alternatives for the RAM of cost included ordinary least square (OLS), log-transformed ordinary least square (Log-OLS) and generalized linear model (GLM). We graphed the residual plot to check the normal distribution and used the Ramsey RESET test to check the presence of heteroskedastic error terms. Box-Cox transformation and modified Park Test(Manning & Mullahy, 2001) were also employed to

determine the family and link function of GLM. Log transformation was a practical alternative because it converted extreme values into log scale and improved the R-squared. Among these alternative models, we decided to use GLM as a function of RAMs for episode cost. OLS is unreliable because of violations of linear regression. Compared to log-OLS, GLM was more suitable because it automatically converted the episode cost to the dollar scale without smearing effects created by re-transformation. We ultimately used GLM as the RAMs 30-day episode payment model with a log link and a gamma distribution.

Part B: Function to Admission Rate

The hospitalization status is binary (1: Yes; 0: No). We used logistic regression to construct the condition-specific RAMs for admission rate. Logistic regression must meet the independence assumption, which includes non-existence of multicollinearity, linearity of log odds, and large sample size. Our data did not violate each of the premises: 30-day episodes of care pattern were independent with respect to individual sample patient; the variation inflation factor of each independent variable was less than 3; As the Ten events per variable (EPV) advocated minimal criterion for sample size (van Smeden et al., 2016), logistics regression should have a minimum of 10 cases for each independent variable in the smaller of the binary group. In our condition-specific samples, the outcome probability ranged from 0.07 to 0.36. We have a maximum of 88 (86 HCC variables plus age and gender) risk variables. The required sample should range from 2,444 (biliary tract disease) to 12,571 (chest pain). Our sample size for each condition ranged from 4312 (biliary tract disease) to 29348 (chest pain), which is statistically large enough to satisfy the large sample assumption.

4.2.6 RAM Testing

We evaluated overall RAMs performance using critical statistics, including pseudo-R-squared, Akaike/Bayesian information criterion (AIC/BIC), Link test, Receiver operating characteristic (ROC/AUC) and Hosmer-Lemeshow (HL) test. Like the R-squared generated OLS, pseudo-R-squared is a statistic created in GLM or logistic regression used as a goodness-of-fit measure. We followed AIC/BIC to assess the probability of proper model selection. Both indices are penalized by adding parameters to the model, but BIC is penalized more than AIC. The RAM is selected based on the lowest BIC. We also checked RAM's misspecification via Link test. Link test was passed when the prediction squared had no explanatory power ($P>0.05$). Two additional critical statistics, ROC/AUC and HL test were adopted only for logistic RAM that examined model classification performance and degree of goodness of fit. To explore the issue of model overfitting, we also conducted a split sample analysis for risk-adjustment model of admission probabilities and comparing each samples' c-statistics and magnitude of coefficients. Through comparison, we observed that each sample's constructed RAM presented a similar coefficient and ROC/AUC in magnitude and significance across risk variables, suggesting overfitting is unlikely to occur.

4.3 Results

4.3.1 Evaluation of RAM Performance

Part A: RAM Performance for Episode Cost

According to the statistics summary in Table 4.2, RAM for episode cost illustrated a moderate goodness-of-fit power. The pseudo-R-squared ranged from 6.45% to 32.81%, which described the proportion of the total variability explained by the model. RAMs in conditions of biliary tract infection, cardiac dysrhythmias, and CHF had low pseudo-R-squares, indicating a small proportion

of variance in the episode cost was explained by the set of candidate variables. Small pseudo-R-squared also implied a considerable discrepancy between the observed and predicted episode cost.

We quantified the RAMs selection between log-OLS and GLM using probabilistic statistical measures, such as AIC/BIC. Though the comparison results were not documented in the table, the GLM denoted lower AIC/BIC, thus becoming the most appropriate regression model for predicting episode cost. Link tests were passed only in RAMs for conditions of biliary tract disease, cardiac dysrhythmias, and diabetes. For the RAMs in the rest of conditions, the prediction squared has explanatory power. Our episode cost in such conditions may be incorrectly specified, or the independent variables were misspecified conditional on specification. Models that failed to pass Link test are needed to consider re-categorizing age groups.

Table 4.2 Key statistics for selected risk adjustment models of 30-day episode cost

Condition-specific disease	**Pseduo-R^2**	**AIC/BIC (2 decimal)**	**Linktest (pass or not pass)**	**HL test(p)**
Biliary Tract Disease	0.1239	19.22/-90776.26	pass	N/A
Cardiac Dysrhythmias	0.0912	19.51/-102743.3	pass	N/A
Chest Pain	0.2544	18.04/-831935.1	not pass	N/A
CHF	0.0645	20.32/-119214.2	not pass	N/A
COPD	0.3033	17.80/-472762.2	not pass	N/A
DM	0.2467	19.18/-152919.9	pass	N/A
Fluid Electrolyte Disorder	0.2489	19.14/-165549.4	not pass	N/A
Gastroenteritis	0.2196	19.14/-136571.6	not pass	N/A
Pneumonia	0.2731	18.83/-212084.2	not pass	N/A
Skin and Subcutaneous Infection	0.3281	17.65/-443919.1	not pass	N/A
Urinary Tract Infections	0.3222	17.94/-606998.6	not pass	N/A

CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus

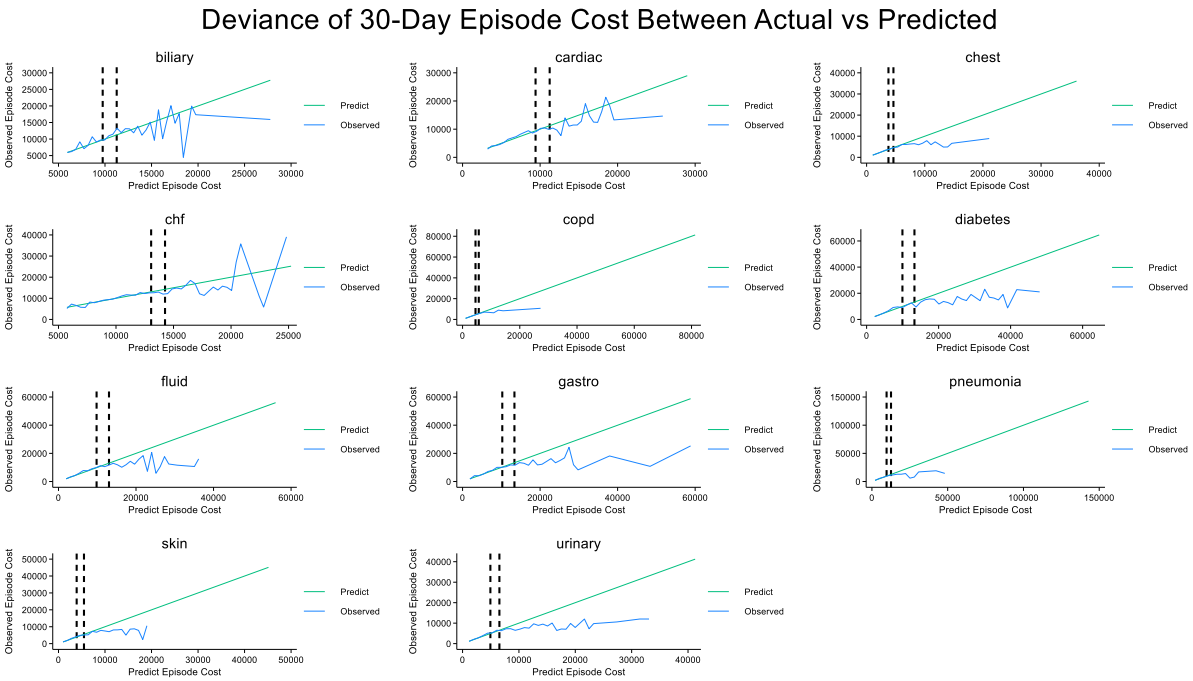

Figure 4.1 Polynomial smoothing plot of condition-specific, 30-day episode cost between actual Vs predicted

Two-way polynomial smoothing plots Vs fit plots were graphed to visualize the RAM-predicted 30-day episode cost against the observed episode cost. In Figure 4.1, blue polylines indicate the unadjusted episode cost associated with 30-day episode of care. Green straight lines denoted episode predicted cost from RAM. Two black dotted, vertical reference lines were drawn by measuring the 90th and 95th percentile of unadjusted episode cost (observed) respectively. We detected roughly 30-50% of polylines overlaid in the smoothing line in biliary tract diseases, cardiac dysrhythmias, and congestive heart failure conditions. Observed overlapping between two lines means that the prediction values from RAM equal or approximate to the observed episode cost. The rest of the eight conditions displayed substantial degrees of deviation, largely at the end of the predicted costs. Among these eight conditions, fluid electrolyte disorder, skin and subcutaneous infection, and urinary tract infections showed wide deviations between the actual and RAMs predicted cost. On Figure 4.1, we have also drawn two dashed black lines referencing

the 90th and 95th percentile actual episode cost, respectively. Visualized discrepancies between predicted and observed cost largely occurred after passing both referenced lines for all conditions. Such upper tail deviation means the RAMs prediction for episode cost are close to the real cost, except for expensive outlier payments. Our RAMs, in general, accurately predicted the actual episode cost for each condition.

Part B. RAM Performance for Admission Rates

RAMs for admission rate, on average, showed a moderate goodness-of-fit power. The pseudo-R-squared ranged from 3.21% to 18.86%, which described the proportion of the total variability explained by the model Models for cardiac dysrhythmias and CHF appeared to display poor goodness of fit due to low-value of pseudo-R-squared. However, based on ROC with reported C-statistics, models correctly classified the admission status. Nine of eleven conditions showed over 70% area under ROC (AUC), indicating a good model capability to distinguish between events admitted from ED and not-admitted events.

The link test was not passed in all conditions, which implies prediction squared had explanatory power to the model due to mis-specified outcomes. However, the logistic model has no control over the specification of the dependent variable other than having likelihood functions changed. An alternative is refitting the model using probit function. significant p from Hosmer-Lemeshow test statistics demonstrated a poor goodness of fit of RAM, except for biliary tract disease. It presented unmatched admission rates between observed and RAMs redacted across subgroups.

Table 4.3 Key statistics for condition-specific risk adjustment models for probability of admission

Condition-specific disease	Pseudo R^2	ROC/AUC	AIC/BIC	Linktest(p)	HL test(p)
Biliary Tract Disease	0.1213	0.7421	9226.818 9336.193	not pass	0.1249
Cardiac Dysrhythmias	0.0574	0.6556	13564.83 13675.89	not pass	0.0003

Chest Pain	0.1639	0.812	32958.73 33208.98	not pass	<0.0000
CHF	0.0321	0.6186	18521.08 18656.64	not pass	0.0352
COPD	0.1881	0.8113	28344.45 28528.47	not pass	<0.0000
DM	0.1093	0.7331	17200.27 17363.10	not pass	<0.0000
Fluid Electrolyte Disorder	0.143	0.7696	15889.51 16069.47	not pass	<0.0000
Gastroenteritis	0.1781	0.7836	14382.50 14550.93	not pass	0.0001
Pneumonia	0.1424	0.7609	21711.84 21872.79	not pass	<0.0000
Skin and Subcutaneous Infection	0.1886	0.8134	23568.37 23777.42	not pass	<0.0000
Urinary Tract Infections	0.2031	0.823	30427.02 30705.75	not pass	<0.0000

CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus

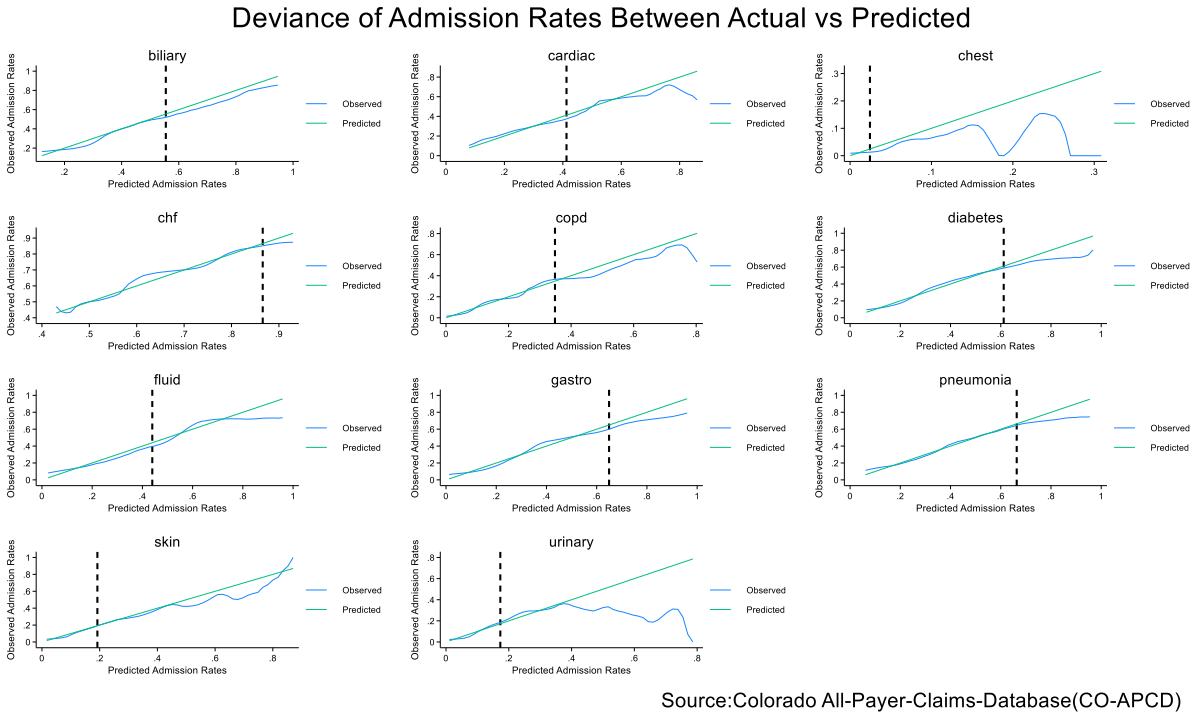

Figure 4.2 Polynomial smoothing plot of condition-specific, 30-day episode admission rate between actual Vs predicted

In Figure 4.2, blue polylines denoted the unadjusted(observed) admission probabilities associated with the 30-day episode of care. The solid, green smoothing line demonstrated the admission rate predicted from RAMs. All conditions observed substantial overlap between observed and

predicted admission. For conditions of biliary tract diseases, congestive heart failure, gastro, and pneumonia, more than 70% of their polylines were overlaid by the smoothing lines, indicating a high prediction accuracy. On the other hand, the predicted admission rate for chest pain and urinary tract infections displayed high deviance from observed admission. 60%-70% of the polyline area for such conditions was not overlapped by smoothing lines. A black reference line was drawn by measuring the 90th percentile of observed admission rates. Same as the circumstance under Figure 4.2, the condition-specific predicted admission strayed from the observed value after passing the reference line, illustrating that most errors cluster in the upper tail influenced by extreme values. It is safe to conclude that our constructed RAMs provided predictions close to observed admission rate despite a few mispredictions in extremum.

4.4 Discussion

We recommended keeping/dropping conditions in RAMs based on overall performance of goodness-of-fit, model specification, and prediction accuracy. RAMs of episode cost showed moderate goodness-of-fit. On average, about 23% variance of episode cost is explained by the model components. Some conditions (i.e., COPD, skin and subcutaneous infections, and urinary tract infections) even presented more than 30% of explanatory power. Although model misspecification existed, deviant behavior in prediction occurred only at the end of the cost distribution. Model misspecification could be improved by replacing extreme episode payment values with furthering winsorization to 95% level (2.5th percentile is lower bound; 97.5th percentile is upper bound).

The RAMs for the admission rate also gave a satisfactory performance. All ROC curves exceeded the 60% cutoff, indicating a well-classified model. Link test results were suboptimal, which implies the misspecification of outcomes. Nonetheless, changing the function to probit did not make models fit better considering larger AIC/BIC. The extreme values of the admission rate may be caused by small number of episodes. Since all variance errors are clustered in upper tails, keeping the extreme value of observed admission rates does not affect the overall prediction accuracy. Based on the above reasons, we have recommended keeping all conditions in the following risk-adjusted analysis.

Chapter 5 Risk-Adjusted Analysis

AIM 3: Examined variation in ED-level, condition-specific adjusted cost ratio and admission ratio, which is calculated by random-effect regression model that includes ED-level variables prediction divided by Risk Adjustment Model (RAM) prediction outcome (which excludes ED-level variables) respectively. Ranked EDs' performance based on cost ratios and admission ratios and explored patterns of care consistency among EDs across conditions.

5.1 Analysis Overview

We examined variation across EDs in risk-adjusted episode cost and admission rate. To accomplish this, we developed the episode-level predicted outcome based upon condition-specific RAM developed in Chapter 4. We then calculated the expected outcome given treatment at a specific ED by re-running the same RAM but incorporating information from a random intercept, allowing the outcome to be higher/lower for each episode based on which ED a patient was seen at. Once the expected/predicted ratio for each episode has been constructed, we aggregated them to the ED-level. Our final measures are the ED-level, condition-specific ratios of expected/predicted outcomes. It indicates whether the given ED was expected to present higher/lower performance than predicted based on their case-mix within each condition. With these conditions-specific point estimates, we compared the performance across EDs and evaluated whether a given ED's performance was higher/lower than the average performance of sampled EDs. We examined measures validity that variation in cost/admission rates across EDs are significant. The measure's reliability also has been tested based on prespecified criterion that between-ED variation is sufficiently more considerable than within-ED variation. If this is the case, we can conclude that the measures are reliable. In addition, we used interval estimates derived

from bootstrap resampling and simulation to measure the uncertainty around the point estimate. Moreover, we examine whether the estimates of ED performance are consistent across eleven conditions. We examine whether ED consistently provides high/low cost/admission care patterns for conditions. We conduct formal dissimilarity analysis. Lastly, if a consistent pattern were observed in large proportions of sampled EDs, we hypothesize that the risk-adjusted measures for cost and admissions should be correlated with unobserved latent variables. We then conducted an exploratory factor analysis separately for RAPRs/RAARs to test our hypothesis and to research the extent of correlation between risk-adjusted measures and corresponding factors.

5.2 Methods

5.2.1 Sample Size

Using administrative claims data, we measured risk-adjustment cost and admission rate for patients covered by all types of payers for an episode of care that begins with an index visit for a selected condition and ends 30 days after the index visits. The condition–specific sample size of episodes, patients, and EDs was described in table 5.1. Only EDs with a minimum of 25 episodes specific to each clinical condition were included to ensure the stability of estimates in accordance with current publicly reported risk-adjusted measures (Anderson et al., 2020; Fillingham et al., 2020; Venkatesh et al., 2015). We also tabulated the excluded EDs with the corresponding number of patients, episodes and EDs.

Table 5.1 Condition-specific Risk-adjusted Measures samples by no episodes, patients, and EDs

Condition	**Final Sample Size**			**Excluded sample**		
	No. of episodes	**No. of patients**	**No. of EDs**	**No. of episodes**	**No. of patients**	**No. of EDs**
Biliary Tract Disease	4002	3923	35	310	306	56
Cardiac Dysrhythmias	5061	4727	37	318	300	50
Chest Pain	28998	27722	70	349	345	27
CHF	4811	4359	32	196	188	39

COPD	15237	1427	58	433	425	39
DM	5857	5075	38	385	358	48
Fluid and Electrolyte Disorders	4757	4591	42	369	365	51
Gastroenteritis	4606	4481	35	322	315	90
Pneumonia	7441	7303	43	477	473	51
Skin and Subcutaneous Tissue Infections	15446	14709	64	309	307	31
Urinary Tract Infections	19684	18597	60	473	461	37

CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus

5.2.2 Statistical Analysis

5.2.2.1 Point Estimates

Part A: Risk-Adjusted Payment & Ratio

We used multilevel mixed effects generalized linear model (MEGLM) to isolate ED-specific cost signals accounting for the clustering of visits within ED. The model also estimated the within-ED correlation of the observed cost and tested that quality difference across EDs leads to systemic-caused variation in condition-specific cost associated with a 30-day episode of care. Ultimately, we calculated the predicted (RAM) and expected (RAM with random- or fixed-effect) cost for each ED.

ED-level, 30-day, risk-adjusted cost was computed as the ratio of excepted-to-predicted 30-day cost multiplied by the unadjusted average episode cost. The expected episode cost was calculated via the MEGLM by applying the estimated marginal coefficients to the observed patient characteristics with the random intercept added. Patient-level and ED-level expected costs are estimated using the average of all episodes cost per patient or ED. The predicted cost for each episode is calculated through the MEGLM by applying the estimated marginal coefficient to the

patient-mix factors observed. We then evaluated the predicted cost for each patient and each ED by averaging the predicted cost for all episodes within the patient and with- EDs, respectively.

Specifically, let Y_{ij} denote the condition-specific, 30-day episode cost for the j^{th} episodes to the i^{th} ED; and Z_{ij} denotes the candidate risk factors where $Z_{ij}= (Z_{1ij}, Z_{2ij}, \ldots, Z_{pij})$ is a set of **p** patient-specific variables (for example, age, gender, HCCs) for j^{th} episodes to i^{th} ED. We assumed the episode cost for equation (1) is related linearly to the risk factors via a known link function, h(.), as follows:

Eq 1 $$h(Y_{ij}) = \alpha + \beta Z_{ij}$$

In this case, h(.) is the log link with a gamma distribution for the episode cost. Based upon the assumption of a consistent treatment pattern of care for a patient present in ED with the same condition, we employed MEGLM to account for the natural clustering of the episodes within EDs. and adjust for the selected risk factors. The model used a log link and a gamma distribution with an EDs random intercept as follows.

Eq 2 $$h(Y_{ij}) = \alpha_i + \beta Z_{ij}$$

Eq 3 $$\alpha_i = \mu + u_i \qquad u_i \sim N(0, \tau^2)$$

Where α_i represents the ED fixed- or random intercept, we define Z_{ij} the same as in Eq 1, which is the unadjusted, 30-day episode cost. μ is the average intercept across all EDs in the sample, and τ^2 is the between-ED variance component. We then fitted the hierarchical GLM using the risk factors set from Eq 2 and Eq 3 and estimated the parameters $\hat{\mu}$, $\{\alpha_i, \alpha_2 \ldots, \alpha_I\}$, $\hat{\beta}$, and τ^2. The risk-adjusted payment (RAP_i) was computed by the expected 30-day episode cost (Eq 5) to the predicted episode cost (Eq 4), aggregated to the ED level multiplied by the unadjusted average cost, $\overline{Y}$. The equation follows:

Eq 4 *Predicted (RAM model)* $$\hat{Y}_{ij}(Z_{ij}) = h^{-1}(\hat{\alpha}_i + \hat{\beta} Z_{ij})$$

Eq 5 *Expected (Random- or Fixed effect)* $\hat{e}_{ij}(Z_{ij}) = h^{-1}(\hat{\mu} + \hat{\beta} Z_{ij})$

Eq 6 $$\widehat{RAP}_i\ (Z_{ij}) = \frac{\sum_{j=1}^{n_i} \hat{e}_{ij(Z)}}{\sum_{j=1}^{n_i} \hat{Y}_{ij(Z)}} \times \bar{Y}$$

Or simply, the risk-adjusted payment ratio (RAPR) is:

Eq 7 $$\widehat{RAPR}_i\ (Z_{ij}) = \frac{\sum_{j=1}^{n_i} \hat{e}_{ij(Z)}}{\sum_{j=1}^{n_i} \hat{Y}_{ij(Z)}}$$

In Eq 6 and Eq 7, i refers to i^{th} ED, j denotes j^{th} episode within ED, and n_i is the total number of episodes within i^{th} ED. If the expected total episode cost was higher (or lower) than the predicted episode cost for a given ED, risk-adjusted payment would be higher (or lower) than the unadjusted average payment. Following the same logic, the risk-adjusted payment ratio $\widehat{\text{RAPR}}_\text{i}\ (Z_{ij})$ would be greater/lower than 1 if "expected" more/less than "predicted" payment. The Multilevel mixed effects generalized linear models (MEGLM) were estimated using the STATA **meglm** procedure.

Part B: Risk-Adjusted Admission Rate & Ratio

The method for measuring ED-level, risk adjust admission rates were similar to strategies in statistical approach used in episode cost estimates. Due to the natural clustering of observations within ED, multilevel logistic regression models were conducted with the entire sample. The admission rate was conducted as a function of patient demographics and selected HCCs. Again, multilevel logistic regression isolates within-variation from between-ED variation. The multilevel logistic models were estimated using the STATA software **xtlogit** procedure**.**

Recalling Eq 1, Y_{ij} represents the admission status (1 if the patient is admitted, otherwise is 0) for a condition-specific 30-day episode for j^{th} episodes admitted to i^{th} ED. Z_{ij}= (Z_{1ij}, Z_{2ij}, …, Z_{pij}) represents a set of **p** candidate risk variables. We assumed the admission probability for Eq 1 is

related linearly to the covariates via a known link function, h(.), the log function links the admission probabilities to the patient risk factors.

ED level, 30-day risk-adjusted admission rate was calculated as the ratio of the expected-to-predicted number of admissions multiplied by the unadjusted average admission probabilities. The estimated regression coefficient was multiplied by the observed patient characteristics for each episode. The quantity was then transformed to the probability scale using the natural log function. We first calculated the expected admission probability for each episode and then aggregated them to the patient- and ED-level, respectively. The expected admission probability for each episode is calculated through the multilevel logistic model with added ED random intercept. The predicted probability was via a multilevel logistic model by applying the estimated regression coefficients to the observed risk factors. The predicted admission number for each patient and ED was estimated by averaging episode admission probability and aggregating it to the patient and the ED level, respectively.

Using the log link, we first conducted the logistic regression model from Eq 1. Having identified the risk variables that were selected, Next, we fitted the multilevel logistic regression using Eq 2 and Eq 3. The Eq 2 with natural log transform is Eq 8:

Eq 8 $$logit\ (Prob\ (Y_{ij} = 1)) = \alpha_j + \beta Z_{ij}$$

where Z_{ij} consisted of covariates retained in the logistic regression model. $Y_{ij} = 1$ if i^{th} index visit were admitted to hospital from the j^{th} ED, 0 otherwise.

Recalling Eq 4 - Eq 5 and estimating the parameter $\hat{\mu}$,$\{\alpha_i, \alpha_2, \ldots, \alpha_I\}$,$\hat{\beta}$,and τ^2, we calculated a risk-adjusted admission rate $\widehat{\mathrm{RAA}}_i$

Eq 9
$$\widehat{RAA}_i\ (Z_{ij}) = \frac{\sum_{j=1}^{n_i} \hat{e}_{ij(Z)}}{\sum_{j=1}^{n_i} \hat{Y}_{ij(Z)}} \times \bar{Y}$$

The risk-adjusted Admission Rates (RAA_i) were computed by the expected 30-day episode admission rate (Eq 5) to the predicted admission rate (Eq 4) aggregate to ED level, multiplied by the unadjusted average admission probabilities, $\underline{Y}$. Risk-adjusted admission ratio ($RAAR_i$) (expected/predicted) is calculated without $\underline{Y}$.

Eq 10
$$\widehat{RAAR}_i\ (Z_{ij}) = \frac{\sum_{j=1}^{n_i} \hat{e}_{ij(Z)}}{\sum_{j=1}^{n_i} \hat{Y}_{ij(Z)}}$$

In Eq 8 and Eq 9, I denotes the total number of ED, and n_i is the number of episodes within i^{th} ED.

Risk adjusted admission rate, $\widehat{\mathrm{RAA}}_i(Z_{ij})$, would be higher/lower than the national unadjusted average admission probabilities if more/fewer "expected" than "predicted" admission in an ED. Risk adjusted admission ratio, $\widehat{\mathrm{RAAR}}_i(Z_{ij})$, would be greater/lower than 1 if more/fewer "expected" than "predicted" admission rate in an ED.

We decided to utilize the RAPR and RAAR as our point estimate measures in the results. The risk-adjusted ratios are superior to original scales because it allowed us to compare similarities of care patterns across conditions.

5.2.2.2 Interval Estimates

To characterize the level of uncertainty around point estimates, we used the bootstrapping and simulation technique to derive the 2.5th and 97.5th percentile of RAPR and RAAR, which are ED-level, risk-adjusted, 95% confidence interval estimates. We chose bootstrap over other resampling techniques because it not only provides more robust and precise estimates of confidence intervals, but also it avoids unnecessary distributional assumptions (Fillingham et al., 2020; Glance et al., 2020).

RAPR and RAAR interval estimates computation used the same procedure consisting of four steps below. Let **I** denote the total number of EDs. Each step was simulated 1,000 times, which is the rule of thumb for bootstrap samples:

Step 1. We bootstrapped the sample by **I** EDs and took i^{th} ED with replacement.

Step 2. We fitted the Multilevel model using all episodes within each re-sampled EDs. If some ED were selected more than once in a bootstrapped sample, they are treated as distinct so that we have **I** random effects to estimate the variance component. During this Step, we computed $\hat{\beta}^{(b)}$(estimated regression coefficients of the risk factor); $\hat{\mu}^{(b)}$ and $\tau^{2(b)}$ (parameters governing the random effects, risk-adjusted outcomes, and distribution); $\{\hat{\alpha}_i^{(b)}, \widehat{var}\left(\hat{\alpha}_i^{(b)}\right), i = 1,2, \dots, I\}$(the set of ED-specific intercepts and corresponding variances)

Step 3. ED random effects were generated by sampling from the distribution of ED-specific distribution obtained in Step 2. Specifically, we approximated the distribution for each random effect by a normal distribution and drew a $\hat{\alpha}_i^{(b^*)} \sim N(\hat{\alpha}_i^{(b)}, \widehat{var}\left(\hat{\alpha}_i^{(b)}\right))$ for each unique set of ED sampled in Step 1.

Step 4. for j[th] episodes in each unique i[th] ED sampled in Step 1, we calculated the expected outcome :$\hat{Y}_{ij}^{(b)}$, error term: $\hat{e}_{ij}^{(b)}$, risk-adjusted outcomes from b[th] bootstrap sample:$\widehat{RAPR}_i(Z)^{(b)}$ and $\widehat{RAAR}_i(Z)^{(b)}$, where random effects: $\hat{\alpha}_i^{b^*}$, ED adjusted outcomes: $\hat{\beta}^{(b)}$and distribution: $\hat{\mu}^{(b)}$, obtained from Step 2 and Step 3.

95% confidence interval estimates for the risk-adjusted outcomes were calculated by identifying the 2.5th and 97.5th percentiles of the 1,000 estimates.

5.2.2.3 Reliability Analysis

One of the criterions of judging performance of provider-level quality measures is assessing whether measures variations were observed across providers. Simultaneously, these differences should be reliable enough that between-provider variation is larger than with-provider variation. We conducted the signal-to-noise analysis to assess the reliability of condition-specific outcome ratios. The signal is the proportion of the variability in measures that natural differences in hospital performance explain. This approach determines to which extent variation in the measure is due to underlying ED performance rather than random variation (i.e., statistical noise) within EDs. John Adam and his colleagues from Rand Corporation constructed a standardized approach to estimating signal-to-noise ratio, and it has been widely accepted in the healthcare quality field. We, therefore, adopted their techniques to calculate the reliability score for episode cost(John L. Adams & McGlynn, 2010) and admission rates(Adams, 2009), respectively.

In general, we calculated the reliability score as

Eq 11

$$Reliability = \frac{\sigma^2_{between}}{\sigma^2_{between}+\sigma^2_{within}}$$

The reliability score is the ratio of between-ED variance of measure to the sum of between-ED variance and within-ED variance of measure. A reliability of zero indicates that all measured difference is attributable to random sampling error. Reliability to value of 1 suggests that the measure perfectly captures the systemic difference between EDs.

Part A: Episode Cost Profiling

Our risk-adjusted cost measures were built by MEGLM, but no existing literature illustrates how to conduct reliability scores under the GLM function. Regarding cost profiles, we estimated reliability as a function of a simple Multilevel linear model (MLM). We hypothesized that the MLM reliability score should be close to MEGLM's estimate because the between-ED variance in both models was affected by the same factors, and their within-ED variation was assumed to follow the normal Gaussian distribution.

A simple two-level MLM separates the observed variability in ED scores into two parts: variance between EDs and variance within the ED. The equivalent definition of reliability from this framework is

Eq 12

$$Reliability = \frac{\sigma^2_{between-E.D}}{\sigma^2_{between-E.D}+\sigma^2_{within-E.D}} = \frac{\sigma^2_{ED\ to\ ED}}{\sigma^2_{ED\ to\ ED}+\frac{\sigma^2_{average\ episode\ error}}{n}}$$

where within-ED variance is the average error variance for the episodes attributed to ED divided by n, where n is the number of episodes to each ED. This metric demonstrated ED ’s cost profile has different reliability because the number of episodes attributed can vary widely from ED to ED. Both between- and within-ED variance were computed in STATA using **mixed**.

Part B: Admission Profiling

We estimated the reliability of admission using the beta-binomial model, which was a more natural fit than multilevel logistic regression for assessing the reliability of pass/fail rate measures. The approach assumes that each ED has an admission rate of p, which varies across ED presumably due to variations in practice styles in the range of 0 to 1. The observed admission rate p was initially calculated using ED level, number of admission events (m) divided by the number of episodes. However, providers with 0% or 100% admission rates will always have an estimated reliability score of 1. This limitation made the original beta-binomial approach susceptible to yielding grossly overestimated reliability scores for small or moderate volumes of episodes for EDs with admission rates equal to 0% or 100% (Zhou & Lin, 2023). Therefore, we employed a revised approach from a preprinted paper that improved beta-binomial estimation to generate more reasonable estimates for EDs. Details of statistical analysis and results that illustrated the revised method outperformed the original beta-binomial approach regarding bias and standard errors were described in Zhou et al. (2023), in which the revised p was calculated as

Eq 13
$$p^{*}=\frac{0.5+m}{1+n}$$

Again, the reliability score equation is

Eq 14
$$Reliability == \frac{\sigma^2_{between-E.D}}{\sigma^2_{between-E.D}+\sigma^2_{within-E.D}}$$

Considering the setting of admission profile, the equation is rewritten as

Eq 15
$$Reliability = \frac{\sigma^2_{ED\ to\ ED}}{\sigma^2_{ED\ to\ ED}+\sigma^2_{binomial}} = \frac{\sigma^2_{ED\ to\ ED}}{\sigma^2_{ED\ to\ ED}+\frac{p(1-p)}{n}}$$

The between-E. D variance was computed in STATA software using **betabin**.

5.2.3 Care Consistency in ED

In the analysis above, condition-specific risk-adjusted measures of ED performance is successfully constructed as standardized ratios, which offers a solution to compare EDs' cost and admission rates in episodes of care across conditions. We are intrigued by whether ED presents a monotonic performance on episode cost and admission decisions across conditions. It is presumed that if a given ED's RAPR is higher or lower than EDs' average RAPR for a specific condition, this ED will also have higher or lower than the average RAPR for other conditions. The same presumption also applies to RAAR. It is also expected that some EDs' RAPR/RAAR with a wide within-ED variance are similar to their average. On the other hand, it is least expected that some EDs' risk-adjusted measures are higher than average estimates for one condition, but lower than average for other conditions. Such flipping would weaken our assumption of monotonic ED performance across conditions.

If the above assumption holds, a collection of ED's risk-adjusted measures presenting either higher, lower, or similar to the condition-specific average risk-adjusted measures across conditions would be observed.

For each condition-specific sample, we ranked ED performance from lowest to highest based upon its point estimates of risk-adjusted measures. We then used point and interval estimates of risk-adjusted measures to graph an interval plot exhibiting ED ranking on each measure of the condition-specific cohort (Figure F- 1 to Figure F- 22). As Figure F- 1 to Figure F- 22 indicated, the orange diamond and blue interval plot denoted certain EDs point and interval estimates of

RAPR and RAAR, respectively. The red dashed line is the average risk-adjusted measure among EDs.

Figure F- 1 to Figure F- 22 shows whether specific ED risk-adjusted measures are higher, lower, or equal to the average ED estimates. Meanwhile, we expect to observe a consistent performance in EDs across conditions. Based on point and interval estimates of condition-specific RAPR and RAAR, we measured the care consistency of each ED across conditions. For each ED, the level of RAPR and RAAR is classified as

- 'Low' if their upper bound of interval estimates (97.5th percentile) is below the ED-level, condition-specific mean of RAPR and RAAR.
- 'Medium' if a given ED's interval estimates contain the mean.
- 'High' if their lower bounds (2.5th percentile) exceed the mean.

With above classification of RAPR and RAAR measures, we came up with EDs' care consistency classification method with details below:

Not all EDs have cases for all eleven conditions. Therefore, the level of RAPR and RAAR will be empty if the ED does not have admission for its corresponding conditions. We also eliminated EDs with "Medium" risk-adjusted measures across all conditions because they do not exhibit notable patterns. We are interested in finding care consistency patterns for EDs with "High" or "Low" risk-adjusted measures. The proportion of care consistency in a given ED is calculated by the aggregated counts of "High" or "Low" risk-adjusted measures divided by the sum of "High" and "Low" counts for each ED. "Medium" and empty counts were excluded. The proportion of consistency of "High" and "Low" ranged from 0 to 1:

- We arbitrarily assumed all “High” or all “Low” RAPR and RAAR to be representative of perfect care consistency in each ED. Therefore, a percentage of “High” or “Low” of 100% indicates perfect care consistency.
- The proportion ≥ 0.7 & < 1 exhibits a dominant high or low pattern of care.
- The proportion ≥0.3 & <0.7 is defined as a mixed pattern.

Consequently, among 73 EDs across condition-specific cohorts, 18 were excluded from the care consistency analysis as they have “Medium” level RAPR and RAAR in all conditions. These EDs' 95% CIs are broad and include the mean of condition-specific RAPR and RAAR. We determined they neither belong to “Low” or “High” consistency nor present mixed patterns. As a result, only 55 EDs' care consistency was analyzed. Figure 5.1 below shows EDs’ care consistency pattern.

We also measured the similarity/dissimilarity of care consistency among EDs using 22-point estimates (RAPR and RAAR) as benchmarks. Measuring similarity from multiple dimensions requires many calculated axes, but only a few are viewed owing to graphic limitations. We seek a solution where a small number of ordination axes are explicitly displayed, and the data are fitted to the original dimensions. We, therefore, conducted a Non-metric Multidimensional Scaling (NMDS) analysis to assess the similarity/dissimilarity of care consistency among EDs from a matrix of the point estimates of condition-specific RAPR and RAAR. NMDS is an ordination technique used to create a configuration of data points in a lower-dimensional space (usually two or three) that approximates the pairwise dissimilarity in the original dimensional structure as closely as possible. Although both Multidimensional Scaling(MDS) and NMDS can assess the distinction and distance across EDs, we are prone to NMDS because it holds fewer assumptions and focuses mainly on ranking dissimilarities rather than their numerical values(Gu et al., 2018;

Lee et al., 2014; Woods et al., 2018). Only 31 of 55 EDs were examined for their dissimilarity of care consistency using NMDS because of no missing data requirement. We conducted NMDS analysis on these EDs through several processes:

1. We create a dissimilarity matrix using every ED's RAPR and RAAR point estimates representing the pairwise distances between all EDs in our data set. We used the Euclidean distance to measure pairwise distance because it is the most common and intuitive distance measure validated by a great body of literature (Graffelman, 2020; Lee et al., 2014; Woods et al., 2018; Zand et al., 2015). We further computed the Euclidean distance on standardized variables to provide more footing for all RAPR and RAAR point estimates.
2. We chose the two dimensions for the reduced space and used the randomized algorithm to initialize the configuration of points in the reduced space.
3. The stress function represents the discrepancy between the Euclidean distance in the reduced space and the original dissimilarity matrix. Therefore, the stress function was minimized by iteratively adjusting the positions of data points in the reduced space.
4. We plotted the final configuration of data points in the two-dimensional space, representing the NMDS ordination of the original data.

NMDS can be executed in STATA using **mds** with option **nonmetric.**

5.2.4 Exploratory Factor Analysis (EFA)

The prior analysis focused on the evaluation of the 11 individual admission and 11 individual episode cost measures. A hypothesis for this study was that there were underlying variations in likelihood of admission or episode costs that were associated with ED performance and decisions

that were ED specific and these patterns would be observed in condition-specific measures. If the hypothesis that there are ED specific tendencies in likelihood of admission or episode cost is true, then the results across measures should be correlated. That is, EDs with higher than predicted admission patterns or episode costs for one measure should show similar patterns for the other measures. This general tendency is a latent variable unobserved directly. Generally, we believe that all RAPRs/RAARs are somewhat correlated with unobserved variables (or latent variables) that can only be inferred indirectly via a correlation matrix. Extracting meaningful information by examining a simple correlation matrix of a large number of measures is difficult. This motivates us to conduct a comprehensive exploratory factor analysis (EFA) separately for RAPRs/RAARs. A comprehensive EFA gives us a better understanding of factorability and factor selection and allows us to interpret individual (factor loading) and joint variation (communalities) of risk-adjusted measures in response to corresponding factors.

We conducted factor analysis following three steps. First, a correlation matrix was constructed to examine the appropriateness of factor analysis. A correlation matrix sufficient for factor analysis will have at least a few correlations > 0.30 in absolute value (Hahs-Vaughn & ProQuest, 2017). Diagnostics for the appropriateness of factor analysis were conducted including computed determinant of matrix, Kaiser Meyer Olkin (KMO) measure, and Bartlett test with predetermined threshold or P-value respectively. Second, we ran Principal Component Analysis (PCA) to determine the number of factors accounting for the interrelations among RAPRs/RAARs. We first used the Eigenvalue cut-off approach with a threshold of one to assess the number of factors to retain. We then used additional approaches of PCA including eigenvalues scree plot, parallel analysis, minimum average partial (MAP) correlation, and maximum likelihood factoring (MLF)

to validate our judgment from Eigenvalue cut-off rule. We expected these other approaches to reach the same conclusion as Eigenvalue approach and any conflicts in the suggested number of factors were based on the number suggested by most of the approaches. Third, we conducted factor analysis using the iterated principal factors approach. If multiple factors were identified, matrix rotation was used to apply weight to the factors loading. Moreover, the rotated matrix spread out the eigenvalue more evenly, enhanced explanatory power of factor loading (can be interpreted as standardized regression coefficient) and reduced model error measured by uniqueness, compared to an unrotated one. We used orthogonal rotation because it is generally more replicable in future samples than oblique rotation. Finally, we reported each RAPR/RAAR communalities (1-uniqueness), which refers to the individual proportion of variation explained by given factor/s.

We were able to conduct EFA on only 31 EDs with all non-zero risk-adjusted measures. All statistical analyses were performed with the STATA 18.0 (MP, College Station, TX). For correlation matrix identification, the determinant value threshold of correlation matrix is $P > .00001$ (Watkins et al., 2022). Kaiser Meyer Olkin (KMO) test (Tabachnick & Fidell, 1989) determined the range of threshold as follows: 0.00 to 0.49-unacceptable,0.50 to 0.59-miserable, 0.60 to 0.69-mediocre, 0.70 to 0.79-middling, 0.80 to 0.89-meritorious, and 0.90 to 1.00-marvelous. Bartlett's test with $P<.05$ considered significant. For PCA, the cut-off Eigenvalue rule is greater than 1, however it is not generally recommended. In parallel analysis, we adhered to factors selection criterion that PCA calculated eigenvalue value should exceed the randomly generated eigenvalue. Using minimum average partial correlation, factors are selected based on the smallest MAP value. In Maximum likelihood Factoring (MLF), we chose the number of factors with the smallest AIC/BIC. For factor analysis, the absolute value of minimum loading criteria on a given

factor is 0.4 (the factor loading value can be negative). Cut-off value of 0.4 for communalities is recommended with sample size below or equal to 100 (MacCallum et al., 2001). Tables of correlation matrix and scree plots were attached in Appendix H.

5.3 Results

5.3.1 Extent of Variation

Part A: Risk-Adjusted Payment Ratio (RAPR)

Table 5.2 presents the number of EDs, the ED-level, risk-adjusted payment, the ED level, risk-adjusted payment ratio (RAPR) with standard error, and ratio's selected percentile level for each condition-specific sample. Recall from the method section RAPR is an estimator of expected-to-predicted payment. An RAPR of 1.0 indicates estimated ED episode cost was similar to would be predicted for the ED's patients by the risk adjustment model. A ratio greater than 1.0 indicates estimated ED episode cost was higher than would be predicted for the ED's patients by the risk adjustment model, and less than 1.0 means estimated ED episode costs were lower than would be predicted for the ED's patients by the risk adjustment model.

Table 5.2 Distribution of ED-level, condition-specific, risk-adjusted 30-day episode payment

Condition	# Of EDs	RAP (USD)	Risk adjusted payment ratio (RAPR)								
			Mean	S.E	Range including percentiles						
					Min	10th	25th	50th	75th	90th	Max
Biliary Tract Disease	35	$7,847	1.02	0.09	0.83	0.90	0.96	1.02	1.07	1.14	1.21
Cardiac Dysrhythmias	37	$6,411	0.99	0.09	0.80	0.87	0.94	0.99	1.05	1.11	1.22
Chest Pain	70	$2,621	1.02	0.12	0.80	0.85	0.94	1.01	1.08	1.20	1.32
CHF	32	$10,398	1.03	0.11	0.82	0.92	0.97	1.04	1.08	1.15	1.29
COPD	58	$2,574	0.98	0.12	0.76	0.83	0.92	0.97	1.06	1.13	1.26
DM	38	$5,525	1.01	0.07	0.80	0.92	0.98	1.01	1.05	1.08	1.18
Fluid and Electrolyte Disorders	42	$5,168	0.99	0.10	0.80	0.84	0.93	0.98	1.05	1.11	1.26
Gastroenteritis	35	$6,234	1.02	0.08	0.89	0.93	0.96	1.00	1.08	1.13	1.20
Pneumonia	43	$5,337	1.04	0.14	0.79	0.91	0.94	1.00	1.12	1.31	1.46
Skin and Subcutaneous Tissue Infections	64	$2,138	0.98	0.13	0.70	0.84	0.90	0.97	1.05	1.15	1.28

Urinary Tract Infections	60	$2,657	0.98	0.13	0.68	0.81	0.90	0.98	1.05	1.22	1.38

RSP: means of risk-adjusted payment.
CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus
S.E: standard error

To each condition-specific disease, the key results of statistical analysis for ED level, RAPR associated with a 30-day episode of care presented below:

- After risk adjustment, the mean value of adjusted payment to biliary, cardiac, CHF, COPD, DM, gastro, and pneumonia exceeded their unadjusted payment. On the other hand, the mean value of adjusted payment to chest pain, fluid disorder, skin, and urinary was below their unadjusted payment. The largest estimated difference between unadjusted episode cost against adjusted cost occurred in biliary ($2,513), and the smallest estimated difference occurred in DM ($7).
- The mean of RAPR is close to its median which suggests that the mean value of RAPR is a desired measure of central tendency.
- The mean RAPR for all conditions ranged from 0.98 to 1.04. Moreover, the standard error of RAPR ranged from 0.07 to 0.14.
- The variation of RAPR is minimal across the EDs. The variation (25^{th}, 75^{th}) of RAPR ranged from 0.11 to 0.18. By following the rule of absolute difference of 15% (Pines et al., 2016), statistical variation was observed only in pneumonia (0.18), skin and subcutaneous infections (0.15) and urinary tract infections (0.15).
- The extreme value of RAPR (minimum or maximum) was moderately over/under predicted. The minimum RAPR ranged from 0.68 to 0.89. For those EDs with maximum RAPR, their expected performance on cost is 10% to 30% lower than their predicted cost. The Maximum RAPR ranged from 1.20 to 1.46; Their reflected ED expected performance on episode payment is 20% to 45% higher than their predicted payment.

Based on key findings above, we reached the conclusion that variation of RAPR is narrow, but still presented substantial difference in dollar scale.11%-18% difference in variation refers to $360 to $1,144 in episode cost.

Part B: Risk-Adjusted Admissions Ratio (RAAR)

Table 5.3 Distribution of ED-level, condition-specific, admission rates

Condition	# of EDs	RAA (%)	Risk Adjusted Admission Ratio (RAAR)								
			Mean	S.E	Range including percentiles						
					Min	10th	25th	50th	75th	90th	Max
Biliary Tract Disease	35	37.85	0.95	0.16	0.64	0.75	0.81	0.93	1.08	1.15	1.24
Cardiac Dysrhythmias	37	30.14	0.94	0.28	0.46	0.61	0.72	0.94	1.18	1.34	1.47
Chest Pain	70	9.88	0.78	0.39	0.28	0.46	0.57	0.66	0.86	1.40	2.76
CHF	32	73.76	0.96	0.15	0.49	0.77	0.91	0.99	1.06	1.09	1.17
COPD	58	11.49	0.82	0.33	0.38	0.42	0.57	0.75	1.02	1.31	1.70
DM	38	30.71	0.94	0.16	0.51	0.74	0.84	0.96	1.02	1.09	1.36
Fluid and Electrolyte Disorders	42	19.38	0.85	0.29	0.41	0.47	0.58	0.90	1.05	1.16	1.49
Gastroenteritis	35	37.86	1.00	0.16	0.54	0.77	0.94	1.02	1.11	1.16	1.27
Pneumonia	43	33.70	0.97	0.17	0.63	0.73	0.83	0.99	1.09	1.21	1.27
Skin and Subcutaneous Tissue Infections	64	7.05	0.80	0.34	0.34	0.45	0.51	0.82	0.99	1.34	1.76
Urinary Tract Infections	60	6.32	0.87	0.32	0.34	0.54	0.62	0.81	1.04	1.34	1.93

RAA: means of risk-adjusted admission.
CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus
S.E: standard error

Table 5.3 presented number of EDs, the ED-level, risk-adjusted admission rate, the ED level, risk-adjusted admission ratio (RAAR) with standard error, and ratio's selected percentile level for each condition-specific sample. RAA are varied across conditions. Conditions for urinary tract infections, skin and subcutaneous tissue infections, and chest pain have low rates of admission. Those conditions have less than 10% of probability getting admitted. On the other hand, CHF presented 74% probability of hospitalization. The rest of the conditions have moderate level of

admission probability, which roughly ranges from 20% to 40%. For each condition-specific disease, the key results of descriptive analysis for ED level, condition-specific RAAR associated with a 30-day episode of care are presented below:

- After risk adjustment, all adjusted admission is higher than unadjusted admission, ranging from 0.95% (biliary) to 46.82%(CHF).
- Except for Chest pain, the mean of RAAR is close to its median. This illustrated mean value of RAAR is a desired measure of central tendency.
- The mean of RAAR ranged from 0.78 to 1.00. Standard error ranged from 0.16 (biliary) to 0.39 (chest pain). In general, the data of RAAR were widely spread, and the expected admission is either smaller than or equal to the predicted admission.
- The variation of RAAR is substantial across the EDs. The variation of RAAR ranged from 0.15 (CHF) to 0.48 (skin). According to the 15% absolute difference, substantial variations of RAAR across the ED were detected in all eleven conditions.
- The extreme value of RAAR (minimum or maximum) was greatly over/under-predicted. The minimum RAAR ranged from 0.28 to 0.64. For those ED with extreme RAAR, their expected performance on admission is 36% to 70% lower than their predicted admission rate. On the other hand, the maximum of their predictive ratio ranged from 1.24 to 2.76, and their reflected ED expected performance on admission rate is about 24% to 175% higher than their predicted admission.

According to the key statistics, we estimated wide variation in RARR. Specifically, for each condition, the estimated variation in RAAR is much larger than variation in RAPR estimates.

The general trend of RAPR and RAAR response to each condition were summarized in Figure 5.1 and Figure 5.2 respectively. Each ED's estimated condition-specific RAPR and RAAR with corresponding confidence intervals were plotted in the Figure F- 1 to Figure F- 22 from Appendix F. These RAPR and RAAR were also ranked from lowest to highest upon on-average estimates. Both average estimates (diamond) and interval estimates (interval plot) of RSPR and RSAR visualized the between-ED variation and within-ED variation, respectively.

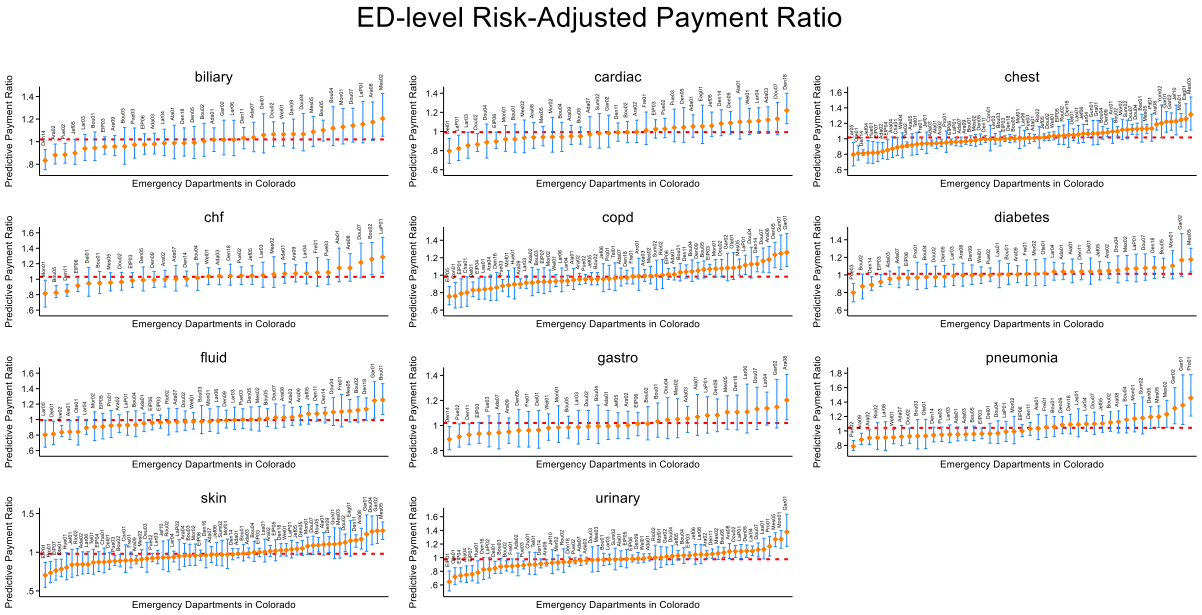

Figure 5.1 ED-level, Condition-specific, risk-adjusted 30-day episode payment ratio pooling each ED

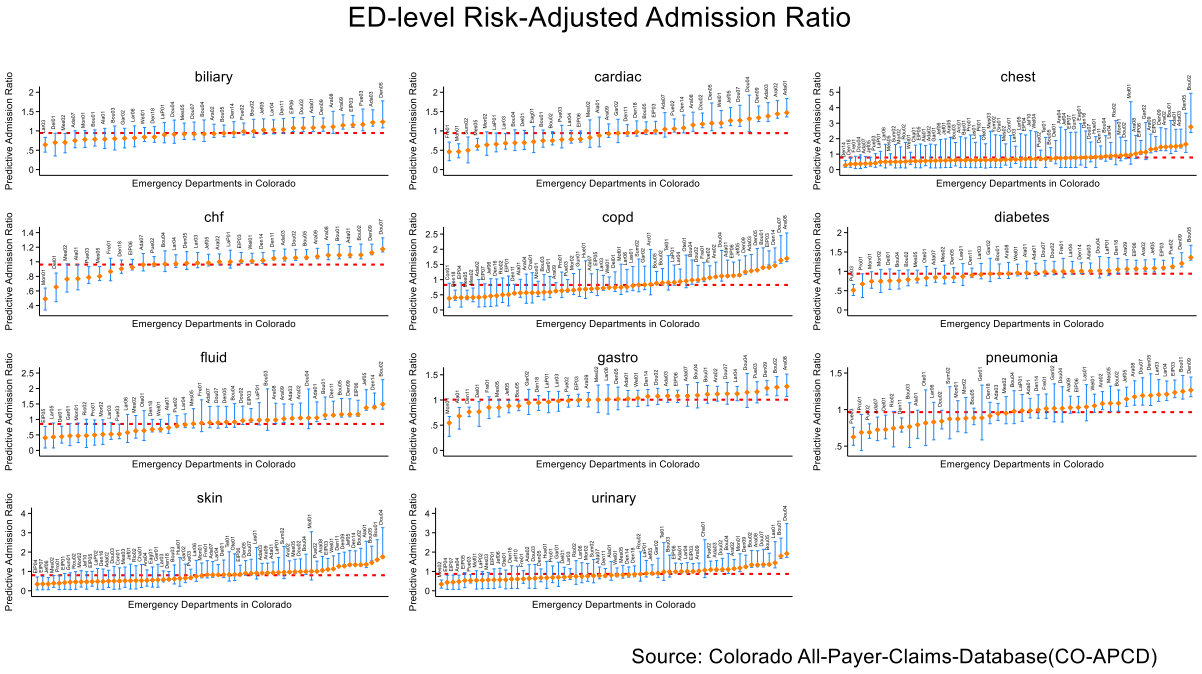

Figure 5.2 ED-level, condition-specific, risk-adjusted average admission ratios pooling each ED

5.3.2 Reliability Score

Part A: Episodes Cost Profiling

The distribution of reliability scores for condition-specific cost is demonstrated in Table 5.4. At a testing volume threshold of at least 25 episodes per ED, the reliability score ranged from 0.63 to 0.86. For each condition, the mean of reliability is close to its 50th (median) percentile. This proved the reliability mean is an appropriate measure for central tendency. Gastroenteritis had low reliability at the 25th percentile (0.50), but their reflected mean and median still implied higher between-ED variation than within-ED variation. Though not documented in the table, 100% of EDs at the reporting case minimum have reliability greater than or equal to 0.6, which satisfies the CMS standard for a moderate reliability threshold (Glance et al., 2020). Except for diabetes and gastroenteritis, the other nine conditions had a mean reliability score surpassing 0.7, the threshold

of good reliability under CMS standards. As a result, nine out of eleven conditions indicated statistical significance of reliability for RAPR measures.

Overall, the analysis results described high measure score reliability, averaging 0.77 at a volume threshold of 25 episodes. High reliability scores indicate that the between-ED variance is relatively large compared to the within-ED variance. The standard deviation varied from 0.11-0.17, indicating a narrow data distribution range. Mean reliability increased with the number of episodes in the given ED. Based on the above statistics, we can conclude that differences in reliability scores are due to meaningful differences in underlying ED performance on spending from 30-day episodes of care rather than random errors. The reliability for each condition-specific RAPR is sufficiently large enough that we would not discard any conditions from future analysis.

Table 5.4 Distribution of reliability score results of cost by condition-specific disease (overall testing volume threshold of 25 episode)

Condition	#of EDs	#of Episodes	Mean (S.E.)	25th Pct.	50th Pct.	75th Pct.
Biliary Tract Disease	35	4,002	0.771(0.11)	0.661	0.777	0.886
Cardiac Dysrhythmias	47	5,061	0.706(0.16)	0.584	0.737	0.843
Chest Pain	79	28,998	0.859(0.13)	0.748	0.901	0.972
CHF	32	4,811	0.739(0.15)	0.634	0.804	0.870
COPD	58	15,237	0.833(0.12)	0.756	0.852	0.942
DM	38	5,857	0.671(0.17)	0.569	0.673	0.828
Fluid and Electrolyte Disorders	42	4,757	0.793(0.11)	0.689	0.813	0.885
Gastroenteritis	35	4,606	0.631(0.16)	0.500	0.634	0.763
Pneumonia	43	7,441	0.794(0.14)	0.679	0.835	0.906
Skin and Subcutaneous Tissue Infections	64	15,446	0.825(0.13)	0.701	0.855	0.939
Urinary Tract Infections	60	19,684	0.853(0.12)	0.767	0.833	0.953

Pct: percentile
CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus
S.E: standard error

Part B: Admission Profiling

Table 5.5 presented the distribution of reliability scores for condition-specific admission. For each condition, the mean and median of reliability are close. The mean reliability for each condition ranged from 0.9 to 0.99. No condition presented low reliability at 25th percentiles. The standard deviation varied from 0.01 to 0.05 implied a minimal range of data distribution. Though not documented in the table, 100% of EDs in the reporting case have a reliability score greater than or equal to 0.7, which satisfied CMS's criteria of good reliability (Glance et al., 2020).

In sum, testing results illustrated outstanding measure score reliability with an average of 0.96. Specifically, the reliability performance for RAAR is much higher than performance for RAPR. Mean reliability increased with the number of episodes in the given ED. High reliability scores indicate the between-ED variance is relatively large compared to the within-ED variance. The difference in reliability score was driven by a systemic difference in ED performance on admission choice instead of random variation. We would adopt all eleven conditions for future analysis since the measurement is considered reliable.

Table 5.5 Distribution of Reliability Score Results of Admission by Condition-Specific Disease (overall testing volume threshold of 25 episode)

Condition	#of EDs	#of Episodes	Mean (S.E.)	25th Pct.	50th Pct.	75th Pct.
Biliary Tract Disease	35	4,002	0.910(0.05)	0.865	0.917	0.958
Cardiac Dysrhythmias	37	5,061	0.956(0.03)	0.945	0.970	0.979
Chest Pain	70	28,998	0.973(0.03)	0.958	0.990	0.997
CHF	32	4,811	0.972(0.03)	0.962	0.983	0.991
COPD	58	15,237	0.988(0.01)	0.983	0.991	0.996
DM	38	5,857	0.925(0.05)	0.897	0.928	0.967
Fluid and Electrolyte Disorders	42	4,757	0.985(0.01)	0.980	0.987	0.992
Gastroenteritis	35	4,606	0.919(0.05)	0.892	0.933	0.959
Pneumonia	43	7,441	0.946(0.04)	0.921	0.956	0.978
Skin and Subcutaneous Tissue Infections	64	15,446	0.990(0.01)	0.987	0.992	0.996
Urinary Tract Infections	60	19,684	0.991(0.01)	0.989	0.994	0.998

Pct: percentile

CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus
S.E: standard error

5.3.3 Care Consistency in ED

5.3.3.1 Proportion of Care Consistency (High Versus Low)

The pattern of care consistency among EDs is illustrated in Table G- 1 (Appendix G) and Figure 5.3. Table G- 1 described the ED's identifier and their consistent proportion of "High", "Low", and "Medium" for treated conditions with two measures (RAPR and RAAR). We ignored EDs with a proportion of "Medium" 100% since they exhibited consistent middle pattern trends for all condition-specific episodes of care. Therefore, only 55 out of 73 EDs were assessed for their care consistency when dealing with different conditions. As Figure 5.3 exhibited, the proportion of "High"/"Low" indicated how well the given EDs provide similar patterns of care even when treating different conditions. ED with a solid red or blue bar refers to a perfect care consistency as "High"/"Low" are across all risk-adjusted measures. ED with a bar with a proportion of blue or red greater than 0.7 but less than 1 presents a dominant pattern. ED with a bar that the proportion of "High"/"Low" greater than 0.3 but less than 0.7 indicates mixed ("flipped") pattern. Among the 55 EDs in Figure 5.3, 31 EDs have perfect care consistency (proportion of "High"/"Low"=1) on their episode cost and admission. 12 EDs have dominated care consistency in the "High"/"Low" trend. The rest of the EDs have roughly even split their care consistency. In general, 80% of EDs in Colorado (43/55) followed the consistent pattern of care on episode cost and admission across conditions. They either routinely spent expensive episode costs and hospitalized rates of patients higher than average level, or they spent economically and have lower hospitalization rates than the average across all conditions. 12 of EDs (20%) expressed mixed patterns of care and presented high cost/admission rates on some conditions but low cost/admission rates on others.

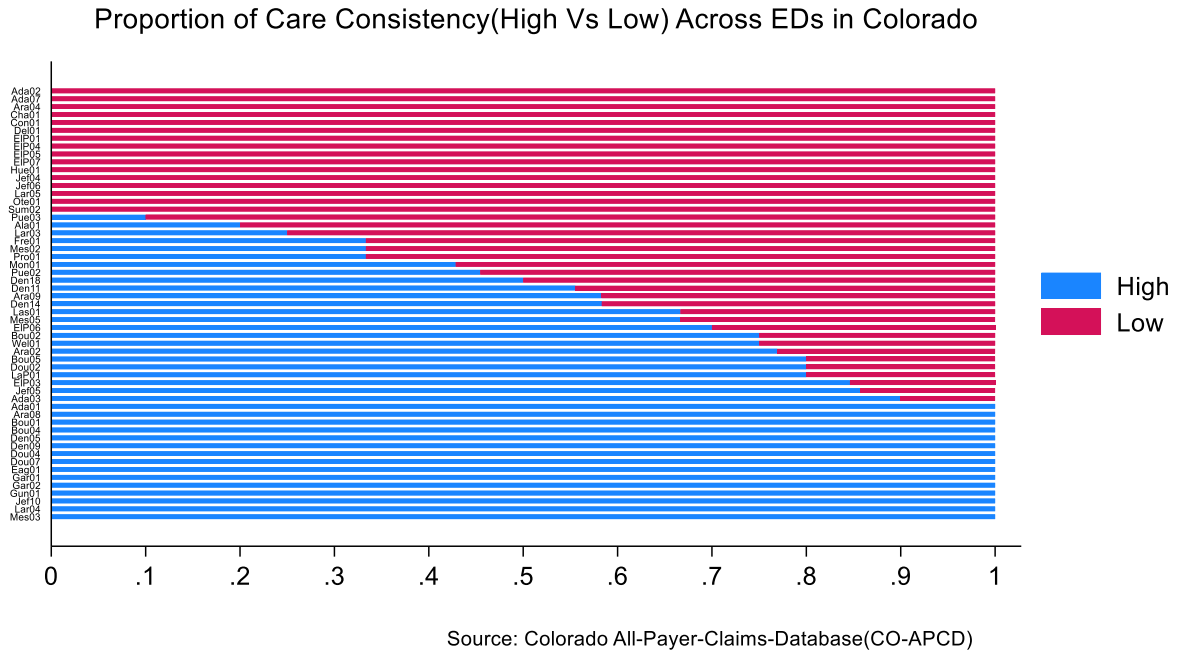

Figure 5.3 Proportion of Care Consistency (High Vs Low) among EDs from Colorado

5.3.3.2 Nonmetric Multidimensional Scaling (NMDS)

We performed non-metric multidimensional scaling for dissimilarities between EDs with respect to condition-specific RAPRs and RAARs. In Figure 5.4, dissimilarity of EDs originally derived from RAPRs and RAARs were transformed to ordination of Euclidean distance (orange point) and were plotted on two axes. The default measure of dissimilarity is Euclidean distance on standardized variables. This dataset comprised 22-point estimates of condition-specific RAPR and RAAR on 31 EDs. The eigenvalues of the double-centered distance matrix interpreted the extent of dimensions account for the dissimilarity between the EDs. In our case two dimensions account for more than 92% of the dissimilarity. NMDS plots the EDs so that all of them fall within a triangle defined by Ara08, Mes05, and Pue03. Most of the EDs were clustered and gathered around the rectangle area by four dashed red reference lines. ED with Euclidean distance in rectangle area were considered having similar ordination from two dimensions. 9 EDs were isolated from the

clustering area, Mes05 (High:0.67; Low:0.33) and Mon01 (High0.43; Low:0.57) were presented roughly equal mixed patterns, and the rest of them had high proportion or perfect care consistency from the previous result.

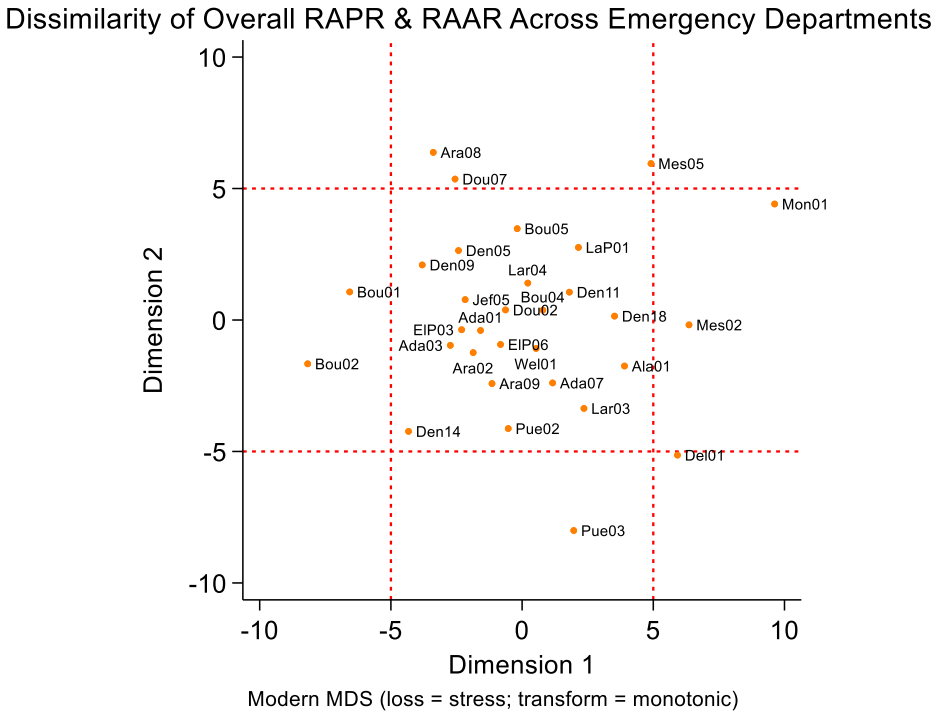

Figure 5.4 Dissimilarities between among EDs from Colorado

5.3.4 Exploratory Factor Analysis (EFA)

5.3.4.1 EFA for RAPRs

Table 5.6 Factor analysis summarized results of RAPRs

Exploratory Factor Analysis			
Factorability of Correlation Matrix			
Determinant of the correlation matrix	0.003		
Bartlett test of sphericity	0.000		
KMO of Sampling Adequacy	0.668		
Number of Factors Retention			
Eigenvalue cut-off	2-factors		
Scree plot	2-factors		
Parallel Analysis	2-factors		
Minimum Average Partial Correlation	1-factor		
Maximum likelihood	1-factor or 2-factors		
Orthogonal Matrix Rotation			
Factor/s	***Eigenvalue***	***Proportion***	***Cumulative***

Factor1	3.79784	0.3453	0.3453	
Factor2	1.1899	0.1082	0.4534	
RAPRs	***Factor 1 loading***	***Factor 2 loading***	***Uniqueness***	***Communalities***
Biliary Tract Disease	0.6782	0.0528	0.5373	0.4627
Cardiac Dysrhythmias	-0.0421	0.2154	0.9518	0.0482
Chest Pain	0.6717	0.034	0.5477	0.4523
CHF	0.0189	0.7002	0.5094	0.4906
COPD	0.5422	-0.1716	0.6765	0.3235
DM	0.5859	-0.2118	0.6119	0.3881
Fluid and Electrolyte Disorders	0.1576	0.0081	0.9751	0.0249
Gastroenteritis	0.7377	0.5309	0.1740	0.8260
Pneumonia	0.7002	0.1028	0.4991	0.5009
Skin and Subcutaneous Tissue Infections	0.7005	-0.3154	0.4099	0.5901
Urinary Tract Infections	0.8351	-0.4279	0.1195	0.8805

CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus

Results of EFA for RAPRs in 31 EDs were summarized in Table 5.6. Pearson correlation matrix manifested multiple correlations >0.3, including some rather high in the 0.7 (Appendix H). The determinant of matrix and KMO measure is 0.003 and 0.668, respectively. According to the cut-off Eigenvalue rule (Eigenvalue >1), the optimal number of factors to be retained for EFA is two. Two factors cumulatively accounted for 50.72% of variation in RAPRs after matrix rotation. The biliary tract disease, chest pain, COPD, DM, pneumonia, and skin and subcutaneous tissue infections of RAPRs were correlated with factor 1. CHF RAPRs were correlated with factor 2. Gastro and urinary were associated with both factors. None of the factors were correlated with cardiac and fluid. The communality for each RAPRs is Biliary Tract Disease, 0.46; Cardiac Dysrhythmias, 0.05; Chest Pain, 0.45; CHF, 0.49; COPD, 0.32; DM, 0.39; Fluid and Electrolyte Disorders, 0.02; Gastroenteritis, 0.83; Pneumonia, 0.50; Skin and Subcutaneous Tissue Infections, 0.59; and Urinary Tract Infections, 0.88.

5.3.4.2 EFA for RAARs

Table 5.7 Factor analysis summarized results of RAARs

Exploratory Factor Analysis	
Factorability of Correlation Matrix	
Determinant of the correlation matrix	0.002
Bartlett test of sphericity	0.000
KMO of Sampling Adequacy	0.701
Number of Factors Retention	
Eigenvalue cut-off	3-factors
Scree plot	1-factor

Parallel Analysis	1-factor		
Minimum Average Partial Correlation	1-factor		
Maximum likelihood	1-factor or 2-factors		
Factor Matrix			
Factor/s	***Eigenvalue***	***Proportion***	***Cumulative***
Factor1	4.41829	0.4017	0.4017
RAARs	**Factor 1 loading**	**Uniqueness**	**Communalities**
Biliary Tract Disease	0.5225	0.727	0.273
Cardiac Dysrhythmias	0.5638	0.6821	0.3179
Chest Pain	0.5216	0.7279	0.2721
CHF	0.8781	0.229	0.771
COPD	0.7732	0.4021	0.5979
DM	0.5089	0.741	0.259
Fluid and Electrolyte Disorders	0.7781	0.3945	0.6055
Gastroenteritis	0.5895	0.6525	0.3475
Pneumonia	0.5478	0.6999	0.3001
Skin and Subcutaneous Tissue Infections	0.5361	0.7126	0.2874
Urinary Tract Infections	0.6221	0.613	0.387

CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus

Results of RAARs' EFA are depicted in Table 5.7. Pearson correlation matrix presented multiple high correlations > 0.30, and some of them close to 0.7. The value of the determinant of matrix and KMO is 0.0016. The cut-off Eigenvalue rule suggests that the optimal factor number to be retained for EFA is 3. However, we used the single-factor solution based on consistent results from the scree plot, parallel analysis, and maximum likelihood technique. The single factor explained 40.17% of variation in RAARs. As factor loading indicated, all RAARs were correlated with Factor 1. The communality for each RAPR is Biliary Tract Disease, 0.27; Cardiac Dysrhythmias, 0.32; Chest Pain, 0.27; CHF,0.77; COPD, 0.60; DM, 0.26; Fluid and Electrolyte Disorders, 0.61; Gastroenteritis, 0.35; Pneumonia, 0.30; Skin and Subcutaneous Tissue Infections, 0.29; and Urinary Tract Infections, 0.39.

5.4 Discussion

In general, substantial variations were observed in risk-adjusted measures for cost from three selected conditions[2] and for admission rate from all conditions. The reliability results revealed that

[2] Cardiac Dysrhythmias, CHF, Fluid and Electrolyte Disorders

all constructed measures assess an attribute of the ED practice, not of the patients. By visualizing results from Figure 5.3 and Figure 5.4, care consistency of cost and admission across conditions were inspected in most sampled EDs. This consistency demonstrated that after risk adjustment, EDs followed a similar pattern in expenditure on an episode of care and choice of admission regardless of conditions. They also displayed similarities of ordination in the overall performance of all conditions. EFA captured the evidence of the correlation between RAPRs/RAARs and given factors, respectively. It re-emphasized a tendency for EDs with higher than predicted admission patterns or episode costs for one condition to exhibit similar patterns for the other conditions. There is more robust evidence for a single latent variable for the RAARs, with all the measures loading at 0.5 or higher on factor 1. This scenario differs from the 2-factor scenario for RAPRs, where the loading on factor 1 is low but loading on factor 2 for CHF RAPRs, and factor loading are low on both factors for Cardiac Dysrhythmias and Fluid and Electrolyte Disorders RAPRs. Given that the RARRs presented more stable factor structures and higher reliability than counterparts from RAPRs, it suggests the risk-adjusted admission measures are more consistent measures of underlying ED performance than the risk-adjusted episode cost measures. .

Chapter 6 Systemic Difference in Risk-Adjusted ED Performance

Aim 4: Examine the association between risk-adjusted ED performance and hospital systemic characteristics.

6.1 Analysis Overview

Wide variations in risk-adjustment outcome ratios were observed in Chapter 5. Although previous models were risk-adjusted, it is unclear if the outcome ratio variation can be explained by non-modifiable, hospital-related factors such as ownership, location, teaching status, and total volume of ED visits. We hypothesized that the ED-level variation in RAMs is associated with differences in these systemic factors. We extracted the hospital systemic variable in sampled hospitals by creating a data linkage between the sample and the 2018 American Hospital Association (AHA) Survey. Next, simple linear regression was conducted to investigate the association between ED's systemic difference and its risk-adjusted performance ratio.

6.2 Methods

6.2.1 Data Extraction and Management

ED-level systemic characteristics were obtained from the 2018 American Hospital Association Survey (AHA) and linked with All-Payer-Claims Database (APCDs) using Medicare Provider ID. Required variables included ownership (Governmental not-for-profit hospitals; Non-governmental not-for-profit hospitals; Non-governmental for-profit hospitals), location (Rural/Urban), teaching status (Non-teaching hospitals; Minor teaching hospitals; Major teaching hospitals), county and zip code. We used total number of episodes in each ED to measure annual ED volume. AHA

survey only collected hospital information. The AHA survey did not include hospital characteristics of Freestanding Emergency Departments (FSEDs). We created a dummy variable for FSEDs to differentiate them within the ownership category and characterized them as non-teaching. We verified FSED's zip code, county, and location via National Provider Identifier (NPI) and a rural/urban county map (*Colorado-Rural-vs-Frontier-Counties*, 2013).

6.2.2 Sample Size

We adhered to the same samples as Chapter 5 with ED as sample unit. There are 73 EDs with records of minimum one of eleven conditions of admission. Sub-sample size for each condition is described in Table 6.1.

Table 6.1 Condition-specific EDs sample

Condition	**No. of EDs**
Biliary Tract Disease	35
Cardiac Dysrhythmias	37
Chest Pain	70
CHF	32
COPD	58
DM	38
Fluid and Electrolyte Disorders	42
Gastroenteritis	35
Pneumonia	43
Skin and Subcutaneous Tissue Infections	64
Urinary Tract Infections	60

6.2.3 Statistical Analysis

We first conducted a descriptive analysis to identify the distribution of each hospital's systemic factors associated with sampled EDs. Violations of linear model assumptions were checked using a series of regression diagnoses. We graphed the normal quantile plot to check the normality of residuals and used the Park Test and Breusch-Pagan test to check the presence of heteroskedastic variance. We also examined multicollinearity using the Variance Inflation Factor (VIF). The outcome measures are ED-level, condition-specific RAPR and RAAR, illustrated in Chapter 5.

Multivariate linear regressions were conducted for each condition-specific sample to explore the relationship between outcome measures and ownership, teaching status, location, and ED volume (number of episodes). The regression may not detect many significant factors due to small sample size. However, we compared raw beta coefficients across the condition samples for consistency across measures in sign and magnitude of the association of the factors with outcome. R-squared was reported to evaluate the proportion of variation explained by systemic characteristics. Link Test and Ramsey RESET (regression specification-error test) test, which assessed model specification and goodness-of-fit, were performed.

6.3 Results

6.3.1 Descriptive Statistics

Table 6.2 presented the frequency of ownership, teaching responsibility, location and mean of ED volume in condition-specific samples. On average, the majority of EDs are Non-governmental (67.08%), Major teaching (51.80%), located in Urban areas (88.26%) hospital-based EDs with an average of 197 episodes per annum. A relatively lower proportion of EDs for cases of chest, skin, COPD, and urinary conditions presented characteristics of Non-governmental, Major teaching, residing in Urban. However, ED for treating those conditions provided a higher number of average episodes of care than those for treating the rest of the conditions. Except for these four conditions, the frequency and proportion of ED categories are similar across conditions.

Table 6.2 Frequency table for systemic characteristics in condition-specific EDs samples

	BTD	CD	Chest	CHF	COPD	DM	Fluid	Gastro	Pneumonia	Skin	UTI
N	**35**	**37**	**70**	**32**	**58**	**38**	**42**	**35**	**43**	**64**	**60**
Ownership (%)											
Governmental											
	3 (8.57)	3 (8.11)	15 (21.43)	3 (9.38)	10 (17.24)	4 (10.53)	6 (14.29)	3 (8.57)	5 (11.63)	9 (14.06)	8 (13.33)
Not-for-profit (Ref)											
	26 (74.29)	27 (72.97)	38 (54.29)	23 (71.88)	34 (58.62)	27 (71.05)	29 (69.05)	26 (74.29)	31 (72.09)	38 (59.38)	36 (60.00)

For-profit											
	6 (17.14)	7 (18.92)	8 (11.43)	6 (18.75)	8 (13.79)	7 (18.42)	7 (16.67)	2 (17.14)	7 (16.28)	9 (14.06)	9 (15.00)
FSEDs											
	0	0	9 (12.86)	0	6 (10.34)	0	0	0	0	8 (12.50)	7 (11.67)
Teaching status (%)											
Non-teaching (Ref)											
	10 (28.57)	11 (29.73)	42 (60.00)	9 (28.12)	28 (48.28)	13 (34.21)	16 (38.10)	11 (31.43)	17 (39.53)	36 (56.25)	33 (55.00)
Major teaching											
	22 (62.86)	23 (62.16)	25 (35.71)	20 (62.50)	24 (41.38)	22 (57.89)	23 (54.76)	21 (60.00)	23 (53.49)	25 (39.06)	24 (40.00)
Minor teaching											
	3 (8.57)	3 (8.11)	2 (4.29)	3 (9.38)	3 (5.17)	3 (7.89)	3 (7.14)	3 (8.57)	2 (6.98)	3 (4.69)	3 (5.00)
Location (%)											
Rural (Ref)											
	2 (5.11)	2 (5.41)	14 (20)	2 (6.25)	11 (18.97)	5 (13.16)	5 (11.90)	2 (5.71)	6 (13.95)	10 (15.62)	8 (13.33)
Urban											
	33 (94.29)	35 (95.49)	56 (80)	30 (93.75)	47 (81.03)	33 (86.84)	37 (88.10)	33 (94.29)	37 (86.05)	54 (84.38)	61 (86.67)
Mean of ED Volume (S.E)											
	114 (80.61)	137 (95.87)	414 (521.19)	150 (102.49)	263 (290.72)	154 (125.80)	113 (89.93)	131 (92.95)	173 (138.41)	241 (267.41)	328 (358.28)

CHF: congestive heart failure; COPD: Chronic obstructive pulmonary disease; DM: Diabetes Mellitus

6.3.2 Systemic Differences in RAPRs

Regression results of RAPR were analyzed in Table 6.3, which includes coefficient estimates with standard error, marked statistical significance and R-squared. The absolute value of beta coefficient across conditions assessed the consistency of systemic characteristics. A large number of beta coefficients are insignificant due to underpowered sample size, but we still explored their consistency pattern based on extent and direction of estimates. Overall, about 17% to 37% of the variance in RAPR was explained by the hospital ownership, teaching status, location, and ED volume.

With respect to ownership and compared to not-for-profit ownership, the reference case, across the eleven conditions governmental hospitals have three nonsignificant positive coefficients

estimated, one significant positive coefficient for pneumonia, and seven nonsignificant negative coefficients, suggesting no consistent pattern of difference relative to nonprofits. For-profit hospitals have ten nonsignificant negative coefficients and only one positive coefficient, a pattern suggesting either no difference from nonprofits or a slightly lower 30-day episode cost. For all four of the conditions for which there are sufficient numbers of cases for FSEDs to be included in the analysis, all coefficients are negative and statistically significant, indicating consistent lower 30-day episode costs for these facilities. With respect to teaching, and compared to non-teaching facilities, minor teaching hospitals have three positive and statistically significant coefficients, five positive non-significant coefficients and three negative non-significant coefficients, a pattern suggesting either no difference from nonteaching hospitals or somewhat higher episode costs. With respect to major teaching hospitals, while there is one large significant association of teaching status and higher episode costs for cardiac dysrhythmias, there is no consistent pattern for the other conditions. Urban facilities compared to rural facilities have consistent positive coefficients, with two significant at the 0.05 level and two significant at the 0.10 level. Higher ED volume is consistent with small lower levels of episode costs.

Table 6.3 Multivariate Linear Regression Results to RAPR

Condition	Hospital Ownership (S.E)			Teaching Status (S.E)		Urban (S.E)	ED volume (S.E)	R-Squared
	Governmental	For-profit	FSEDs	Minor	Major			
Biliary Tract Disease	-0.0645 (0.08)	-0.0270 (0.04)		-0.0473 (0.04)	-0.0506 (0.08)	0.0039 (0.7)	-0.0003 (0.0002)	0.2509
Cardiac Dysrhythmias	0.0311 (0.08)	-0.0163 (0.04)		0.1125** (0.03)	0.1843* (0.08)	0.0241 (0.08)	-0.0002 (0.0001)	0.3266
Chest Pain	-0.0038 (0.04)	-0.0651 (0.04)	-0.1940*** (0.05)	0.0355 (0.04)	-0.0518 (0.07)	0.0744† (0.04)	-0.0001* (0.0000)	0.3385
CHF	0.0079 (0.09)	-0.0280 (0.05)		0.1016* (0.04)	0.0756 (0.09)	0.0564 (0.08)	-0.0007** (0.0002)	0.3675
COPD	-0.0452 (0.05)	-0.0063 (0.05)	-0.1447** (0.05)	0.0248 (0.04)	0.0393 (0.08)	0.0905† (0.05)	-0.0000 (0.0000)	0.2176
DM	-0.0611 (0.05)	0.0229 (0.03)		-0.0478 (0.03)	-0.0345 (0.06)	0.0024 (0.04)	0.0000 (0.0001)	0.1660

Fluid and Electrolyte Disorders	-0.0078 (0.05)	-0.0162 (0.04)		0.0074 (0.04)	0.1052 (0.08)	0.1420** (0.05)	-0.0003 (0.0002)	0.2469
Gastroenteritis	-0.0329 (0.07)	-0.0378 (0.04)		0.0289 (0.03)	0.0150 (0.07)	0.0233 (0.06)	-0.0004* (0.0001)	0.2132
Pneumonia	0.1547* (0.08)	-0.0341 (0.06)		-0.0276 (0.05)	-0.1502 (0.10)	0.0878 (0.06)	-0.0003† (0.0002)	0.2809
Skin and Subcutaneous Tissue Infections	-0.0012 (0.05)	-0.0474 (0.04)	-0.1518* (0.05)	0.0870* (0.04)	0.1179 (0.08)	0.1132* (0.05)	-0.0001* (0.0000)	0.3367
Urinary Tract Infections	0.0460 (0.06)	-0.0530 (0.05)	-0.2193** (0.05)	0.0145 (0.04)	-0.0697 (0.09)	0.1006 (0.05)	0.0000 (0.0000)	0.3112

Not-for-profit hospitals, Non-teaching hospitals, and Rural were used as reference groups. Specifically, all FSEDs are non-government, not-for-profit in the sample.

*, **, *** indicates significance levels at the (P<.05, P<.01, P<.001), respectively. † indicates significance between .05 and .1.

6.3.3 Systemic Differences in RAAR

Regression results of RAAR were analyzed in Table 6.4, which includes the abovementioned statistical parameters. R-squared in Table 6.4 illustrated that hospital ownership, teaching status, location, and annual ED volume can interpret 15% to 50% of variance in RAAR across condition samples.

We observed a similar pattern of consistency for hospital characteristics as in RAPR. Concerning ownership and compared to not-for-profit ownership, governmental hospitals have five nonsignificant positive coefficients estimated across the eleven conditions, one significant positive coefficient for Gastroenteritis, and five nonsignificant negative coefficients, suggesting no consistent pattern of difference relative to nonprofits. As For-profit hospital estimates indicated, roughly half of them have nonsignificant negative coefficients, and the other half have positive coefficients, suggesting either no difference from nonprofits or a slightly lower admission rate. For four conditions with cases treated in FSEDs, three out of four coefficients are negative and statistically significant, indicating consistently lower admission rates for these facilities. With respect to teaching, and compared to nonteaching facilities, minor teaching hospitals have three positive and significant coefficients, six positive nonsignificant coefficients and two negative

nonsignificant coefficients, a pattern suggesting no difference from nonteaching hospitals. With respect to major teaching hospitals, while there is one large significant association between teaching status and higher admission rates for Fluid and Electrolyte Disorders, there is no consistent pattern for the other conditions. Compared to rural facilities, urban facilities have constant positive coefficients, with two significant at the 0.001 level and two significant between 0.05 and 0.1. Higher ED volume is consistent with slightly higher levels of admission rates.

Table 6.4 Multivariate Linear Regression Results to RAAR

Condition	Hospital Ownership (S.E)			Teaching Status (S.E)		Urban (S.E)	ED volume (S.E)	R-squared
	Governmental	For-profit	FSEDs	Minor	Major			
Biliary Tract Disease	0.0597 (0.11)	0.0579 (0.06)		0.1516** (0.05)	0.1586 (0.11)	0.1601 (0.11)	0.0005 (0.0003)	0.5078
Cardiac Dysrhythmias	0.2276 (0.23)	0.1139 (0.11)		0.3014** (0.10)	0.2660 (0.22)	0.1584 (0.21)	0.0002 (0.0005)	0.3890
Chest Pain	0.0330 (0.15)	0.2167 (0.16)	0.0309 (0.16)	0.0374 (0.14)	-0.1277 (0.29)	0.0261 (0.14)	0.0002 (0.0001)	0.1544
CHF	-0.0038 (0.13)	0.0195 (0.07)		0.0755 (0.06)	0.0907 (0.13)	0.2088† (0.11)	0.0003 (0.0003)	0.3364
COPD	0.0858 (0.13)	-0.0650 (0.12)	-0.3308* (0.14)	0.0872 (0.11)	0.1466 (0.20)	0.1885 (0.13)	0.0002† (0.0002)	0.3001
DM	-0.0877 (0.11)	0.0189 (0.07)		-0.0418 (0.06)	-0.0835 (0.13)	0.0478 (0.09)	0.0007* (0.0002)	0.2845
Fluid and Electrolyte Disorders	-0.1595 (0.13)	-0.0799 (0.11)		0.2009† (0.10)	0.4928* (0.19)	0.1622 (0.13)	0.0003 (0.0006)	0.4127
Gastroenteritis	0.2581* (0.12)	-0.0658 (0.06)		0.1856** (0.05)	-0.0469 (0.12)	0.4525*** (0.11)	-0.0005† (0.0003)	0.4977
Pneumonia	-0.0415 (0.10)	-0.0251 (0.08)		0.0049 (0.07)	-0.1009 (0.13)	0.1644† (0.08)	0.0002 (0.0002)	0.1991
Skin and Subcutaneous Tissue Infections	-0.1204 (0.13)	-0.1693 (0.17)	-0.3103 (0.12)	0.1533 (0.10)	0.3452 (0.22)	0.0276 (0.12)	0.0002 (0.0002)	0.3506
Urinary Tract Infections	0.1089 (0.15)	-0.1058 (0.12)	-0.3141 (0.14)	0.1312 (0.11)	0.0585 (0.22)	-0.0170 (0.14)	0.0001 (0.0001)	0.2214

Not-for-profit hospitals, Non-teaching hospitals, and Rural were used as reference groups. Specifically, all FSEDs are non-government, not-for-profit in the sample.

*, **, *** indicates P -value significance levels at the (P<.05, P<.01, P<.001), respectively. † indicates significance between .05 and .1.

6.4 Discussion

In the above analysis, we investigated EDs' systemic characteristics impact on risk-adjusted performance with RAPR and RAAR as measures. Given the small sample size, the analysis of

systemic characteristics associated with ED differences in RAPRs and RAARs are exploratory, and that consistency of regression coefficients in terms of similar level of P-value and magnitude is examined as well as formal tests of statistical significance. Since beta coefficient values indicate the extent of independent variables' significance, we concluded that hospital ownership is the most important predictor. FESDs predicted much lower RAPR and RAAR than hospital-based EDs, when holding other systemic factors constant. EDs in minor teaching hospitals were expected to have higher RAPR but lower RAAR than those in major teaching hospitals. Urban EDs were expected to incur a higher RAPR and much higher RAAR than rural ones. ED volume has minimal influence on risk-adjusted ratios unless ED volume increases with a massive number of episodes.

Focusing on R-squared, the regression model on RAPR displayed poor performance in diabetes but moderate performance in the rest of the conditions. Regression on RAAR performed better than RAPR apart from chest pain and pneumonia, where they have small degree of variance explained in RAAR. All regression models have passed Link and Ramsey RESET tests, indicating unbiased estimates.

Chapter 7 Overall Discussion and Future Work

7.1 Overall Discussion

7.1.1 Discussion Overview

In this section, results of previous chapters are discussed in depth to provide a holistic overview of the study. We first evaluated the degree of variation in unadjusted outcome measures and established the requirement for risk-adjustment models. Next, model performance and extent of variation in adjusted outcome measures are investigated. The differential effects of risk- and systemic factors, the evidence for care consistency, the extent of individual and joint correlation between measures and underlying factors, and the influence on ED-specific, value-based payment initiatives are also studied. We explored the variability of episode cost and hospital admissions for condition-specific patients, examining through risk adjustment models the role of patient demographics and comorbidities, examining the extent to which there appeared to be variation in these costs associated with the ED patients visited, and exploring some of the sources of variation in ED performance.

7.1.2 Unadjusted Analysis

In Chapter 3, we found substantial variations in unadjusted episode cost and admission rates. For each condition, the ED-level variation is relatively smaller than the patient-level variation. Moreover, the within-ED variation is much greater than the between-ED variation. We observed substantial differences in the unadjusted episode cost and admission rates from the ED between patients of different ages, sex, and comorbidities. In conclusion, our findings illustrated the

importance of risk adjustment in estimating episode cost and admission rates. We opted to carry the risk adjustment model forward into our following analysis.

7.1.3 Risk Adjustment Model

In Chapter 4, we develop and assess risk-adjustment models for each condition we studied, with separate models for admission and episode costs. Our approach to constructing risk-adjustment measures is consistent with quality measure records recommendations for publicly reported outcomes measures from NQF, CMS and YNHHSC (Horwitz et al., 2014; Keenan et al., 2008; Krumholz et al., 2011; Lindenauer et al., 2011). Secondly, these proposed measures are based on administrative claims data for all-payer types of beneficiaries and are being developed with meaning from clinical and methodological considerations. Thirdly, the risk-adjustment process accounts for patient age and comorbidities identified from secondary diagnosis if the indexed visits, outpatient visits, inpatient visits, outpatient visits, and carrier files for physician and other ancillary services during the 12 months before the index visit. Lastly, the hierarchical model accounts for hospital case mix and the clustering of episodes within EDs, thereby making the risk-adjusted measures suitable for public reporting.

We conducted analyses using GLM with a log link function, gamma distribution for episode cost and using logistic regression for admission rate to assess the condition-specific RAM performance at the patient level. We calculated the explained variation for cost as measured by the generalized R-squared statistic and C-statistics for admission by the receiver operating characteristic area under the curve (ROC/AUC). The R-squared varied from 6.45% to 32.81% for episode cost RAMs with a mean of 22.51% across conditions, indicating moderate explanatory power of risk variables

overall. Low R-squared performances were observed in conditions of CHF (6.45%), cardiac dysrhythmia(9.12%), and biliary tract disease (12.39%). Nevertheless, other VBP measures that have been adopted have comparably low explained variance as well. For admission rate RAMs, the AUC ranged from 0.61 to 0.82 with an average of 0.76 across conditions. High AUC denoted good classification between events admitted from ED and not-admitted events. The Hosmer–Lemeshow (HL) test examined model misspecification for admission rate. We found explanatory power in squared terms of risk variables from both cost and admission RAMs. We recognize that it would be preferable to add risk variables squared terms to improve model performance, but that approach is not advisable given that there is no precedent applied in risk-adjustment methodology. Although only biliary tract disease RAMs have passed HL test, the specification errors were clustered in the extreme value of observation. As Figure 4.2 exhibited, the predicted admission rate is close to its observed value. Before approaching the 90th percentile reference line, we detected slight deviance between expected and observed admission rates in each condition-specific sample. Additionally, our cohort for model development cohort ranged from 4,225 to 28,053, and it is not uncommon to present a significant statistic ($p<0.05$) of the HL test in a large sample.

In sum, our approach to risk adjustment is tailored to and appropriate for a publicly reported outcome measure. Moderate pseudo-R-squared and high C-statistic estimates from the RAMs suggests that despite the known limitations of statistics and methodology, all proposed models can stand in place of a model with more detailed clinical information for ED-level profiling. The explained variation of the model and AUC are modest, but the purpose of RAM is to profile ED performance based on patient status on admission, not to predict outcomes for individual patients.

7.1.4 Risk-Adjusted Analysis

In Chapter 5, we detected smaller but significant variations in risk-adjusted measures compared to those observed in unadjusted estimates. The difference between unadjusted and adjusted estimates results from patients' difference in age, sex, and number of comorbidities during the 30-day episode. The average RAPRs for episode cost ranged from 0.98 (SE=0.12) to 1.04 (SE=0.14). The variation in RAPRs ranged from 11% to 18% across conditions. On average, RAPR for conditions of pneumonia (0.18), skin and subcutaneous infections (0.15) and urinary tract infections (0.15) observed substantial variation among EDs, as determined by 15% (25^{th}, 75^{th}) absolute difference threshold (Pines et al., 2016). For Admission rates, the mean of RAARs varied from 0.82 (SE=0.33) to 1.00 (SE=0.16). Substantial variations in RARRs were observed among all eleven conditions, ranging from 15% to 48%. As a result, ED presented more differences in admission decisions than in cost estimation when undergoing treatment for identical conditions.

Our risk-adjusted measures are sufficiently reliable to capture differences in episode cost and hospitalization among sampled EDs. By referencing Adam et al.'s method (Adams, 2009; John L. Adams & McGlynn, 2010), our study showed that the striking signal-to-noise ratio, expressed as the between-ED variation, is larger than the within-ED variation. Average reliability of RAPR and RAAR measures ranged from 0.63 (SE=0.16) to 0.86 (SE=0.13) and 0.91 (SE=0.05) to 0.99 (SE=0.01) respectively. Such outstanding reliability results suggested that our constructed condition-specific, risk-adjusted measures are relevant and reliable. It also implied that variation in risk-adjusted estimates was more likely contributed by between-hospital variation and the amount of information each ED provided than random variation in patient experience.

We classified the extent of risk-adjusted measures for EDs into three mutually exclusive categories. ED's risk-adjusted measures were set as “low” if the given 97.5th estimates were below the mean estimates among all EDs. The risk-adjusted measures were set as “high” if the provided 2.5th estimates were above the average among all EDs. They were defined as “medium” if the average estimates for EDs are between their own 2.5th and 97.5th interval estimates. Under these criteria, we assessed the percentage of “low”/“high” risk-adjusted measures across conditions-specific samples in EDs. The percentage of EDs with “high” RAPR ranged from 8.57% (biliary tract disease) to 22.86% (chest pain), and the percentage of EDs with “low” RAPR ranged from 2.63% (diabetes) to 25.5% (urinary tract infections). The proportion of “low” RAAR and “high” RAAR EDs were 8.57% (gastro) to 46.88% (CHF) and 2.86% (chest pain) to 20% (gastro) separately.

Additionally, we established specific criterion to characterize the ED pattern of episode care. ED patterns were defined as “high-cost high-admission” if at least 70% of their risk-adjusted measures were classified as “high”. “Low-cost low-admission” are those patterns with a 70% threshold of risk-adjusted measures defined as “low”. “Mixed-cost mixed-admission” are those patterns presented in proportion to “low”/“high” risk-adjusted measures exceeding 30% but lower than 70%. The “medium-cost medium-admission” pattern performed “medium” risk-adjusted measures in all conditions. Among the 73 EDs in condition-specific samples, 43 executed “high-cost high-admission” or “low-cost low-admission” patterns, 12 had mixed pattern performance, and the rest presented “medium-cost medium-admission” patterns. This descriptive finding suggested that approximately 60% of sampled EDs maintain the cost and admission rate at a similar level.

We conducted a series of correlation analyses to further explore the ED pattern across risk-adjusted measures. For each condition-specific sample, we ranked ED performance from lowest to highest upon its point estimates of risk-adjusted measures. We then created a separate correlation matrix of RAPR and RAAR ranking among sampled EDs. Strong correlation (coefficients >0.3) among RAPR rankings were found in 7 pairwise conditions, and high correlation among RAARs orders were found in all conditions. Therefore, EDs which have high spending on one condition would be likely to claim high reimbursements on other diseases, and vice versa. Meanwhile, similar evidence was also observed in ED hospitalization patterns. We also conducted the NMDS to visualize the correlation matrix across risk-adjusted measures from a reduced dimension method. Because we can only conduct NMFS on EDs with all risk-adjusted measures, 31 out of 73 EDs were analyzed. In NMDS, 22 (about 70%) EDs presented similarities in nonmetric care patterns, as measured by the ranking of risk-adjusted measures. All evidence tells the same story: ED provides a consistent routine for episode care. They either performed high hospitalization with luxury expenditure or admitted a small number of patients originating from ED with economical cost.

In conclusion, substantial variations were captured in our constructed risk-adjusted measures. Constructed measures are eligible and reliable to be used as measurements of condition-specific ED performance. The routine care pattern across conditions in EDs revealed that the variation estimates of risk-adjusted measures can be better explained if the ED's structural information is provided.

In EFA for RAPRs, we found mediocre factorability based on evidence from correlation matrix, determinant value and KMO measures. All these approaches choose a two-factors model, except for the minimum average partial correlation. The underlying factors model performed well because around half of variation in RAPRs was explained by two factors. In the model, 7 out of 11 RAPRs presented acceptable communities, demonstrating the substantial extraction of factors explaining these items' variance. On the other hand, Cardiac Dysrhythmias and Fluid and Electrolyte Disorders RAPRs expressed low communalities and were not correlated with any Factors. Such deficiency suggested that these two items were unrelated to others or a solution with a higher number of factors should be considered. Another issue about this model is that more than half of the variance was unexplained by any of the factors. However, factor/s model rarely exhibits a perfectly simple structure. EFA is generally regarded as a technique for large sample sizes with N = 50 as a reasonable absolute minimum (MacCallum et al., 2001). Distortions such as interfactor correlations (similar items explained by multiple factors) and model errors often occur for N below 50 (MacCallum et al., 2001). Studies about how EFA can yield good results for N well below 50 are needed to reduce the model distortion. However, the analysis suggests there may not be a single latent variable associated with episode cost across EDs.

In EFA for RAARs, we found middling factorability of the correlation matrix. We also found a lower determinant value and a higher KMO measure compared to EFA for RAPRs. For the number of factors retention, there was a disagreement among approaches. We eventually decided to choose a single-factor model based on results from 4 out of 5 approaches. RAARs of CHF, COPD, and Fluid and Electrolyte Disorders presented acceptable communalities in our model. High correlation existed between these items and the model factor. Like the model performance in

RAPRs, the model for RAARs also left nearly 60% of variance unexplained. An alternative to improve communalities is to add additional factors in the model, but this will also increase the occurrence of interactors correlation.

One thing worth noting is that RAARs of the correlation matrix demonstrated a more stable and robust underlying structure than the matrix for RAPRs. This may raise the question of whether RAARs are better than RAPRs in capturing the difference in care provided by EDs. The answer is yes. One good definition of a factor as a theoretical construct is examining its factor loadings with corresponding factors. If the number of factors needed to explain the correlations is small compared to the number of variables, then the factor model is appealing because the associations between the variables can be explained parsimoniously (Tavakol & Wetzel, 2020). As evidence of all RAARs loading highly onto a single factor showed, they indicate overall admission ratio (higher, lower, or equal to predict) within the condition-specific diseases from emergency care. Under this circumstance, we may want to call factor 1 "ED admission rate for most common severe disease". On the other hand, the correlation matrix for RAPRs is a two-factor structure. It is more difficult to explain the association between factors and measures with the existence of interfactor correlation. Therefore, compared to the RAPRs, RAARs had more explicit similar patterns of ED performance. Moreover, previous reliability analysis also exhibited that a greater portion of the difference in ED practice was seized by RAARs, compared to RAPRs captured. As a result, RAARs performed higher credibility and consistency of measurement scale than RAPRs presented.

In general, both data structures of RAPRs and RAARs described sufficient factorability of conducting the EFA respectively. Although factor retention approaches did not reach the same

conclusion, we chose two-factors model for RAPRs and one-factor model for RAARs with the consideration of trade-off between communalities and model distortion and validation from most of the approaches. We did not explore further to conduct confirmatory factor analysis as the current factor models provide sufficient evidence of high correlation between risk-adjusted measures and factor/s. It is concluded that there are consistent patterns of performance on episode cost and hospitalization among conditions. Admittedly, both factor models were imperfect and were challenged by a large portion of unexplained variance among risk-adjusted measures. To improve the model's performance, ongoing research with the aim of producing reliable results with a sample size below 50 in the presence of small distortion is required.

7.1.5 Effects of Systemic Characteristics

In Chapter 6, we discovered that systemic characteristics are partially associated with variation in ED performance. For certain conditions, we found FSEDs have lower episode costs and lower hospitalization rates than not-for-profit hospital-based EDs. Such results partially contradict previous literature (Herscovici et al., 2020; Pines et al., 2018; E. L. Simon et al., 2018). Previous researchers believe FSEDs usually have lower admission rates than hospital-based EDs but consistently agree that FSEDs would have higher health expenditure than hospital-based EDs for identical conditions. Patidar et al.(2017) highlighted that FSEDs might increase access to emergency care and incur higher overall expenditures. Our results, however, challenged this conclusion. We found that after adjusting the patient's age, gender, and number of comorbidities, FSEDs have lower episode costs than Hospital-Based EDs across most common ED-related conditions. FSEDs have lower risk-adjusted hospitalization rates than Hospital-Based EDs, i.e., patients being treated at FSEDs were more likely to be immediately discharged than those being

treated at hospital-based EDs. Our study suggested that developing FSEDs could alleviate overcrowding in hospital-based EDs and provide cost-efficient emergency care. Alexander et al.(2019) mentioned disease acuity, distance, and wait time are the primary motivations for patients prone to FSEDs rather than hospital-based EDs. By adopting many condition scenarios, we addressed the disease-acuity issues to a certain degree. Unfortunately, we cannot adjust any preference variables (i.e., distance from home, wait time) influencing the patient's decision to seek care in FSEDs or hospital-based EDs.

Urban EDs are associated with increasing episode costs as well as admission rates. This finding agrees with documented urban-rural differences in the risk-adjusted rate of ED visits. Empirical studies showed that urban and rural EDs had comparable access to emergency care and confronted similar challenges related to social support, and preference of patient and provider. However, market inequity of hospital resources, including hospital sizes, nursing home bed concentration, availability of follow-up care, and critical access to hospitals suggested that urban EDs were associated with higher visit ED rates following admission (Greenwood-Ericksen & Kocher, 2019; Toth et al., 2015; Xu et al., 2022). Another factor that influences ED utilization is the urban-rural physician practice environment. When standardized working hours were held, complex and simple procedures performed in rural EDs occurred similarly in urban ones (Muelleman et al., 2010). This argument challenged the notions that sick patients are not seen in rural hospitals and that skill decay would appear in these practice environments. In urban hospitals, procedures are divided between emergency physicians and physician consultants. However, in rural hospitals with limited consultants, ED physicians must be relied upon to perform these procedures, or else they must transfer the patient to a referral center (Bennett et al., 2020). As a result, the limited practice

environment in rural ED nurtured physicians' skills of allocating resources, working with little specialist backup, and identifying appropriate patient transfers, but such skill acquisition comes with a cost - compromised patient volume, acuity, and procedures that are more likely to be encountered in urban settings (Carey et al., 2021). Teaching status is another area of interest. In Chapter 6, we noted that teaching hospital-based EDs accounts for 45%-70% of the sample size and that admission rates in teaching hospitals have remained higher than those for non-teaching hospital-based EDs. This conclusion differs from the previous literature review and merits further study in a larger sample.

ED difference in ownership, teaching responsibility, and urban-rural interpreted portion of estimated variation among EDs. Unmeasured characteristics in patient and provider preference heterogeneity, healthcare resources, and natural practice environment might contribute to the remaining variation.

7.1.6 Implications for Value-Based Payment Model & Care Consistency

Our study raises the issue of bringing emergency medicine into value-based payment (VBP) model. Current VBP models focus mostly on primary care initiatives or hospitalization. They offered many approaches of delivering primary care that are accessible, continuous, comprehensive, family-centered, coordinated, compassionate, and culturally effective. Although the AUCM proposal on including EDs in VBP complements or expands upon current Medicare value-based care models and methodologies, their beneficiaries are limited, and the model targeting conditions specific to ED admission is rare(Pines et al., 2016).

Our study examined measures of admission and episode cost for 11 conditions as potential measures of ED performance that could be incorporated into VBP. Our research not only constructed all the above measures but also demonstrated all to be sufficiently reliable to capture the difference in care performance across facilities despite minor flaws. Furthermore, our constructed potential VBP measures have greater value in terms of care consistency. While not the primary focus of our analyses, we discovered a pattern of care consistency in EDs when delivering care episodes to different conditions. We observed that most EDs have a pattern of incurring high episode costs with high patient hospitalization rates, and the behavior is replicated for situations with low episode costs and low hospitalization rates. We also observed similar ED patterns of consistency in hospitals of sufficient volume and located in urban Colorado with satellite/autonomous FSEDs. Sources of high/low spending and admissions can be more conveniently determined for EDs with coherent delivery patterns than those with mixed patterns.

In sum, our constructed VBP measures informed the managers of healthcare organizations to engage emergency physicians, to expand private market with focus on value rather than volume as a way to provide quality access for acute unscheduled care to beneficiaries effectively, to alleviate the crowding from hospital-based EDs by developing more FSEDs, to reduce admissions while ensuring safe discharge of beneficiaries, and to attribute costs to ED physicians who are the sole provider of services for an episode of care.

7.2 Strengths and Limitations

Our study demonstrated several unique strengths. All previous research about variation in EDs only includes Medicare or Medicaid beneficiaries. Our work pioneers the ED-level variation study for all beneficiaries in episode care and constructed reliable risk-adjusted measures. Instead of

picking a single condition, we analyzed ED-level variation in numerous conditions using healthcare quality measures, which are also used as mutual benchmarks across conditions. This can provide insight into the sensitivity of different uncertainty sources resulting from changing conditions. The study used established methods for constructing the risk adjustment model and measures and measuring the reliability of the measures and degree of variation across EDs in their performance on each measure. It used multiple methods to assess whether the different measures were correlated at the ED level, finding this to be the case. Moreover, with many condition-specific measures provided, our study can greatly reduce the gap of risk-adjusted measures for CMS public reporting. Ultimately, our study objectively evaluated care performance for all EDs in Colorado. Our reporting measures also allow local hospitals-based EDs or FSEDs to assess their institution relative to others and thus may incentivize EDs to examine their practices and coordinate with post- discharge providers to seek new efficiencies. Finally, when pair our measures with mortality, we can identify EDs with good patient outcomes at low cost. Such hospitals may provide important examples of positive deviance from which others can learn.

This study posed several limitations. First, our study has a narrow generalizability. Although the study measures of validity and reliability are convincing, a restricted sample of a single state may limit the general application of our findings to other states or entire nations. Second, our constructed risk adjustment models have the possibility of misspecification. RAMs with low R-squared and significant Hosmer–Lemeshow test results are more likely to be biased because of a greater risk of misclassification. Third, whilst we have a set of risk variables that can be measured and controlled, some unobserved characteristics, such as physiological factors, waiting time to ED, distance to the hospital, or any factors affecting patient or physician preference for admission, were

unavailable to be measured. Physicians' decision to hospitalize patients with diagnosis of conditions is more complicated, which cannot be answered with just a cross-sectional analysis of administrative data. Within any given healthcare system, complex organizational factors are in action. Therefore, mixed-methods techniques may facilitate our understanding of the corporate milieu and care processes. However, it is challenging and time-consuming to conduct a qualitative analysis, including obtaining interviews and professional transcripts.

7.3 Ongoing Study and Prospect

This study can be further improved with a few considerations from limitations. If funding support was available, we could build upon the analysis done in the single-year CO-APCD using multiple years, multiple states APCD. There are a few advantages to this approach. First, Colorado is a western U.S. state with a medium population. The variation of episodes and admission rates in a single state cannot be a surrogate of ED-level variation in the U.S. With multiple states of APCD, we also expected to enlarge sample size (number of EDs) for measuring significant variations caused by systemic differences. Time-trend is another crucial factor that could affect the degree of ED-level variation. Longitudinal datasets can detect whether ED-level variations of measures have changed over time. We would treat the year variable as a fixed and random indicator when constructing our improved risk-adjusted measures, respectively.

If time were available in future analysis, we would overcome model misspecification using advanced algorithms. Single regression makes it straightforward to interpret the results. Nonetheless, it becomes complicated with so many independent variables and is at risk of overfitting. A more efficient alternative for model prediction is using the Super Learner (SL)

stacked generalization method to pool prediction results across a library of multiple algorithms (Torquati et al., 2022). Each algorithm derived from a training sample (70% of sample size) was weighted via 10-fold cross-validation. The composite predicted outcome score based on weight is guaranteed in expectation to perform the best component algorithm in the library in terms of a prespecified criterion (Ehwerhemuepha et al., 2021). This ensemble algorithm has been widely used and validated by previous computational psychiatric (Karrer et al., 2019) and medical studies (Bossarte et al., 2023; Leung et al., 2022; Ziobrowski et al., 2023; Ziobrowski, Kennedy, et al., 2021; Ziobrowski, Leung, et al., 2021). Ensemble algorithms are linear and tree-based (e.g., random forest, Bayesian additive regression trees) to capture nonlinearities and interactions and reduce the risk of model misspecification (Leung et al., 2022). Admittedly, Super-learner outperformed traditional GLM and logistic regression in predicting 30-day episode cost and admission rates by correcting mis-specified models.

7.4 Conclusion

In this retrospective, cross-sectional study, we found substantial unadjusted and adjusted variation in ED-level outcome measures from condition-specific index visits to 30-day post-visits. Sizeable variations were partially associated with patient and hospital mix. There is a pattern that EDs keep employing similar standards when deciding on health expenditure and hospitalization for sampled conditions. From a systemic perspective, ED operated by FSEDs, which are independent or affiliated, residing in urban areas or having sufficient ED volumes were associated with variation in ED performance. Implementing risk-adjusted measures designed for emergency, value-based payment models with evidence of consistency of care would improve the quality and efficiency of episode care for patients.

Appendices

A. Colorado Emergency Departments' Identifier Information, Location, and Zip code

Tabel A- 1 Colorado Emergency Departments' Identifier Information, Location, and Zip code

HOSPITALNAME	ED NAME	ED TYPE	NPI	ABBREEDCODE	COUNTY	CITY	ZIPCODE
CHILDREN'S HOSPITAL COLORADO	CHILDREN'S HOSPITAL COLORADO SOUTH CAMPUS	Hospital-Based	1730540238	Ada01	Adams	AURORA	80045
NORTH SUBURBAN MEDICAL CENTER	HCA HEALTHONE LLC	Satellite FSEDs	1821042979	Ada02	Adams	THORNTON	80229
PLATTE VALLEY MEDICAL CENTER	BRIGHTON COMMUNITY HOSPITAL ASSOCIATION	Hospital-Based	1629071758	Ada03	Adams	BRIGHTON	80601
VIBRA HOSPITAL OF DENVER LLC	VIBRA HOSPITAL OF DENVER	Hospital-Based	1124402854	Ada04	Adams	FRESNO	80229
UNIVERSITY OF COLORADO HOSPITAL AUTHORITY		Hospital-Based	1477531580	Ada05	Adams	DENVER	80230
UNIVERSITY OF COLORADO HOSPITAL AUTHORITY	UCHEALTH EMERGENCY ROOM - LITTLETON	Autonomous FSEDs	1619467388	Ada06	Adams	LITTLETON	80127
UNIVERSITY OF COLORADO HOSPITAL AUTHORITY	UCHEALTH EMERGENCY ROOM - COMMERCE CITY	Autonomous FSEDs	1902396708	Ada07	Adams	COMMERCE CITY	80022
SCL HEALTH WESTMINSTER, LLC	SCL HEALTH COMMUNITY HOSPITAL - NORTHGLENN	Satellite FSEDs	1790162055	Ada08	Adams	THE WOODLANDS	80233
CHILDREN'S HOSPITAL COLORADO	CHILDREN'S HOSPITAL COLORADO OUTPATIENT SPECIALTY CARE UPTOWN	Autonomous FSEDs	1215398813	Ada09	Adams	AURORA	80045
LUTHERAN HOSPITAL ASSOCIATION OF THE SAN LUIS VALLEY	SAN LUIS VALLEY HEALTH REGIONAL MEDICAL CENTER	Hospital-Based	1235181744	Ala01	Alamosa	ALAMOSA	81101
SPALDING REHABILITATION LLC	SPALDING REHABILITATION HOSPITAL	Hospital-Based	1841244639	Ara01	Arapahoe	AURORA	80011
CRAIG HOSPITAL		Hospital-Based	1730144593	Ara02	Arapahoe	ENGLEWOOD	80113
HCA-HEALTHONE LLC	THE MEDICAL CENTER OF AURORA	Hospital-Based	1669419792	Ara03	Arapahoe	AURORA	80012

SCCI HOSPITALS OF AMERICA, LLC	KINDRED HOSPITAL AURORA	Hospital-Based	1003892563	Ara04	Arapahoe	AURORA	80011
HCA-HEALTHONE LLC	SWEDISH MEDICAL CENTER	Autonomous FSEDs	1417901489	Ara05	Arapahoe	ENGLEWOOD	80113
UNIVERSITY OF COLORADO HOSPITAL AUTHORITY	UCHEALTH EMERGENCY ROOM - AURORA CENTRAL	Autonomous FSEDs	1619467412	Ara06	Arapahoe	DENVER	80230
LITTLETON ADVENTIST HOSPITAL	PORTERCARE ADVENTIST HEALTH SYSTEM	Satellite FSEDs	1689688988	Ara07	Arapahoe	LITTLETON	80122
HCA-HEALTHONE LLC		Autonomous FSEDs	1437713856	Ara08	Arapahoe	ENGLEWOOD	80112
SCL HEALTH WESTMINSTER, LLC	SCL HEALTH EMERGENCY CENTER	Autonomous FSEDs	1407233778	Ara09	Arapahoe	AURORA	80016
THE MEDICAL CENTER OF AURORA	HCA HEALTHONE LLC	Satellite FSEDs	1659327013	Ara10	Arapahoe	AURORA	80012
SWEDISH MEDICAL CENTER	HCA HEALTHONE LLC	Satellite FSEDs	1396790200	Ara11	Arapahoe	ENGLEWOOD	80113
UPPER SAN JUAN HEALTH SERVICE DISTRICT		Hospital-Based	1245401561	Arc01	Archuleta	PAGOSA SPRINGS	81147
SOUTHEAST COLORADO HOSPITAL DISTRICT		Hospital-Based	1285727297	Bac01	Baca	SPRINGFIELD	81073
GOOD SAMARITAN MEDICAL CENTER, LLC	GOOD SAMARITAN MEDICAL CENTER	Hospital-Based	1407845035	Bou01	Boulder	LAFAYETTE	80026
LONGMONT UNITED HOSPITAL		Hospital-Based	1366465866	Bou02	Boulder	LONGMONT	80501
LONGS PEAK HOSPITAL		Hospital-Based	1154876985	Bou03	Boulder	DENVER	80230
PORTERCARE ADVENTIST HEALTH SYSTEM	CENTURA HEALTH - AVISTA ADVENTIST HOSPITAL	Satellite FSEDs	1891709192	Bou04	Boulder	LOUISVILLE	80027
BOULDER COMMUNITY HEALTH	THE COMMUNITY HOSPITAL ASSOCIATION	Satellite FSEDs	1821074196	Bou05	Boulder	BOULDER	80303
CATHOLIC HEALTH INIATIVES COLORADO	ST ANTHONY NORTH HEALTH CAMPUS	Hospital-Based	1184139750	Bro01	Broomfield	DENVER	80291
SALIDA HOSPITAL DISTRICT	HEART OF THE ROCKIES REGIONAL MEDICAL CENTER	Hospital-Based	1730258971	Cha01	Chaffee	SALIDA	81201
KEEFE MEMORIAL HEALTH SERVICE DISTRICT	KEEFE MEMORIAL HOSPITAL	Hospital-Based	1366840688	Che01	Cheyenne	CHEYENNE WELLS	80810
KEEFE MEMORIAL HOSPITAL		Hospital-Based	1912904814	Che02	Cheyenne	CHEYENNE WELLS	80810

LUTHERAN HOSPITAL ASSOCIATION OF THE SAN LUIS VALLEY	SLV HEALTH CONEJOS COUNTY HOSPITAL	Hospital-Based	1194792762	Con01	Conejos	LA JARA	81140
LUTHERAN HOSPITAL ASSOCIATION OF THE SAN LUIS VALLEY	SLV HEALTH CONEJOS COUNTY HOSPITAL	Hospital-Based	1164499141	Con02	Conejos	LA JARA	81140
DELTA COUNTY MEMORIAL HOSPITAL		Hospital-Based	1417935446	Del01	Delta	DELTA	81416
DENVER HEALTH AND HOSPITAL AUTHORITY		Hospital-Based	1689624686	Den01	Denver	DENVER	80204
KND DEVELOPMENT 65, LLC	KINDRED HOSPITAL - DENVER SOUTH	Hospital-Based	1518327329	Den02	Denver	DENVER	80210
NEC GREELEY EMERGENCY CENTER	GREELEY EMERGENCY CENTER	Autonomous FSEDs	1114379633	Den03	Denver	EVANS	80634
HCA-HEALTHONE LLC	ROSE MEDICAL CENTER	Autonomous FSEDs	1932153905	Den04	Denver	DENVER	80220
PORTERCARE ADVENTIST HEALTH SYSTEM	CENTURA HEALTH PALLIATIVE CARE (ADVENTIST)	Autonomous FSEDs	1326431107	Den05	Denver	DENVER	80291
CATHOLIC HEALTH INITIATIVES COLORADO	ST FRANCIS MIDLEVEL ALLIED HEALTH PROFESSIONALS	Hospital-Based	1851697353	Den06	Denver	COLORADO SPRINGS	80923
PAM SPECIALTY HOSPITAL OF DENVER LLC		Hospital-Based	1205483716	Den07	Denver	ENOLA	80204
CENTURA HEALTH - PORTER ADVENTIST HOSPITAL	PORTERCARE ADVENTIST HEALTH SYSTEM	Hospital-Based	1801800594	Den08	Denver	DENVER	80291
CATHOLIC HEALTH INITIATIVES COLORADO	ST. ANTHONY'S COPPER MOUNTAIN CLINIC	Autonomous FSEDs	1467555722	Den09	Denver	DENVER	80291
SAINT JOSEPH HOSPITAL, INC		Autonomous FSEDs	1164071296	Den10	Denver	LITTLETON	80123
KINDRED HOSPITALS WEST, LLC	KINDRED HOSPITAL - DENVER	Hospital-Based	1861577439	Den11	Denver	DENVER	80218
ROSE MEDICAL CENTER	HCA HEALTHONE LLC	Hospital-Based	1023062098	Den12	Denver	DENVER	80220
NATIONAL JEWISH HEALTH		Hospital-Based	1326015777	Den13	Denver	DENVER	80206
DENVER HEALTH AND HOSPITAL AUTHORITY	DENVER HEALTH EAST GRAND COMMUNITY CLINIC & EMERGENCY CENTER	Autonomous FSEDs	1467762435	Den14	Denver	DENVER	80204

PRESBYTERIAN/ST. LUKE'S MEDICAL CENTER	HCA HEALTHONE LLC	Hospital-Based	1720038946	Den15	Denver	DENVER	80218
CATHOLIC HEALTH INITIATIVES COLORADO	BRECKENRIDGE EMERGENCY AND URGENT CARE CENTER	Autonomous FSEDs	1285102491	Den16	Denver	DENVER	80291
SAINT JOSEPH HOSPITAL, INC	SAINT JOSEPH HOSPITAL	Hospital-Based	1417946021	Den17	Denver	DENVER	80218
UNIVERSITY OF COLORADO HOSPITAL AUTHORITY	UCHEALTH EMERGENCY ROOM - GREEN VALLEY RANCH	Autonomous FSEDs	1639669435	Den18	Denver	DENVER	80249
HCA-HEALTHONE LLC	SKY RIDGE MEDICAL CENTER	Hospital-Based	1194779165	Dou01	Douglas	LONE TREE	80124
PORTERCARE ADVENTIST HEALTH SYSTEM	CASTLE ROCK ADVENTIST HOSPITAL	Hospital-Based	1457867806	Dou02	Douglas	CASTLE ROCK	80109
UNIVERSITY OF COLORADO HOSPITAL AUTHORITY	UCHEALTH EMERGENCY ROOM - THORNTON	Autonomous FSEDs	1366932162	Dou03	Douglas	DENVER	80230
PAHS LARKIN VENTURES LLC	CENTURA HEALTH EMERGENCY AND URGENT CARE MERIDIAN	Autonomous FSEDs	1578920013	Dou04	Douglas	PARKER	80134
SKY RIDGE MEDICAL CENTER	HCA HEALTHONE LLC	Autonomous FSEDs	1659325629	Dou05	Douglas	LONE TREE	80124
CHILDREN'S HOSPITAL COLORADO	CHILDREN'S HOSPITAL COLORADO PARKER ADVENTIST HOSPITAL	Hospital-Based	1144683723	Dou06	Douglas	AURORA	80045
PORTERCARE ADVENTIST HEALTH SYSTEM	PARKER ADVENTIST HOSPITAL	Hospital-Based	1386651297	Dou07	Douglas	DENVER	80291
CENTURA HEALTH-CASTLE ROCK ADVENTIST HOSPITAL	PORTERCARE ADVENTIST HEALTH SYSTEM	Autonomous FSEDs	1912249590	Dou08	Douglas	CASTLE ROCK	80109
VAIL HEALTH HOSPITAL	VAIL CLINIC, INC.	Hospital-Based	1992812333	Eag01	Eagle	VAIL	81657
AVON EMERGENCY AND URGENT CARE CENTER, LLC	CENTURA HEALTH EMERGENCY AND URGENT CARE AVON	Autonomous FSEDs	1033572615	Eag02	Eagle	AVON	81620
UCH-MHS	MEMORIAL HOSPITAL	Hospital-Based	1144397134	ElP01	ElPaso	DENVER	80230
UCH-MHS	UCHEALTH EMERGENCY ROOM - FOUNTAIN	Autonomous FSEDs	1295225274	ElP02	ElPaso	DENVER	80230
UCH-MHS	UCHEALTH EMERGENCY ROOM - WOODMEN	Autonomous FSEDs	1578053567	ElP03	ElPaso	COLORADO SPRINGS	80920

CENTURA HEALTH - PENROSE ST. FRANCIS HEALTH	CATHOLIC HEALTH INITIATIVES COLORADO	Hospital-Based	1932112125	ElP04	ElPaso	DENVER	80291
UCH-MHS	UCHEALTH EMERGENCY ROOM - MEADOWGRASS	Autonomous FSEDs	1639669617	ElP05	ElPaso	COLORADO SPRINGS	80921
UCHEALTH GRANDVIEW HOSPITAL	UCHEALTH COLORADO SPRINGS HOSPITAL LLC	Hospital-Based	1619351160	ElP06	ElPaso	COLORADO SPRINGS	80918
UCH-MHS	UCHEALTH EMERGENCY ROOM - POWERS	Autonomous FSEDs	1124518113	ElP07	ElPaso	DENVER	80230
CENTURA HEALTH - ST. THOMAS MORE HOSPITAL	CATHOLIC HEALTH INITIATIVES COLORADO	Hospital-Based	1922012350	Fre01	Fremont	CANON CITY	81212
VALLEY VIEW HOSPITAL ASSOCIATION		Hospital-Based	1982668133	Gar01	Garfield	GLENWOOD SPRINGS	81601
GRAND RIVER HOSPITAL DISTRICT	GRAND RIVER MEDICAL CENTER	Hospital-Based	1649218991	Gar02	Garfield	RIFLE	81650
KREMMLING MEMORIAL HOSPITAL DISTRICT	DBA MIDDLE PARK MEDICAL CENTER	Hospital-Based	1619962321	Gra01	Grand	KREMMLING	80459
GUNNISON VALLEY HOSPITAL		Satellite FSEDs	1932109048	Gun01	Gunnison	GUNNISON	81230
HUERFANO COUNTY HOSPITAL DISTRICT	SPANISH PEAKS REGIONAL HEALTH CENTER	Hospital-Based	1982612065	Hue01	Huerfano	WALSENBURG	81089
UCHEALTH BROOMFIELD HOSPITAL		Hospital-Based	1528442357	Jef01	Jefferson	DENVER	80230
CENTURA HEALTH - ST. ANTHONY HOSPITAL	CATHOLIC HEALTH INITIATIVES COLORADO	Hospital-Based	1164430567	Jef02	Jefferson	LAKEWOOD	80228
EXEMPLA INC.	EXEMPLA LUTHERAN MEDICAL CENTER	Hospital-Based	1275518383	Jef03	Jefferson	WHEAT RIDGE	80033
SCL HEALTH WESTMINSTER, LLC	SCL HEALTH COMMUNITY HOSPITAL - SOUTHWEST	Hospital-Based	1972980449	Jef04	Jefferson	LITTLETON	80123
UNIVERSITY OF COLORADO HOSPITAL AUTHORITY	UCHEALTH ARVADA WEST MEDICAL CENTER	Autonomous FSEDs	1356831218	Jef05	Jefferson	ARVADA	80007
CENTURA VENTURES LARKIN VENTURES	CENTURA HEALTH EMERGENCY AND URGENT CARE HWY 285 LAKEWOOD	Autonomous FSEDs	1083166623	Jef06	Jefferson	LAKEWOOD	80227

CHIC/LARKIN VENTURES, LLC		Autonomous FSEDs	1750765665	Jef07	Jefferson	BELLAIRE	80401
CHIC/LARKIN VENTURES, LLC		Autonomous FSEDs	1306220603	Jef08	Jefferson	ARVADA	80007
UNIVERSITY OF COLORADO HOSPITAL AUTHORITY	UCHEALTH EMERGENCY ROOM - ARVADA	Autonomous FSEDs	1013407865	Jef09	Jefferson	ARVADA	80002
ORTHO COLORADO, LLC	ORTHO COLORADO HOSPITAL AT ST ANTHONY MEDI	Hospital-Based	1306176839	Jef10	Jefferson	DENVER	80291
COUNTY OF KIOWA HOSPITAL DISTRICT	WEISBROD HOSPITAL AND NURSING HOME	Hospital-Based	1366452732	Kio01	Kiowa	EADS	81036
KIT CARSON COUNTY HEALTH SERVICES DISTRICT	KIT CARSON COUNTY MEMORIAL HOSPITAL	Hospital-Based	1184711475	Kit01	KitCarson	BURLINGTON	80807
ANIMAS SURGICAL HOSPITAL, LLC	ANIMAS SURGICAL HOSPITAL	Hospital-Based	1508842964	LaP01	LaPlata	DURANGO	81301
MERCY REGIONAL MEDICAL CENTER	CATHOLIC HEALTH INITIATIVES COLORADO	Hospital-Based	1083611644	LaP02	LaPlata	DURANGO	81301
ST. VINCENT GENERAL HOSPITAL DISTRICT	ST VINCENT GENERAL HOSPITAL DISTRICT	Hospital-Based	1497710958	Lak01	Lake	LEADVILLE	80461
ESTES PARK MEDICAL CENTER		Hospital-Based	1659586972	Lar01	Larimer	ESTES PARK	80517
POUDRE VALLEY HEALTH CARE INC.	POUDRE VALLEY HOSPITAL	Hospital-Based	1760492714	Lar02	Larimer	FORT COLLINS	80524
POUDRE VALLEY HEALTH CARE INC	HARMONY URGENT CARE	Autonomous FSEDs	1861534703	Lar03	Larimer	DENVER	80230
PARK HOSPITAL DISTRICT	ESTES PARK HEALTH	Hospital-Based	1154312981	Lar04	Larimer	ESTES PARK	80517
MCKEE MEDICAL CENTER		Hospital-Based	1417980566	Lar05	Larimer	LOVELAND	80538
BANNER HEALTH	BANNER FORT COLLINS MEDICAL CENTER	Hospital-Based	1659787554	Lar06	Larimer	PHOENIX	80528
MEDICAL CENTER OF THE ROCKIES	UCHEALTH GREELEY EMERGENCY	Autonomous FSEDs	1104262286	Lar07	Larimer	GREELEY	80634
TRINIDAD AREA HEALTH ASSOCIATION	MT SAN RAFAEL HOSPITAL	Hospital-Based	1184616740	Las01	LasAnimas	TRINIDAD	81082
LINCOLN COMMUNITY HOSPITAL		Hospital-Based	1720107519	Lin01	Lincoln	HUGO	80821
STERLING REGIONAL MEDCENTER		Hospital-Based	1629231238	Log01	Logan	STERLING	80751
LOWER VALLEY HOSPITAL ASSOCIATION	COLORADO CANYONS HOSPITAL AND MEDICAL CENTER	Hospital-Based	1861496697	Mes01	Mesa	FRUITA	81521

PAHS LARKIN VENTURES LLC	CENTURA HEALTH EMERGENCY AND URGENT CARE HIGHLANDS RANCH	Autonomous FSEDs	1215489869	Mes02	Mesa	BELLAIRE	80129
COMMUNITY HOSPITAL	COLORADO WEST HEALTHCARE SYSTEM	Hospital-Based	1497723407	Mes03	Mesa	GRAND JUNCTION	81502
UNIVERSITY OF COLORADO HOSPITAL AUTHORITY	UCHEALTH EMERGENCY ROOM - HIGHLANDS RANCH	Autonomous FSEDs	1356831150	Mes04	Mesa	HIGHLANDS RANCH	80126
ST. MARY'S HOSPITAL AND MEDICAL CENTER, INC.	ST MARYS MEDICAL CENTER	Hospital-Based	1699716027	Mes05	Mesa	GRAND JUNCTION	81501
THE MEMORIAL HOSPITAL		Hospital-Based	1063418424	Mof01	Moffat	CRAIG	81625
SOUTHWEST HEALTH SYSTEM, INC.	CORTEZ PRIMARY CARE	Hospital-Based	1104823939	Mon01	Montezuma	CORTEZ	81321
MONTROSE MEMORIAL HOSPITAL, INC	NUTRITION AND DIABETES BUILDING	Hospital-Based	1205822186	Mon02	Montrose	MONTROSE	81401
EAST MORGAN COUNTY HOSPITAL		Hospital-Based	1427211036	Mor01	Morgan	BRUSH	80723
COLORADO PLAINS MEDICAL CENTER	PHC-FORT MORGAN INC	Hospital-Based	1477638971	Mor02	Morgan	FORT MORGAN	80701
ARKANSAS VALLEY REGIONAL MEDICAL CENTER		Hospital-Based	1760489470	Ote01	Otero	LA JUNTA	81050
HAXTUN HOSPITAL DISTRICT		Hospital-Based	1336103811	Phi01	Phillips	HAXTUN	80731
EAST PHILLIPS COUNTY HOSPITAL DISTRICT	MELISSA MEMORIAL HOSPITAL	Hospital-Based	1891733879	Phi02	Phillips	HOLYOKE	80734
ASPEN VALLEY HOSPITAL DISTRICT		Hospital-Based	1518960814	Pit01	Pitkin	ASPEN	81611
PROWERS COUNTY HOSPITAL DISTRICT	PROWERS MEDICAL CENTER	Hospital-Based	1821052929	Pro01	Prowers	LAMAR	81052
PARKVIEW MEDICAL CENTER, INC.		Satellite FSEDs	1104881507	Pue01	Pueblo	PUEBLO	81003
CENTURA HEALTH - ST. MARY CORWIN HOSPITAL	CATHOLIC HEALTH INITIATIVES COLORADO	Hospital-Based	1306857974	Pue02	Pueblo	DENVER	80291
COMPLETE EMERGENCY CARE PUEBLO LLC		Autonomous FSEDs	1639619620	Pue03	Pueblo	PUEBLO	81005

EASTERN RIO BLANCO COUNTY HEALTH SERVICE DISTRICT	PIONEERS MEDICAL CENTER	Hospital-Based	1801874771	Rio02	Rio Blanco	MEEKER	81641
RANGELY HOSPITAL DISTRICT	RANGELY DISTRICT HOSPITAL	Hospital-Based	1063430346	Rio03	Rio Blanco	RANGELY	81648
VALLEY CITIZENS' FOUNDATION FOR HEALTHCARE, INC.	RIO GRANDE HOSPITAL	Hospital-Based	1396783981	Rio01	Rio Grande	DEL NORTE	81132
YAMPA VALLEY MEDICAL CENTER		Hospital-Based	1790787307	Rou01	Routt	DENVER	80230
STEAMBOAT ER LLC	STEAMBOAT ER	Autonomous FSEDs	1124543442	Rou02	Routt	STEAMBOAT SPRINGS	80487
TELLURIDE MEDICAL CENTER	TELLURIDE MEDICAL CENTER	Autonomous FSEDs	1508807694	San01	SanMiguel	TELLURIDE	81435
SEDGWICK COUNTY MEMORIAL HOSPITAL		Hospital-Based	1740295591	Sed01	Sedgwick	JULESBURG	80737
CATHOLIC HEALTH INITIATIVES COLORADO	ST ANTHONY KEYSTONE MEDICAL CLINIC	Autonomous FSEDs	1851507453	Sum01	Summit	DENVER	80291
CENTURA HEALTH - ST. ANTHONY SUMMIT MEDICAL	CATHOLIC HEALTH INITIATIVES COLORADO	Hospital-Based	1720096092	Sum02	Summit	FRISCO	80443
UCHEALTH PIKES PEAK REGIONAL HOSPITAL		Hospital-Based	1275703910	Tel01	Teller	WOODLAND PARK	80863
ADVANCED CARE HOSPITAL OF NORTHERN COLORADO LLC	NORTHERN COLORADO LONG TERM ACUTE HOSPITAL	Hospital-Based	1598830267	Wel01	Weld	JOHNSTOWN	80537
NORTH COLORADO MEDICAL CENTER		Hospital-Based	1720004450	Wel02	Weld	GREELEY	80631
COMPLETE EMERGENCY CARE COLORADO SPRINGS LLC		Autonomous FSEDs	1821540295	Wel03	Weld	COLORADO SPRINGS	80920
CHIC LARKIN VENTURES, LLC	CENTURA HEALTH EMERGENCY AND URGENT CARE INDIAN PEAKS	Autonomous FSEDs	1003275553	Wel04	Weld	FREDERICK	80514
WRAY COMMUNITY DISTRICT HOSPITAL		Hospital-Based	1083640239	Yum01	Yuma	WRAY	80758
YUMA DISTRICT HOSPITAL		Hospital-Based	1629074182	Yum02	Yuma	YUMA	80759

B. ED-level, Condition-specific, 30-day Unadjusted Measures Interval Plot (Episode Cost and Admission Rates)

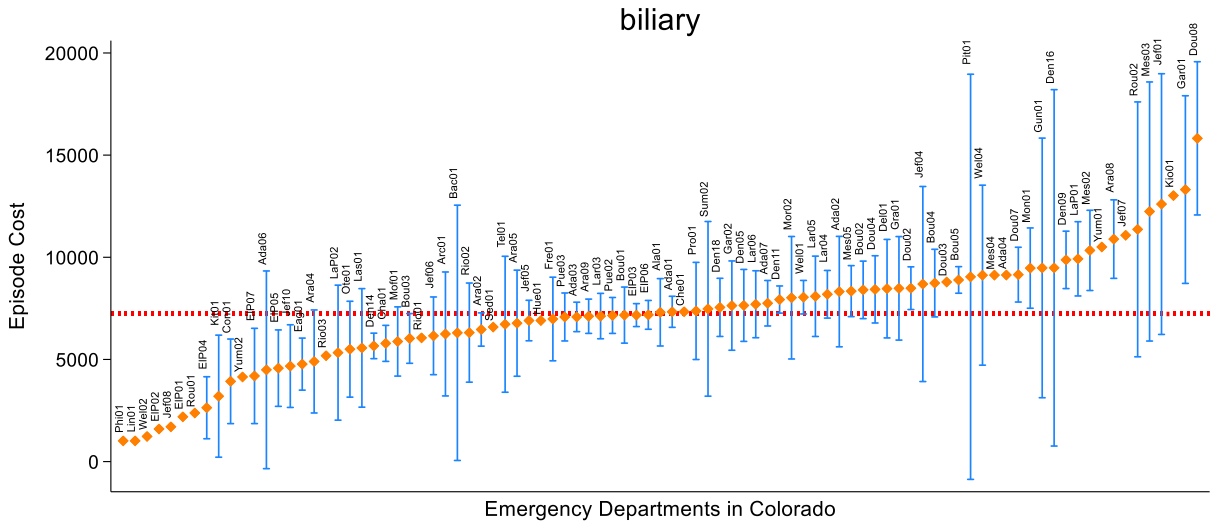

Figure B- 1 ED-level,unadjusted 30-day episode payment for biliary tract disease pooling each ED

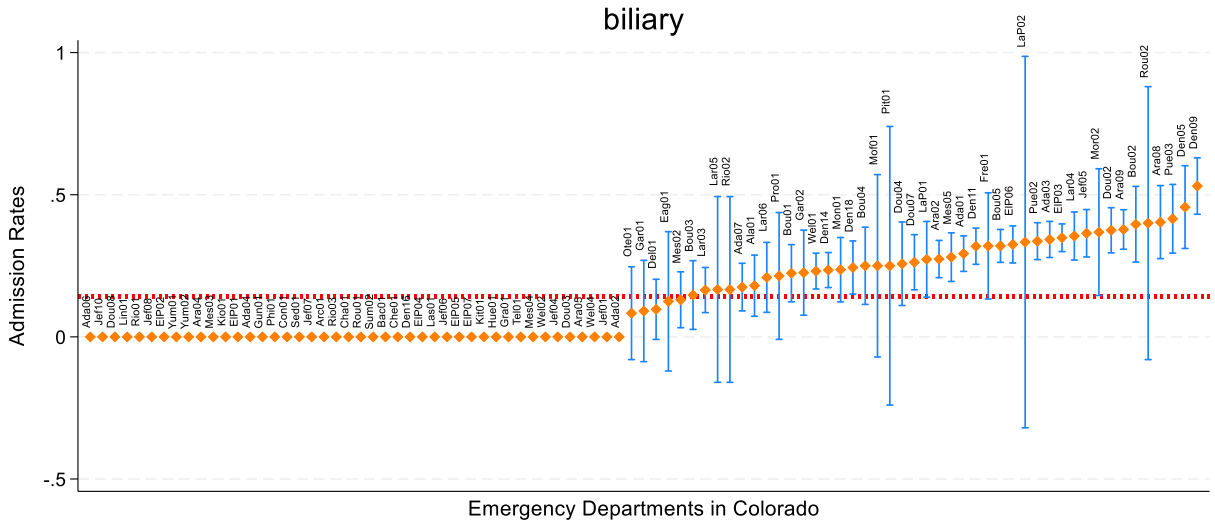

Figure B- 2 ED-level, unadjusted average admission rates for biliary tract disease pooling each ED

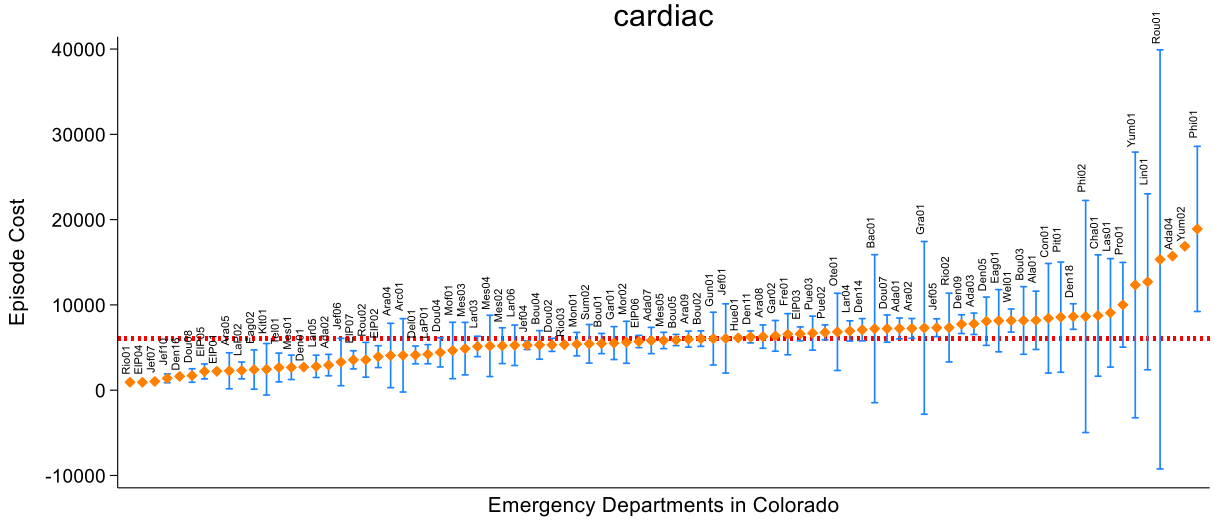

Figure B- 3 ED-level,Unadjusted 30-day episode payment for cardiac dysthymias pooling each ED

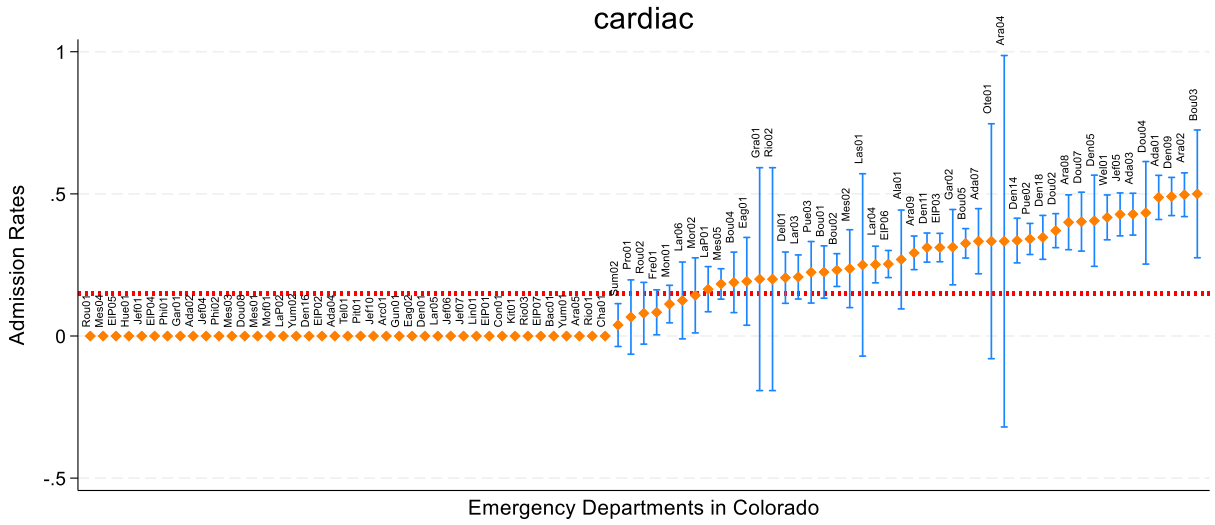

Figure B- 4 ED-level, unadjusted average admission rates for cardiac dysthymias pooling each ED

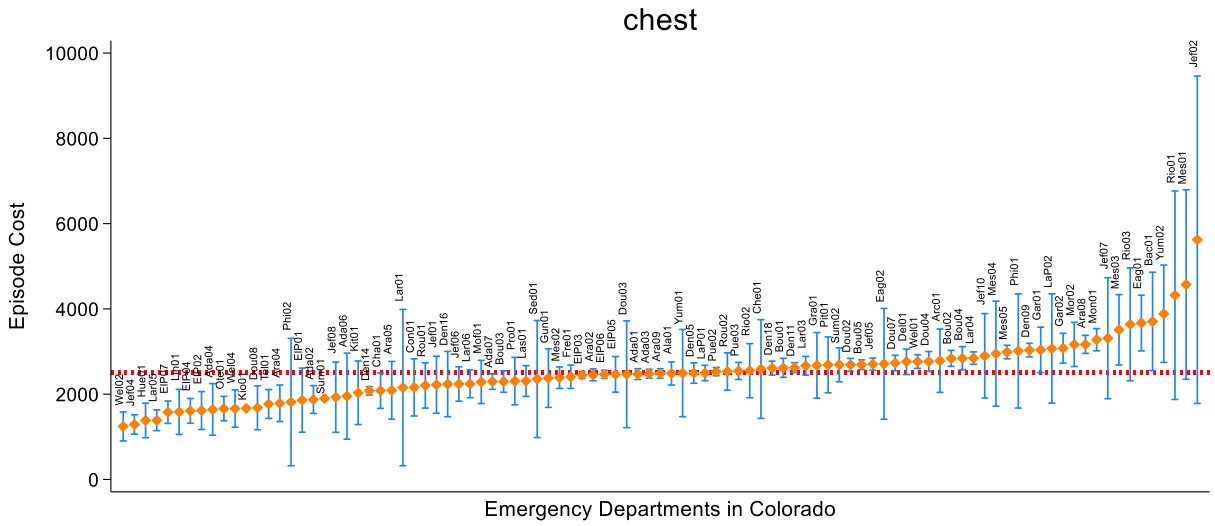

Figure B- 5 ED-level,unadjusted 30-day episode payment for chest pain pooling each ED

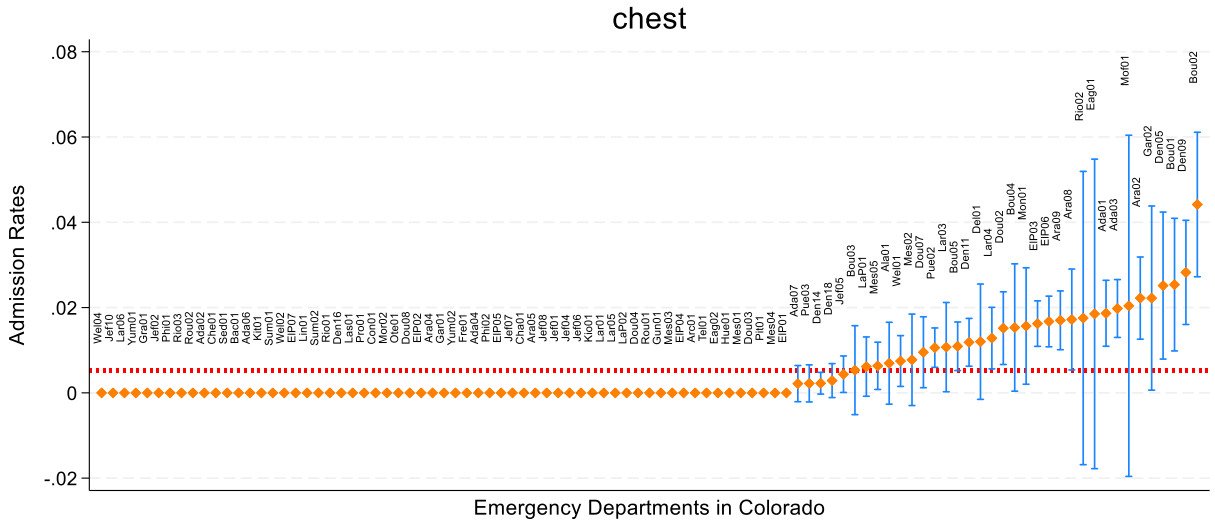

Figure B- 6 ED-level, unadjusted average admission rates for chest pain pooling each ED

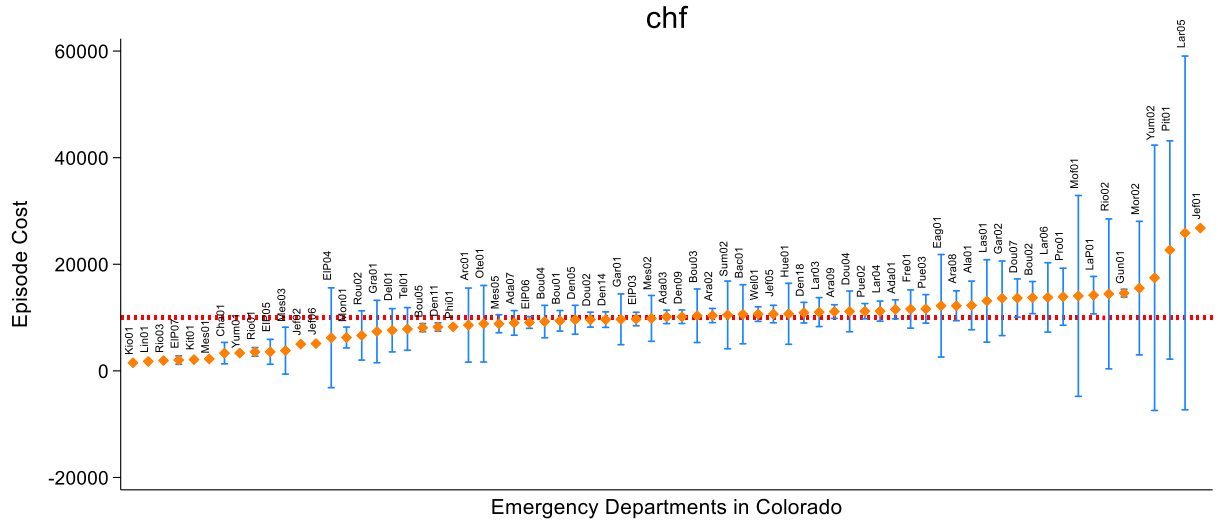

Figure B- 7 ED-level,unadjusted 30-day episode payment for congestive heart failure pooling each ED

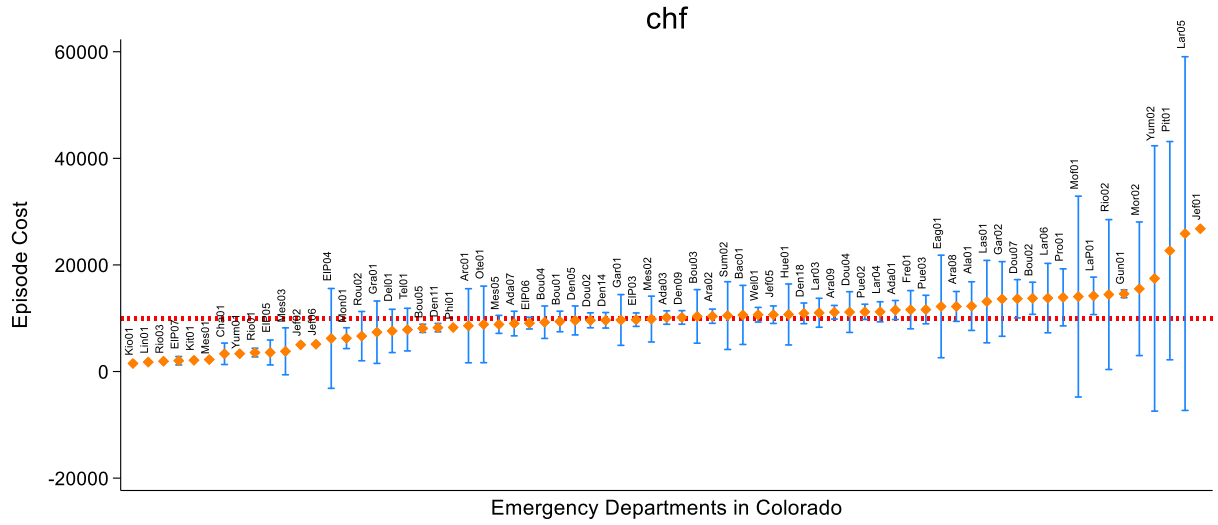

Figure B- 8 ED-level, unadjusted average admission rates for congestive heart failure pooling each ED

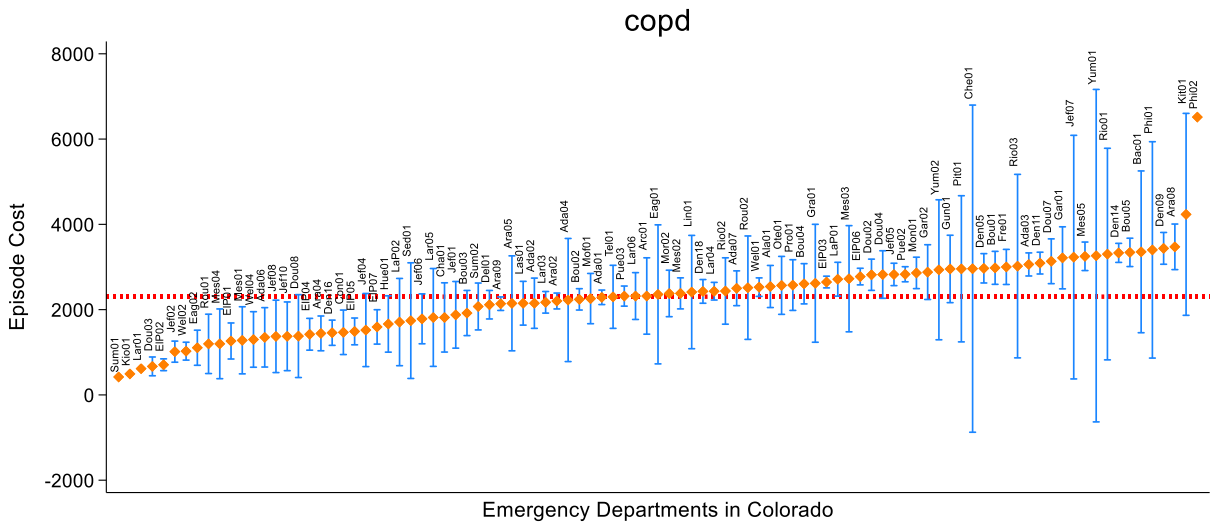

Figure B- 9 ED-level,unadjusted 30-day episode payment for chronic obstructive pulmonary disease pooling each ED

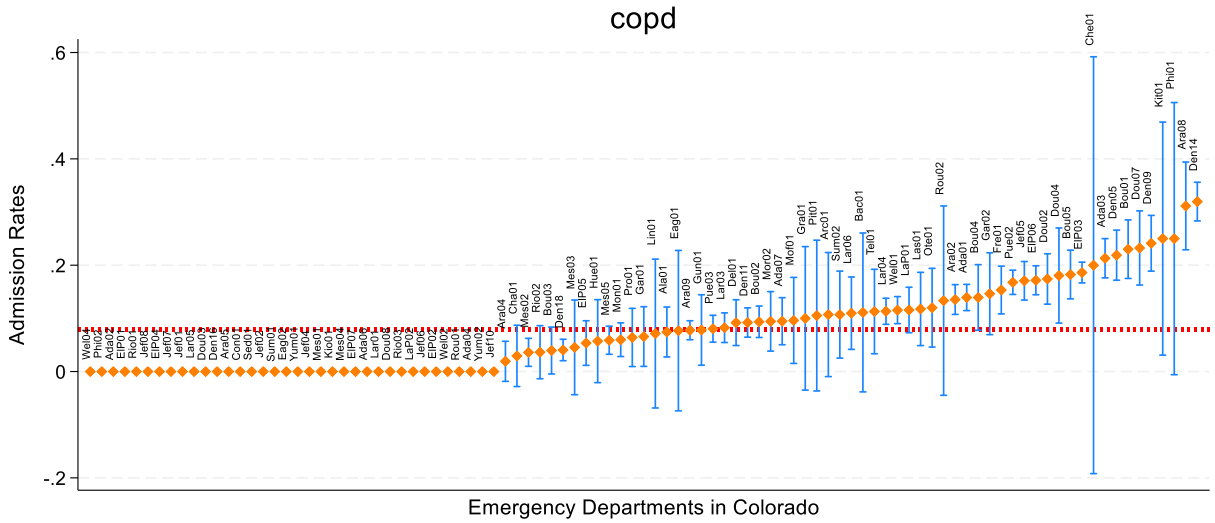

Figure B- 10 ED-level, unadjusted average admission rates for chronic obstructive pulmonary disease pooling each ED

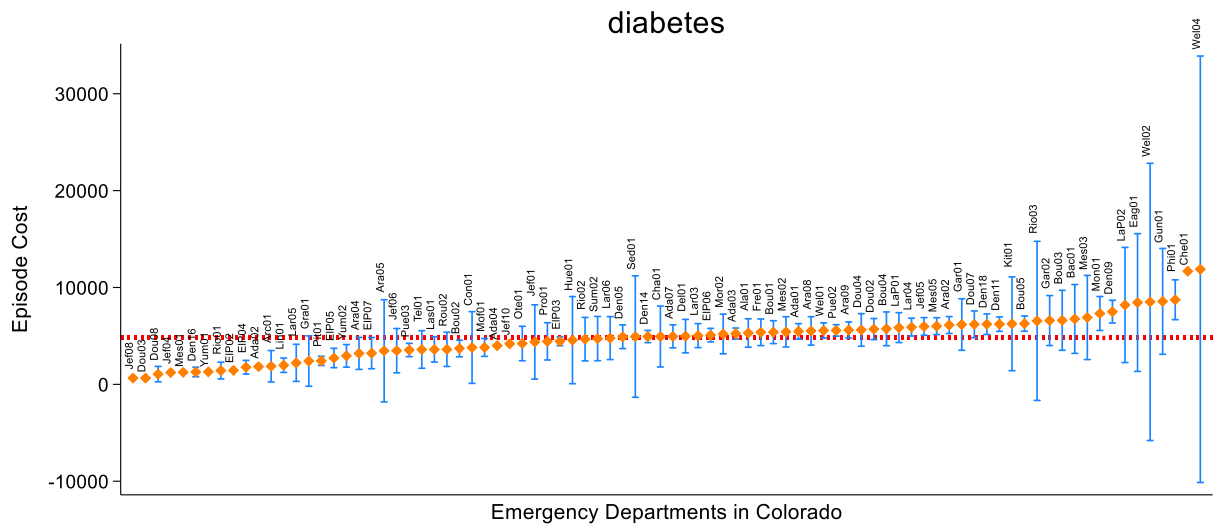

Figure B- 11 ED-level,unadjusted 30-day episode payment for diabetic mellitus pooling each ED

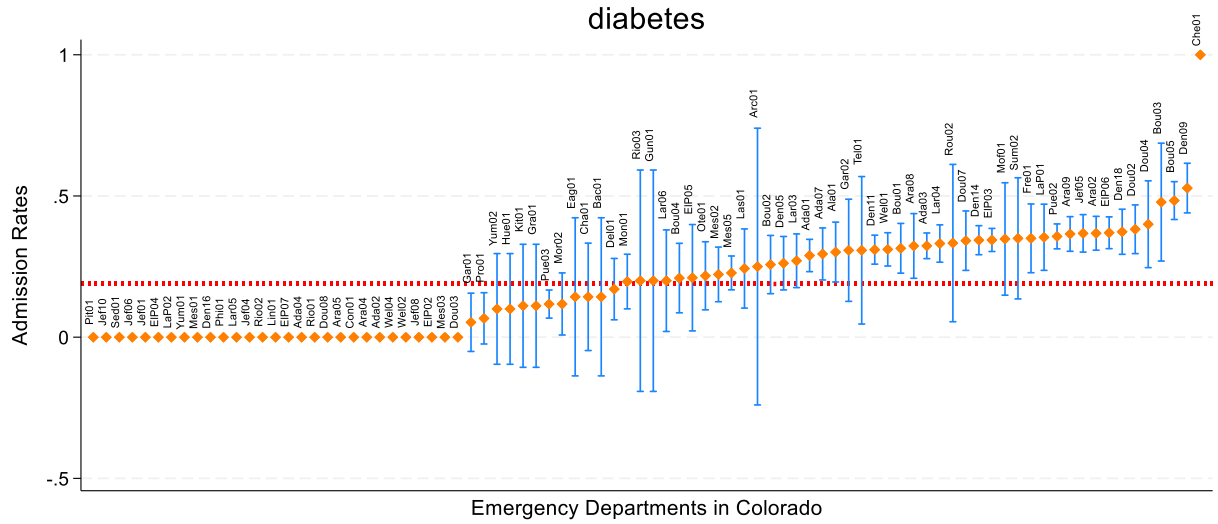

Figure B- 12 ED-level, unadjusted average admission rates for diabetic mellitus pooling each ED

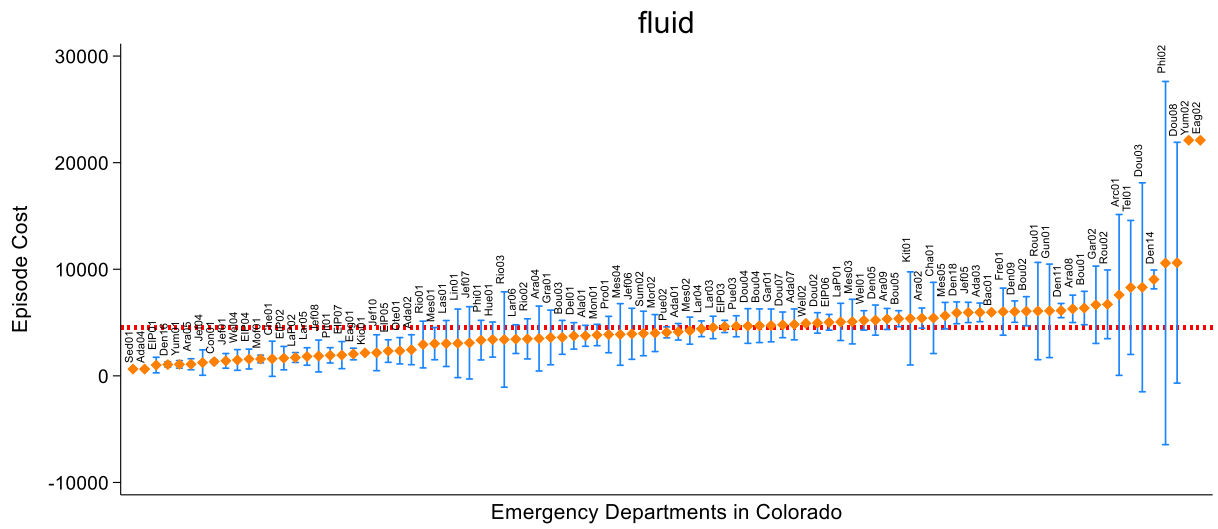

Figure B- 13 ED-level,unadjusted 30-day episode payment for fluid and electrolyte disorders pooling each ED

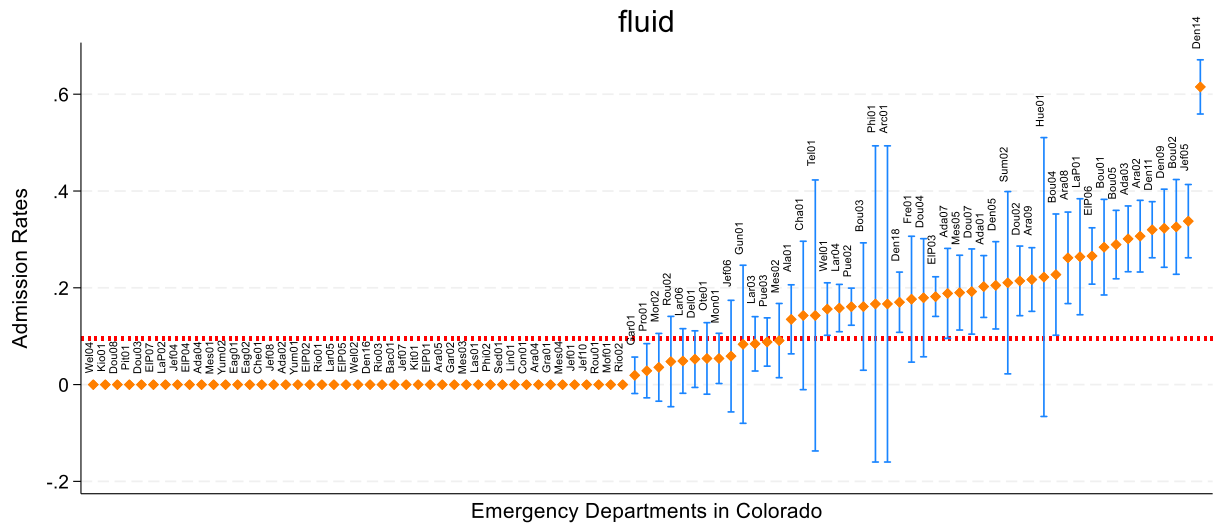

Figure B- 14 ED-level, unadjusted average admission rates for fluid and electrolyte disorders pooling each ED

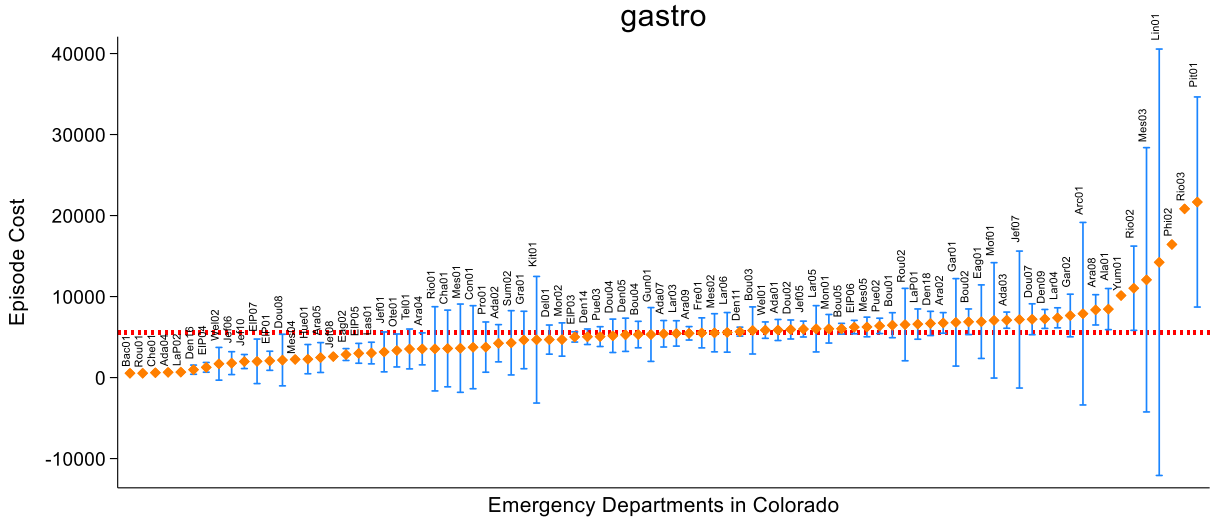

Figure B- 15 ED-level,unadjusted 30-day episode payment for gastroenteritis pooling each ED

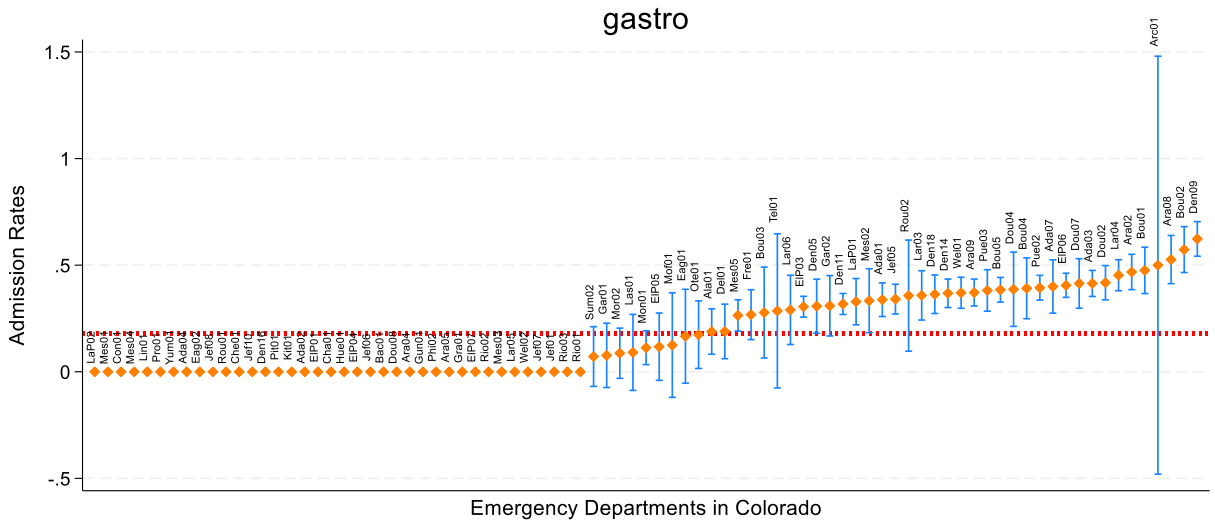

Figure B- 16 ED-level, unadjusted average admission rates for gastroenteritis pooling each ED

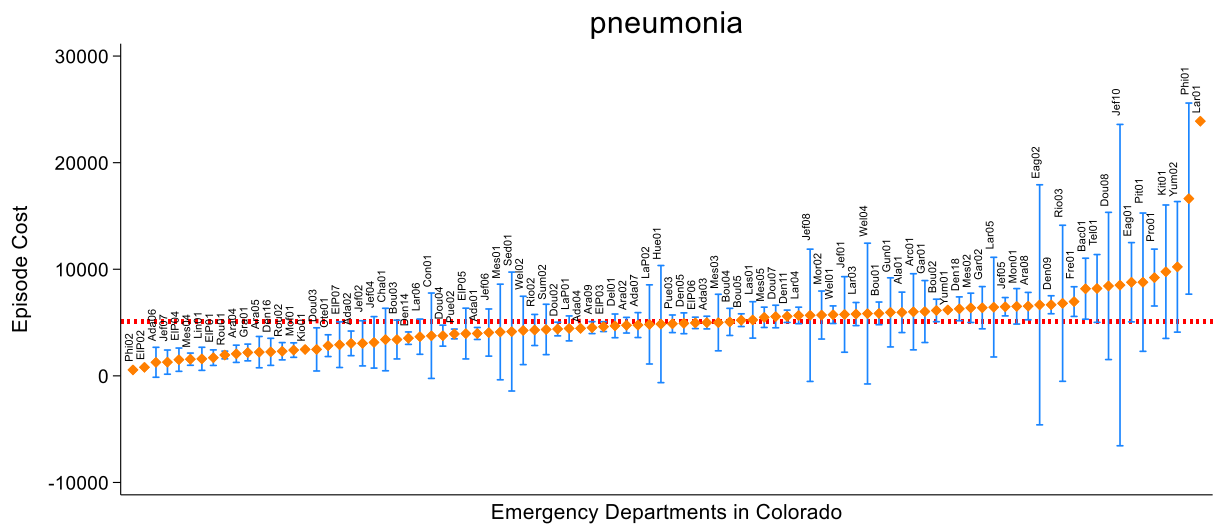

Figure B- 17 ED-level,unadjusted 30-day episode payment for pneumonia pooling each ED

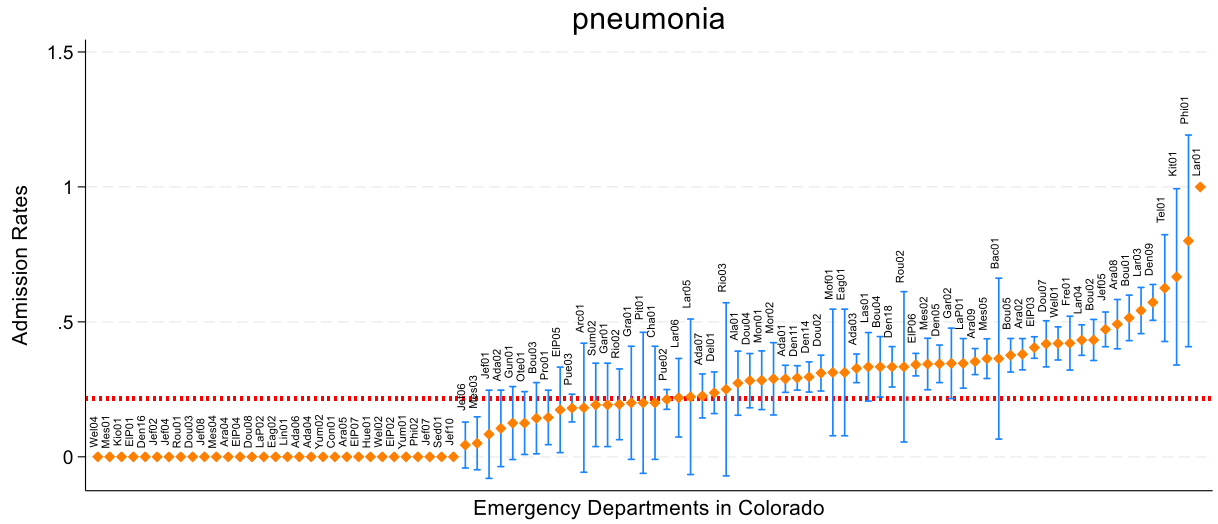

Figure B- 18 ED-level, unadjusted average admission rates for pneumonia polling each ED

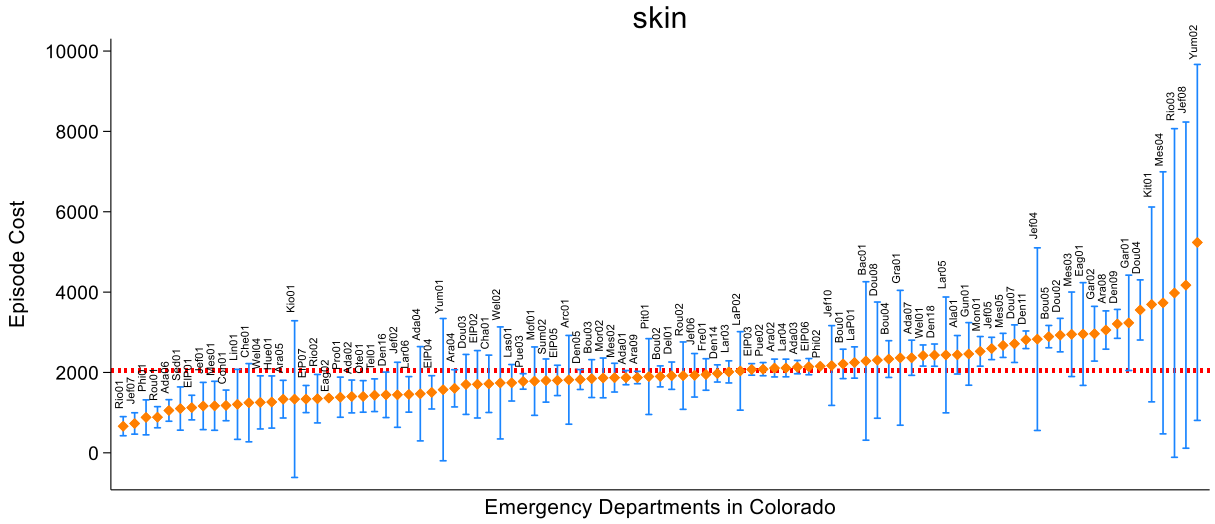

Figure B- 19 ED-level,unadjusted 30-day episode payment for skin and subcutaneous tissue infections pooling each ED

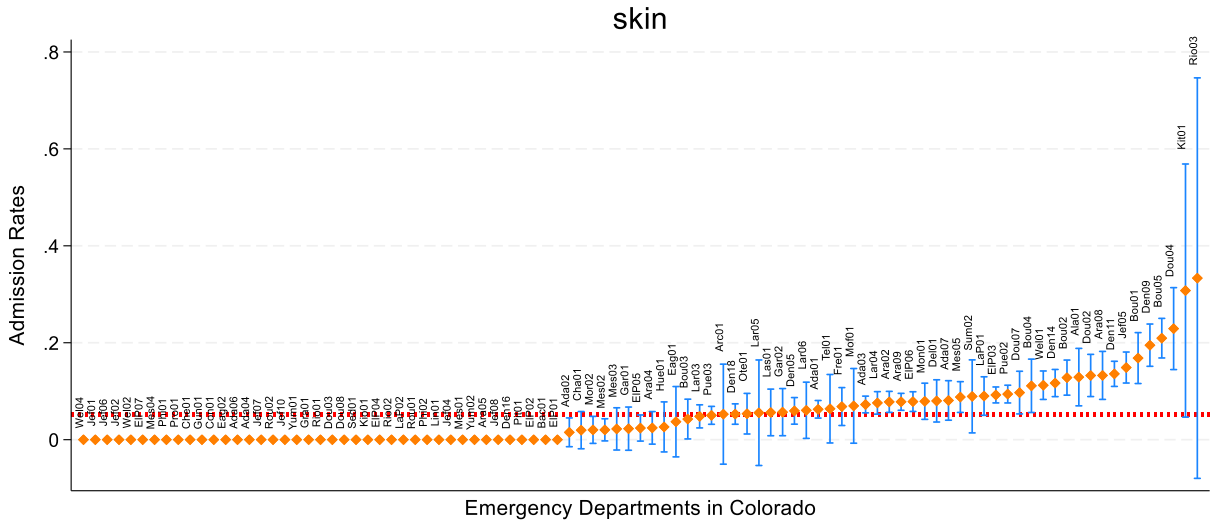

Figure B- 20 ED-level, unadjusted average admission rates for skin and subcutaneous tissue infections pooling each ED

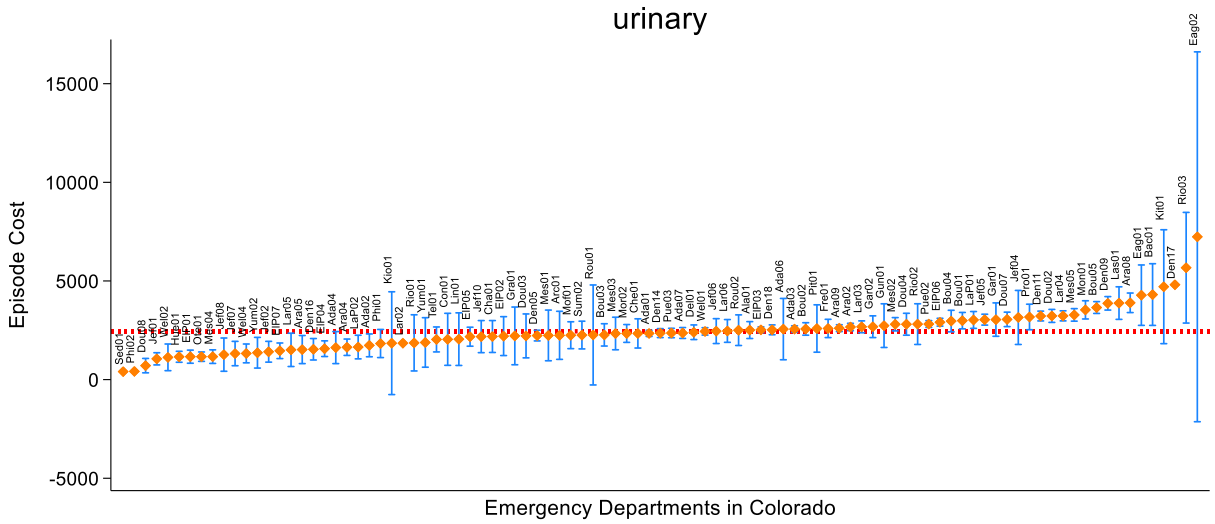

Figure B- 21 ED-level,unadjusted 30-day episode payment for urinary tract infections pooling each ED

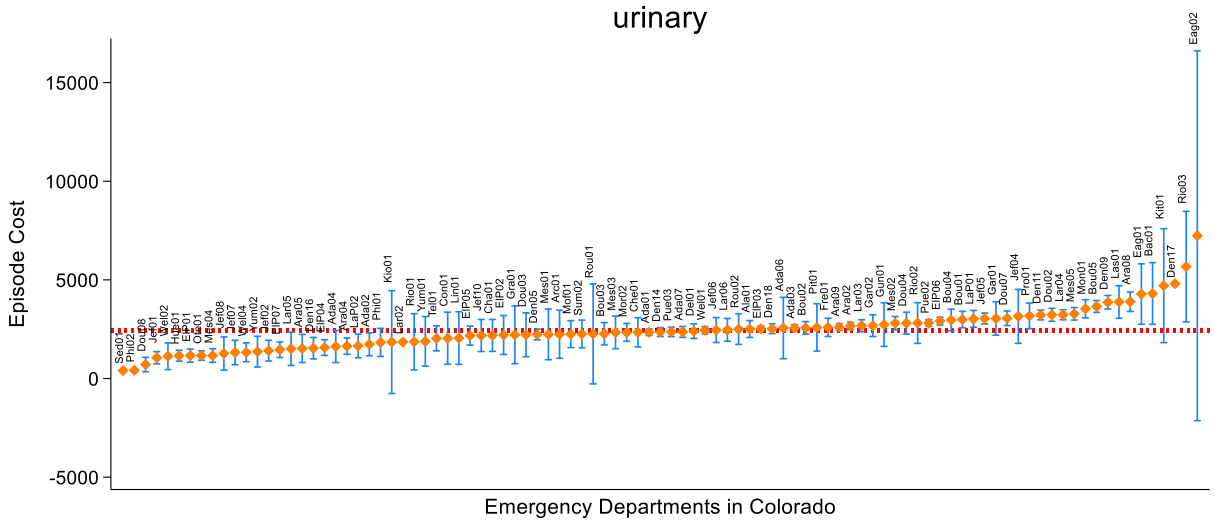

Figure B- 22 ED-level, unadjusted average admission rates for urinary tract infections pooling each ED

C. Condition-specific, Risk-adjustment Cost Models for Final Variables Selection

Table C- 1 Biliary Tract Disease

Category	Variable Description	HCC
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Lung and other severe cancers	9
Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Dementia without complication	52
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Ischemic or unspecified stroke	100
Other Comorbidity	Vascular disease	108
Other Comorbidity	Exudative macular degeneration	124
Other Comorbidity	Acute renal failure	135

Table C- 2 Cardiac Dysrhythmias

Category	Variable Description	HCC
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A

Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Lung and other severe cancers	9
Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Dementia without complication	52
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Ischemic or unspecified stroke	100
Other Comorbidity	Vascular disease	108
Other Comorbidity	Exudative macular degeneration	124
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Hip fracture/dislocation	170

Table C- 3 Chest Pain

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Opportunistic infections	6
Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Lung and other severe cancers	9
Other Comorbidity	Lymphoma and other cancers	10

Other Comorbidity	Colorectal, bladder and other cancers	11
Other Comorbidity	Breast, prostate, and other cancers and tumors	12
Other Comorbidity	Diabetes with acute complications	17
Other Comorbidity	Diabetes with chronic complications	18
Other Comorbidity	Diabetes without complication	19
Other Comorbidity	Morbid obesity	22
Other Comorbidity	Other significant endocrine and metabolic disorders	23
Other Comorbidity	Cirrhosis of liver	28
Other Comorbidity	Intestinal obstruction/perforation	33
Other Comorbidity	Chronic pancreatitis	34
Other Comorbidity	Inflammatory bowel disease	35
Other Comorbidity	Bone/joint/muscle infections/necrosis	39
Other Comorbidity	Rheumatoid arthritis and inflammatory connective tissue disease	40
Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Coagulation defects and other specified hematological disorders	48
Other Comorbidity	Dementia with complications	51
Other Comorbidity	Dementia without complication	52
Other Comorbidity	Substance use disorder, moderate/severe or substance use with complications	55
Other Comorbidity	Schizophrenia	57
Other Comorbidity	Reactive and unspecified psychosis	58
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59
Other Comorbidity	Personality disorder	60
Other Comorbidity	Quadriplegia	70
Other Comorbidity	Paraplegia	71
Other Comorbidity	Spinal cord disorders/injuries	72
Other Comorbidity	Amyotrophic lateral sclerosis and other motor neuron disease	73
Other Comorbidity	Cerebral palsy	74
Other Comorbidity	Multiple sclerosis	77
Other Comorbidity	Parkinson's and Huntington's diseases	78
Other Comorbidity	Seizure disorders and convulsions	79
Other Comorbidity	Coma, brain compression/anoxic damage	80
Other Comorbidity	Cardio-respiratory failure and shock	84

Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Unstable angina and other acute ischemic heart disease	87
Other Comorbidity	Specified heart arrhythmias	96
Other Comorbidity	Ischemic or unspecified stroke	100
Other Comorbidity	Hemiplegia/hemiparesis	103
Other Comorbidity	Vascular disease with complications	107
Other Comorbidity	Vascular disease	108
Other Comorbidity	Chronic obstructive pulmonary disease	111
Other Comorbidity	Fibrosis of lung and other chronic lung disorders	112
Other Comorbidity	Proliferative diabetic retinopathy and vitreous hemorrhage	122
Other Comorbidity	Exudative macular degeneration	124
Other Comorbidity	Dialysis status	134
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Chronic kidney disease (Stage 5)	136
Other Comorbidity	Chronic ulcer of skin, except pressure	161
Other Comorbidity	Major head injury	167
Other Comorbidity	Vertebral fractures without spinal cord injury	169
Other Comorbidity	Hip fracture/dislocation	170
Other Comorbidity	Complication of specified implanted device or graft	176
Other Comorbidity	Major organ transplant status or replacement status	186
Other Comorbidity	Artificial openings for feeding or elimination	188
Other Comorbidity	Amputation status, lower limb/amputation complication	189

Table C- 4 Congestive Heart Failure

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A

Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Breast, prostate, and other cancers and tumors	12
Other Comorbidity	Diabetes with chronic complications	18
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59
Other Comorbidity	Respirator dependence/tracheostomy status	82
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Vascular disease	108
Other Comorbidity	Cystic fibrosis	110
Other Comorbidity	Proliferative diabetic retinopathy and vitreous hemorrhage	124
Other Comorbidity	Dialysis status	134
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Chronic kidney disease (Stage 5)	136
Other Comorbidity	Hip fracture/dislocation	170

Table C- 5 Chronic Obstructive Pulmonary Disease

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Lung and other severe cancers	9
Other Comorbidity	Lymphoma and other cancers	10

Other Comorbidity	Colorectal, bladder and other cancers	11
Other Comorbidity	Diabetes with chronic complications	18
Other Comorbidity	Diabetes without complication	19
Other Comorbidity	Protein-calorie malnutrition	21
Other Comorbidity	Morbid obesity	22
Other Comorbidity	Other significant endocrine and metabolic disorders	23
Other Comorbidity	Cirrhosis of liver	28
Other Comorbidity	Intestinal obstruction/ perforation	33
Other Comorbidity	Inflammatory bowel disease	35
Other Comorbidity	Rheumatoid arthritis and inflammatory connective tissue disease	40
Other Comorbidity	Severe hematological disorders	46
Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Coagulation defects and other specified hematological disorders	48
Other Comorbidity	Dementia with complications	51
Other Comorbidity	Dementia without complication	52
Other Comorbidity	Substance use disorder, moderate/severe or substance use with complications	55
Other Comorbidity	Schizophrenia	57
Other Comorbidity	Reactive and unspecified psychosis	58
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59
Other Comorbidity	Personality disorder	60
Other Comorbidity	Spinal cord disorders/injuries	72
Other Comorbidity	Amyotrophic lateral sclerosis and other motor neuron disease	73
Other Comorbidity	Cerebral palsy	74
Other Comorbidity	Myasthenia gravis/myoneural disorders and guillain-barre syndrome/inflammatory and toxic neuropathy	75
Other Comorbidity	Multiple sclerosis	77
Other Comorbidity	Parkinson's and Huntington's diseases	78
Other Comorbidity	Seizure disorders and convulsions	79
Other Comorbidity	Coma, brain compression/anoxic damage	80
Other Comorbidity	Respirator dependence/tracheostomy status	82
Other Comorbidity	Cardio-respiratory failure and shock	84

Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Unstable angina and other acute ischemic heart disease	87
Other Comorbidity	Specified heart arrhythmias	96
Other Comorbidity	Ischemic or unspecified stroke	100
Other Comorbidity	Hemiplegia/hemiparesis	103
Other Comorbidity	Vascular disease with complications	107
Other Comorbidity	Vascular disease	108
Other Comorbidity	Chronic obstructive pulmonary disease	111
Other Comorbidity	Fibrosis of lung and other chronic lung disorders	112
Other Comorbidity	Aspiration and specified bacterial pneumonias	114
Other Comorbidity	Proliferative diabetic retinopathy and vitreous hemorrhage	122
Other Comorbidity	Exudative macular degeneration	124
Other Comorbidity	Dialysis status	134
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Chronic kidney disease (Stage 5)	136
Other Comorbidity	Chronic ulcer of skin, except pressure	161
Other Comorbidity	Major head injury	167
Other Comorbidity	Vertebral fractures without spinal cord injury	169
Other Comorbidity	Hip fracture/dislocation	170
Other Comorbidity	Complication of specified implanted device or graft	176
Other Comorbidity	Artificial openings for feeding or elimination	188

Table C- 6 Diabetic Mellitus

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A

Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Lung and other severe cancers	9
Other Comorbidity	Diabetes with acute complications	17
Other Comorbidity	Diabetes with chronic complications	18
Other Comorbidity	Diabetes without complication	19
Other Comorbidity	Morbid obesity	22
Other Comorbidity	Other significant endocrine and metabolic disorders	23
Other Comorbidity	Chronic pancreatitis	34
Other Comorbidity	Inflammatory bowel disease	35
Other Comorbidity	Bone/joint/muscle infections/necrosis	39
Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Coagulation defects and other specified hematological disorders	48
Other Comorbidity	Dementia without complication	52
Other Comorbidity	Schizophrenia	57
Other Comorbidity	Reactive and unspecified psychosis	58
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59
Other Comorbidity	Personality disorder	60
Other Comorbidity	Cerebral palsy	74
Other Comorbidity	Multiple sclerosis	77
Other Comorbidity	Parkinson's and Huntington's diseases	78
Other Comorbidity	Seizure disorders and convulsions	79
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Ischemic or unspecified stroke	100
Other Comorbidity	Atherosclerosis of extremity with ulceration or gangrene	106
Other Comorbidity	Vascular disease	108
Other Comorbidity	Chronic obstructive pulmonary disease	111
Other Comorbidity	Proliferative diabetic retinopathy and vitreous hemorrhage	122
Other Comorbidity	Dialysis status	134

Other Comorbidity	Acute renal failure	135
Other Comorbidity	Chronic kidney disease (Stage 5)	136
Other Comorbidity	Chronic kidney disease, severe (stage 4)	137
Other Comorbidity	Chronic ulcer of skin, except pressure	161
Other Comorbidity	Hip fracture/dislocation	170
Other Comorbidity	Artificial openings for feeding or elimination	188

Table C- 7 Fluid and Electrolyte Disorders

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Lung and other severe cancers	9
Other Comorbidity	Lymphoma and other cancers	10
Other Comorbidity	Colorectal, bladder and other cancers	11
Other Comorbidity	Diabetes with acute complications	17
Other Comorbidity	Diabetes with chronic complications	18
Other Comorbidity	Protein-calorie malnutrition	21
Other Comorbidity	Morbid obesity	22
Other Comorbidity	Other significant endocrine and metabolic disorders	23
Other Comorbidity	Inflammatory bowel disease	35
Other Comorbidity	Rheumatoid arthritis and inflammatory connective tissue disease	40
Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Coagulation defects and other specified hematological disorders	48

Other Comorbidity	Dementia with complications	51
Other Comorbidity	Dementia without complication	52
Other Comorbidity	Substance use disorder, moderate/severe or substance use with complications	55
Other Comorbidity	Schizophrenia	57
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59
Other Comorbidity	Quadriplegia	70
Other Comorbidity	Cerebral palsy	74
Other Comorbidity	Seizure disorders and convulsions	79
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Ischemic or unspecified stroke	100
Other Comorbidity	Vascular disease with complications	107
Other Comorbidity	Vascular disease	108
Other Comorbidity	Cystic fibrosis	110
Other Comorbidity	Chronic obstructive pulmonary disease	111
Other Comorbidity	Dialysis status	134
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Chronic kidney disease (Stage 5)	136
Other Comorbidity	Pressure ulcer of skin with full thickness skin loss	158
Other Comorbidity	Chronic ulcer of skin, except pressure	161
Other Comorbidity	Hip fracture/dislocation	170
Other Comorbidity	Complication of specified implanted device or graft	176
Other Comorbidity	Artificial openings for feeding or elimination	188

Table C- 8 Gastroenteritis

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A

Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Lung and other severe cancers	9
Other Comorbidity	Lymphoma and other cancers	10
Other Comorbidity	Protein-calorie malnutrition	21
Other Comorbidity	Morbid obesity	22
Other Comorbidity	Other significant endocrine	23
Other Comorbidity	End-stage liver disease	27
Other Comorbidity	Intestinal obstruction/perforation	33
Other Comorbidity	Inflammatory bowel disease	35
Other Comorbidity	Severe hematological disorders	46
Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Dementia with complications	51
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59
Other Comorbidity	Personality disorder	60
Other Comorbidity	Quadriplegia	70
Other Comorbidity	Cerebral palsy	74
Other Comorbidity	Seizure disorders and convulsions	79
Other Comorbidity	Coma, brain compression/anoxic damage	80
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Hemiplegia/hemiparesis	103
Other Comorbidity	Vascular disease with complications	107
Other Comorbidity	Vascular disease	108
Other Comorbidity	Chronic obstructive pulmonary disease	111
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Chronic kidney disease (Stage 5)	136

Other Comorbidity	Chronic ulcer of skin, except pressure	161
Other Comorbidity	Hip fracture/dislocation	170
Other Comorbidity	Artificial openings for feeding or elimination	188

Table C- 9 Pneumonia

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Lung and other severe cancers	9
Other Comorbidity	Lymphoma and other cancers	10
Other Comorbidity	Breast, prostate, and other cancers and tumors	12
Other Comorbidity	Diabetes without complication	19
Other Comorbidity	Protein-calorie malnutrition	21
Other Comorbidity	Morbid obesity	22
Other Comorbidity	Other significant endocrine and metabolic disorders	23
Other Comorbidity	Inflammatory bowel disease	35
Other Comorbidity	Rheumatoid arthritis and inflammatory connective tissue disease	40
Other Comorbidity	Severe hematological disorders	46
Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Coagulation defects and other specified hematological disorders	48
Other Comorbidity	Dementia with complications	51
Other Comorbidity	Dementia without complication	52
Other Comorbidity	Schizophrenia	57
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59

Other Comorbidity	Quadriplegia	70
Other Comorbidity	Paraplegia	71
Other Comorbidity	Spinal cord disorders/injuries	72
Other Comorbidity	Cerebral palsy	74
Other Comorbidity	Multiple sclerosis	77
Other Comorbidity	Parkinson's and Huntington's diseases	78
Other Comorbidity	Seizure disorders and convulsions	79
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Ischemic or unspecified stroke	100
Other Comorbidity	Vascular disease	108
Other Comorbidity	Chronic obstructive pulmonary disease	111
Other Comorbidity	Proliferative diabetic retinopathy and vitreous hemorrhage	122
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Chronic kidney disease (Stage 5)	136
Other Comorbidity	Chronic ulcer of skin, except pressure	161
Other Comorbidity	Hip fracture/dislocation	170
Other Comorbidity	Complication of specified implanted device or graft	176
Other Comorbidity	Major organ transplant status or replacement status	186
Other Comorbidity	Artificial openings for feeding or elimination	188

Table C- 10 Skin and Subcutaneous Tissue Infections

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A

Other Comorbidity	HIV/AIDS	1
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Lung and other severe cancers	9
Other Comorbidity	Lymphoma and other cancers	10
Other Comorbidity	Colorectal, bladder and other cancers	11
Other Comorbidity	Breast, prostate, and other cancers and tumors	12
Other Comorbidity	Diabetes with acute complications	17
Other Comorbidity	Diabetes with chronic complications	18
Other Comorbidity	Diabetes without complication	19
Other Comorbidity	Morbid obesity	22
Other Comorbidity	Other significant endocrine and metabolic disorders	23
Other Comorbidity	Cirrhosis of liver	28
Other Comorbidity	Intestinal obstruction/perforation	33
Other Comorbidity	Chronic pancreatitis	34
Other Comorbidity	Inflammatory bowel disease	35
Other Comorbidity	Bone/joint/muscle infections/necrosis	39
Other Comorbidity	Rheumatoid arthritis and inflammatory connective tissue disease	40
Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Dementia with complications	51
Other Comorbidity	Dementia without complication	52
Other Comorbidity	Substance use disorder, moderate/severe or substance use with complications	55
Other Comorbidity	Substance use disorder, mild, except alcohol and cannabis	56
Other Comorbidity	Schizophrenia	57
Other Comorbidity	Reactive and unspecified psychosis	58
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59
Other Comorbidity	Personality disorder	60
Other Comorbidity	Spinal cord disorders/injuries	72
Other Comorbidity	Cerebral palsy	74
Other Comorbidity	Muscular dystrophy	76
Other Comorbidity	Multiple sclerosis	77
Other Comorbidity	Parkinson's and Huntington's diseases	78

Other Comorbidity	Seizure disorders and convulsions	79
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Specified heart arrhythmias	96
Other Comorbidity	Ischemic or unspecified stroke	100
Other Comorbidity	Hemiplegia/hemiparesis	103
Other Comorbidity	Vascular disease with complications	107
Other Comorbidity	Vascular disease	108
Other Comorbidity	Chronic obstructive pulmonary disease	111
Other Comorbidity	Proliferative diabetic retinopathy and vitreous hemorrhage	122
Other Comorbidity	Dialysis status	134
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Chronic kidney disease (Stage 5)	136
Other Comorbidity	Pressure ulcer of skin with full thickness skin loss	158
Other Comorbidity	Pressure ulcer of skin with partial thickness skin loss	159
Other Comorbidity	Chronic ulcer of skin, except pressure	161
Other Comorbidity	Major head injury	167
Other Comorbidity	Hip fracture/dislocation	170
Other Comorbidity	Complication of specified implanted device or graft	176
Other Comorbidity	Artificial openings for feeding or elimination	188

Table C- 11 Urinary Tract Infections

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A

Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Lung and other severe cancers	9
Other Comorbidity	Lymphoma and other cancers	10
Other Comorbidity	Colorectal, bladder and other cancers	11
Other Comorbidity	Breast, prostate, and other cancers and tumors	12
Other Comorbidity	Diabetes with acute complications	17
Other Comorbidity	Diabetes with chronic complications	18
Other Comorbidity	Diabetes without complication	19
Other Comorbidity	Protein-calorie malnutrition	21
Other Comorbidity	Morbid obesity	22
Other Comorbidity	Other significant endocrine and metabolic disorders	23
Other Comorbidity	Intestinal obstruction/ perforation	33
Other Comorbidity	Chronic pancreatitis	34
Other Comorbidity	Inflammatory bowel disease	35
Other Comorbidity	Rheumatoid arthritis and inflammatory connective tissue disease	40
Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Coagulation defects and other specified hematological disorders	48
Other Comorbidity	Dementia with complications	51
Other Comorbidity	Dementia without complication	52
Other Comorbidity	Substance use disorder, moderate/severe or substance use with complications	55
Other Comorbidity	Schizophrenia	57
Other Comorbidity	Reactive and unspecified psychosis	58
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59
Other Comorbidity	Personality disorder	60
Other Comorbidity	Quadriplegia	70
Other Comorbidity	Paraplegia	71
Other Comorbidity	Cerebral palsy	74
Other Comorbidity	Muscular dystrophy	76
Other Comorbidity	Multiple sclerosis	77
Other Comorbidity	Parkinson's and Huntington's diseases	78

Other Comorbidity	Seizure disorders and convulsions	79
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Angina pectoris	88
Other Comorbidity	Specified heart arrhythmias	96
Other Comorbidity	Ischemic or unspecified stroke	100
Other Comorbidity	Hemiplegia/hemiparesis	103
Other Comorbidity	Monoplegia, other paralytic syndromes	104
Other Comorbidity	Vascular disease with complications	107
Other Comorbidity	Vascular disease	108
Other Comorbidity	Chronic obstructive pulmonary disease	111
Other Comorbidity	Fibrosis of lung and other chronic lung disorders	112
Other Comorbidity	Dialysis status	134
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Chronic kidney disease (Stage 5)	136
Other Comorbidity	Pressure ulcer of skin with full thickness skin loss	158
Other Comorbidity	Chronic ulcer of skin, except pressure	161
Other Comorbidity	Major head injury	167
Other Comorbidity	Vertebral fractures without spinal cord injury	169
Other Comorbidity	Hip fracture/dislocation	170
Other Comorbidity	Complication of specified implanted device or graft	176
Other Comorbidity	Major organ transplant status or replacement status	186
Other Comorbidity	Artificial openings for feeding or elimination	188
Other Comorbidity	Amputation status, lower limb/amputation complication	189

D. Condition-specific, Risk-adjustment Admission Models for Final Variables Selection

Table D- 1 Biliary Tract Disease

Category	Variable Description	HCC
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Intestinal obstruction/perforation	33
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Artificial openings for feeding or elimination	188

Table D- 2 Cardiac Dysrhythmias

Category	Variable Description	HCC
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2

Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Cardio-respiratory failure and shock	33
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Chronic kidney disease (Stage 5)	136

Table D- 3 Chest Pain

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Diabetes with acute complications	17
Other Comorbidity	Diabetes with chronic complications	18
Other Comorbidity	Other significant endocrine and metabolic disorders	23
Other Comorbidity	Intestinal obstruction/perforation	33
Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Substance use disorder, moderate/severe or substance use with complications	55
Other Comorbidity	Quadriplegia	70
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Specified heart arrhythmias	96

Other Comorbidity	Ischemic or unspecified stroke	100
Other Comorbidity	Vascular disease with complications	107
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Chronic kidney disease (Stage 5)	136
Other Comorbidity	Hip fracture/dislocation	170

Table D- 4 Congestive Heart Failure

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Diabetes without complication	19
Other Comorbidity	Dementia without complication	52
Other Comorbidity	Substance use disorder, moderate/severe or substance use with complications	55
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Angina pectoris	88
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Hip fracture/dislocation	170
Other Comorbidity	Complication of specified implanted device or graft	176

Table D- 5 Chronic Obstructive Pulmonary Disease

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A

Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Protein-calorie malnutrition	21
Other Comorbidity	Substance use disorder, moderate/severe or substance use with complications	55
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Specified heart arrhythmias	96
Other Comorbidity	Chronic obstructive pulmonary disease	111
Other Comorbidity	Aspiration and specified bacterial pneumonias	114
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Hip fracture/dislocation	170

Table D- 6 Diabetic Mellitus

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Diabetes with acute complications	17

Other Comorbidity	Diabetes with chronic complications	18
Other Comorbidity	Diabetes without complication	19
Other Comorbidity	Bone/joint/muscle infections/necrosis	39
Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Ischemic or unspecified stroke	100
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Chronic ulcer of skin, except pressure	161

Table D- 7 Fluid and Electrolyte Disorders

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Diabetes with acute complications	17
Other Comorbidity	Protein-calorie malnutrition	21
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59
Other Comorbidity	Quadriplegia	70
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Ischemic or unspecified stroke	100
Other Comorbidity	Acute renal failure	135

Other Comorbidity	Chronic kidney disease (Stage 5)	136
Other Comorbidity	Pressure ulcer of skin with full thickness skin loss	158
Other Comorbidity	Chronic ulcer of skin, except pressure	161
Other Comorbidity	Hip fracture/dislocation	170

Table D- 8 Gastroenteritis

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Protein-calorie malnutrition	21
Other Comorbidity	End-stage liver disease	27
Other Comorbidity	Intestinal obstruction/perforation	33
Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Angina pectoris	88
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Chronic kidney disease (Stage 5)	136
Other Comorbidity	Chronic ulcer of skin, except pressure	161
Other Comorbidity	Hip fracture/dislocation	170

Table D- 9 Pneumonia

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A

Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Colorectal, bladder and other cancers	11
Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Reactive and unspecified psychosis	58
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59
Other Comorbidity	Quadriplegia	70
Other Comorbidity	Seizure disorders and convulsions	79
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Proliferative diabetic retinopathy and vitreous hemorrhage	122
Other Comorbidity	Acute renal failure	135

Table D- 10 Skin and Subcutaneous Tissue Infections

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Diabetes with acute complications	17

Other Comorbidity	Diabetes with chronic complications	18
Other Comorbidity	Morbid obesity	22
Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Substance use disorder, mild, except alcohol and cannabis	56
Other Comorbidity	Reactive and unspecified psychosis	58
Other Comorbidity	Seizure disorders and convulsions	79
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Hemiplegia/hemiparesis	103
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Chronic ulcer of skin, except pressure	161
Other Comorbidity	Hip fracture/dislocation	170

Table D- 11 Urinary Tract Infections

Category	**Variable Description**	**HCC**
Demographics	Age (0-17)	N/A
Demographics	Age (18-34)	N/A
Demographics	Age (35-44)	N/A
Demographics	Age (45-54)	N/A
Demographics	Age (55-64)	N/A
Demographics	Age (65-74)	N/A
Demographics	Age (75-84)	N/A
Demographics	Age (>=85)	N/A
Demographics	Gender (0: Male;1: Female)	N/A
Other Comorbidity	Septicemia, sepsis, and systemic inflammatory response syndrome/shock	2
Other Comorbidity	Metastatic cancer and acute leukemia	8
Other Comorbidity	Colorectal, bladder and other cancers	11
Other Comorbidity	Diabetes with acute complications	17
Other Comorbidity	Diabetes with chronic complications	18
Other Comorbidity	Morbid obesity	22
Other Comorbidity	Intestinal obstruction/ perforation	33
Other Comorbidity	Inflammatory bowel disease	35

Other Comorbidity	Disorders of immunity	47
Other Comorbidity	Major depressive, bipolar and paranoid disorders	59
Other Comorbidity	Spinal cord disorders/injuries	72
Other Comorbidity	Multiple sclerosis	77
Other Comorbidity	Seizure disorders and convulsions	79
Other Comorbidity	Cardio-respiratory failure and shock	84
Other Comorbidity	Congestive heart failure	85
Other Comorbidity	Acute myocardial infarction	86
Other Comorbidity	Fibrosis of lung and other chronic lung disorders	112
Other Comorbidity	Pneumococcal pneumonia, empyema, lung abscess	115
Other Comorbidity	Acute renal failure	135
Other Comorbidity	Chronic kidney disease (Stage 5)	136
Other Comorbidity	Chronic ulcer of skin, except pressure	161
Other Comorbidity	Hip fracture/dislocation	170

E. Condition-specific, Risk-Adjustment Model Figures

NOTE: Blue line indicates the unadjusted episode cost associated with 30-day episode of care. Green line denotes 30-day episode cost predicted from risk-adjustment model. Two black dotted reference lines denote the 90th and 95th percentile of unadjusted episode cost respectively.

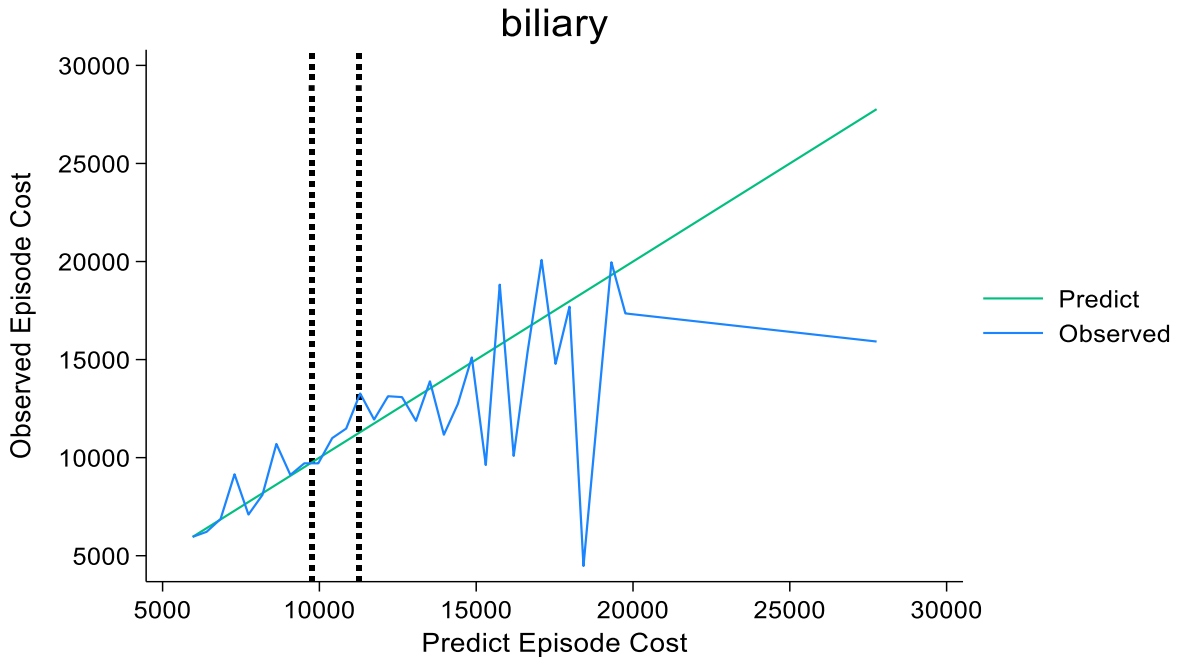

Figure E- 1 Polynomial smoothing plot 30-day episode cost for biliary tract disease between actual Vs predicted

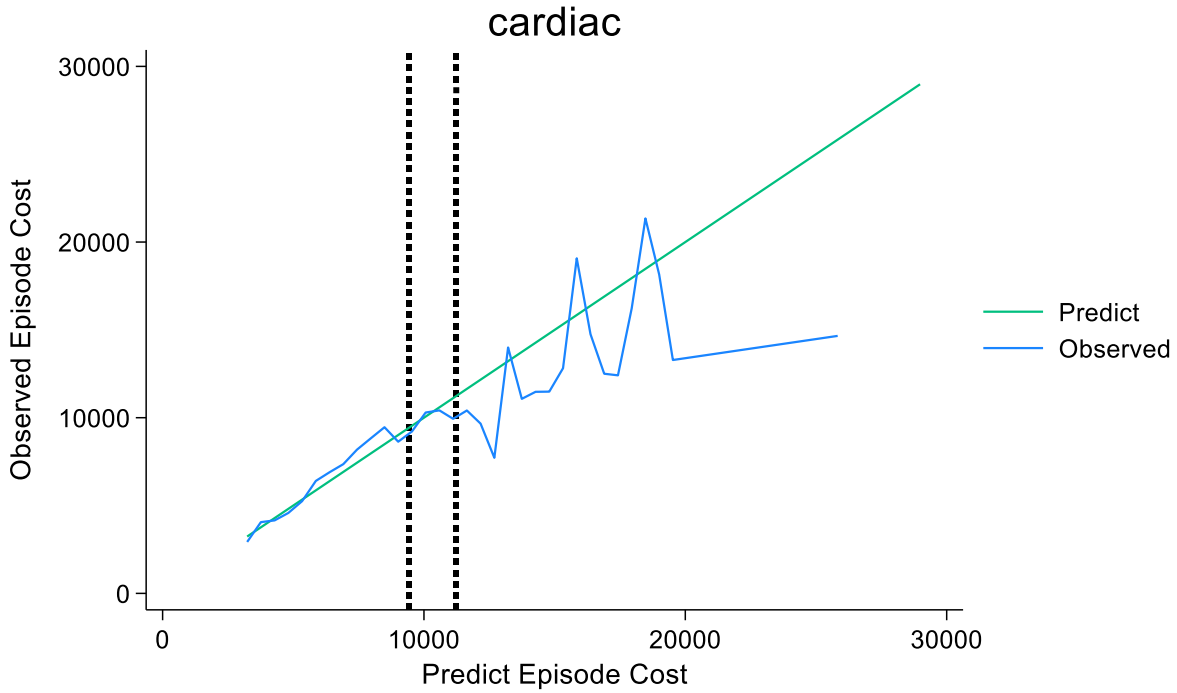

Figure E- 2 Polynomial smoothing plot of 30-day episode cost for cardiac dysthymias between actual Vs predicted

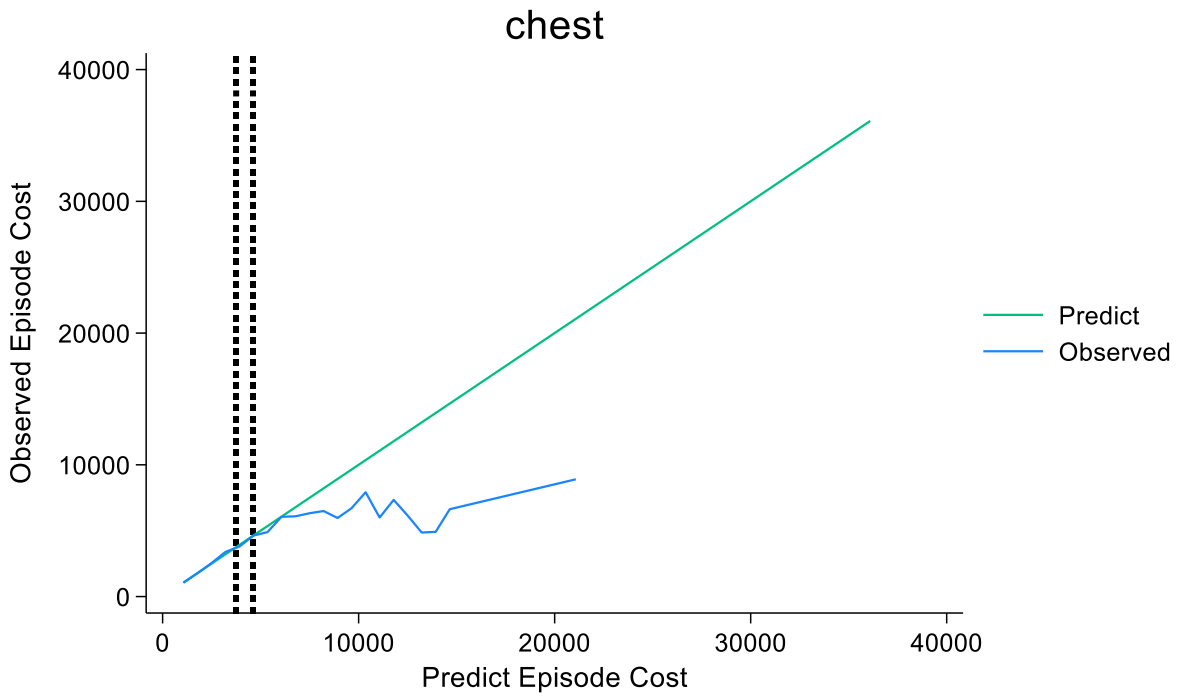

Figure E- 3 Polynomial smoothing plot of 30-day episode cost for chest pain between actual Vs predicted

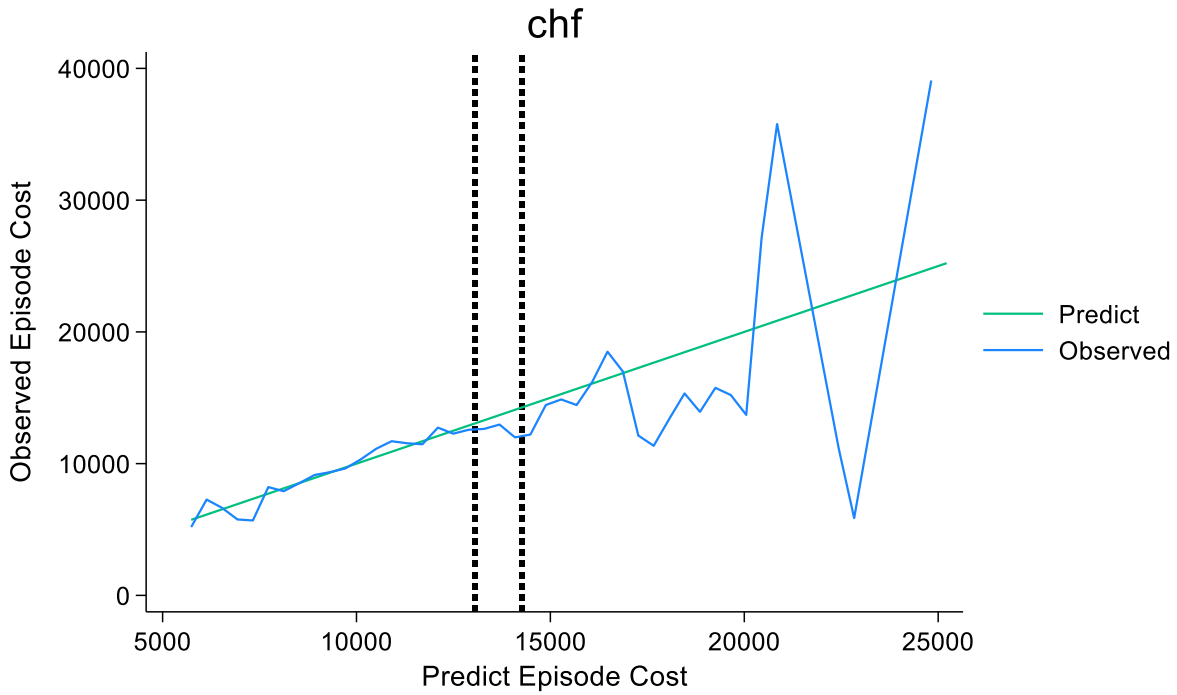

Figure E- 4 Polynomial smoothing plot of 30-day episode cost for congestive heart failure between actual Vs predicted

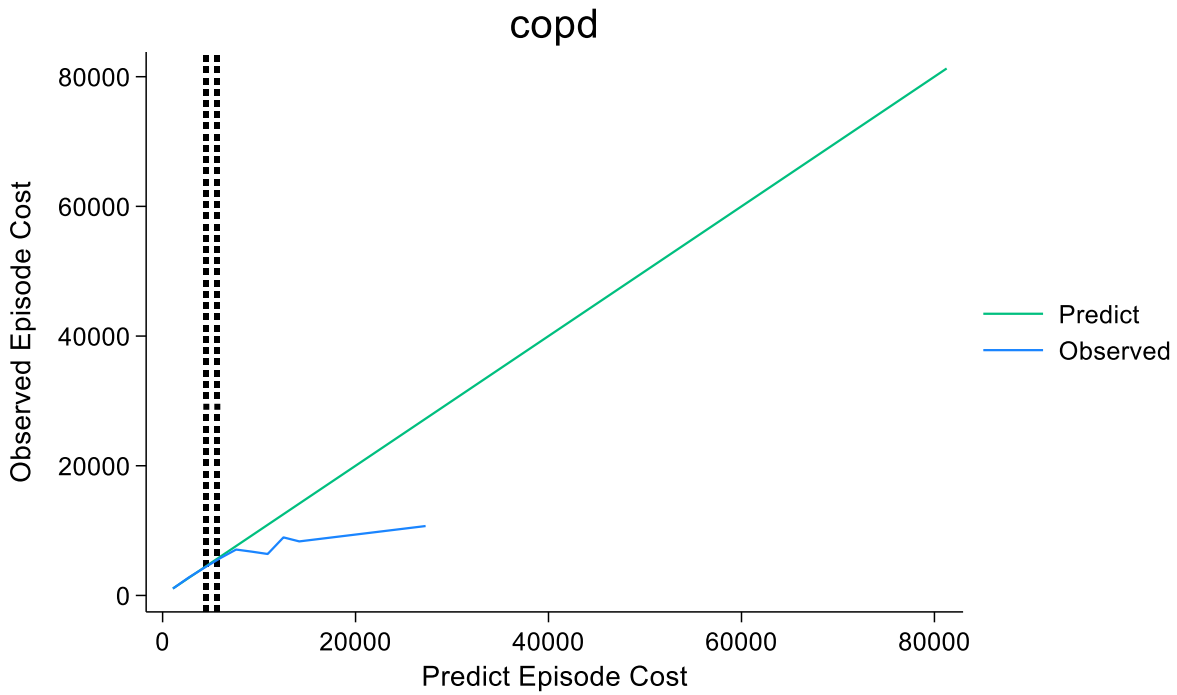

Figure E- 5 Polynomial smoothing plot of 30-day episode cost for chronic obstructuve pulmonary disease between actual Vs predicted

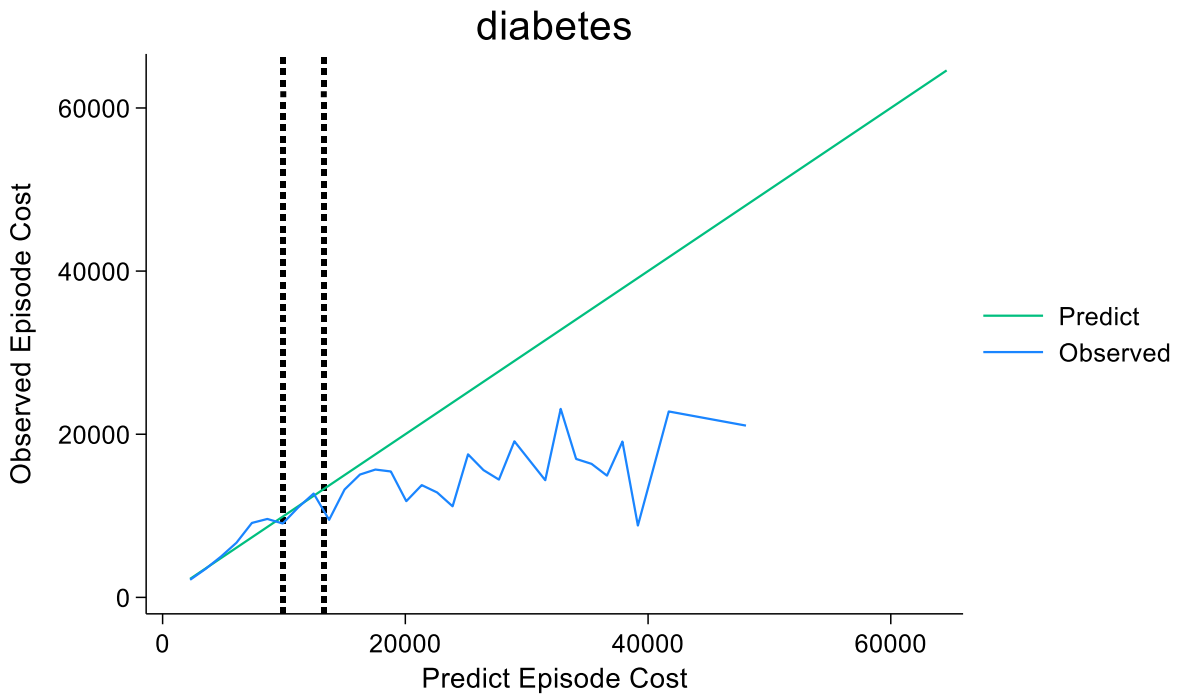

Figure E- 6 Polynomial smoothing plot of 30-day episode cost for diabetic mellitus between actual Vs predicted

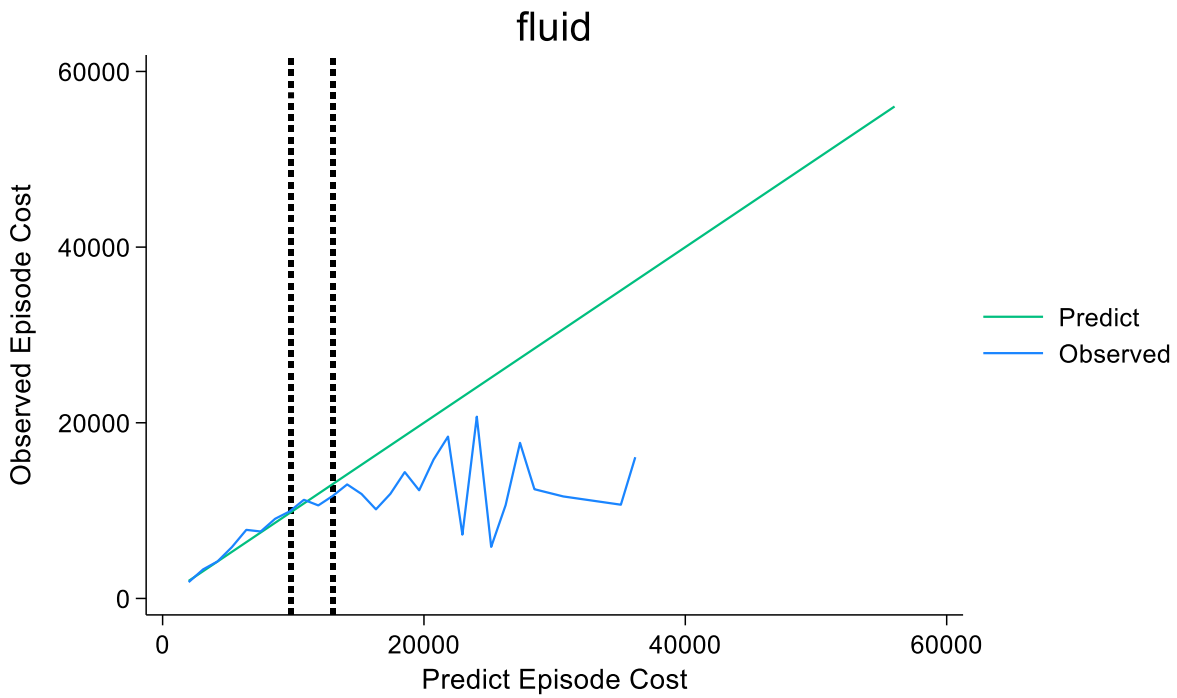

Figure E- 7 Polynomial smoothing plot of 30-day episode cost for fluid and electrolyte disorders between actual Vs predicted

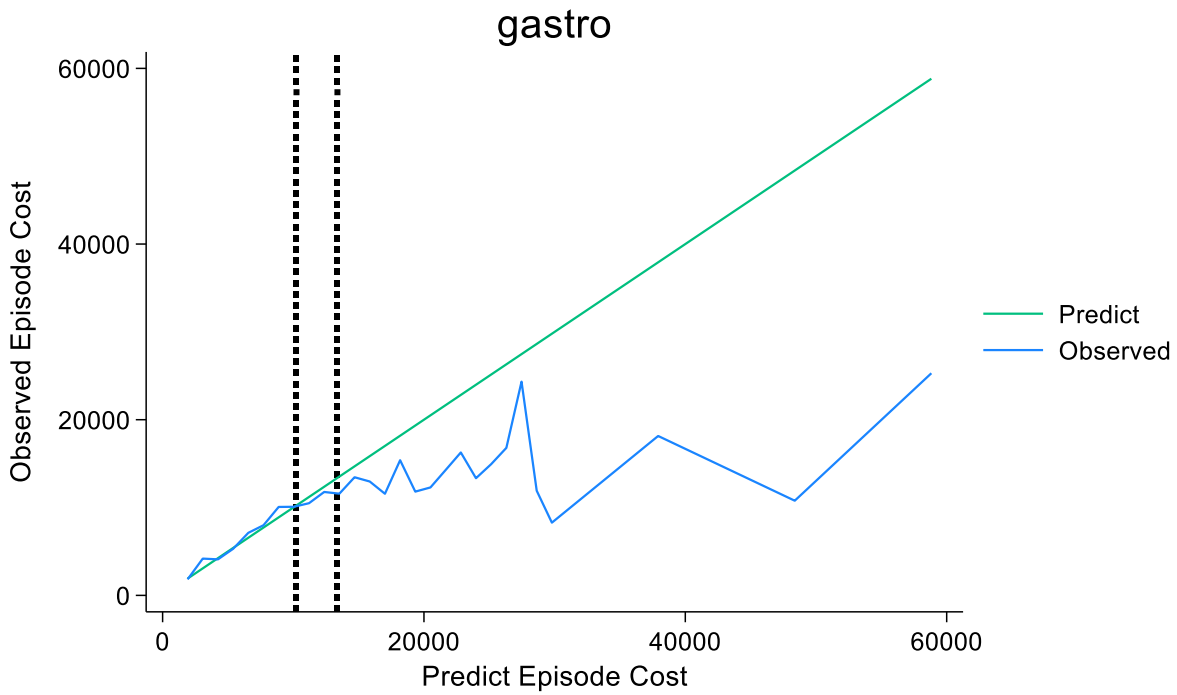

Figure E- 8 Polynomial smoothing plot of 30-day episode cost for gastroenteritis between actual Vs predicted

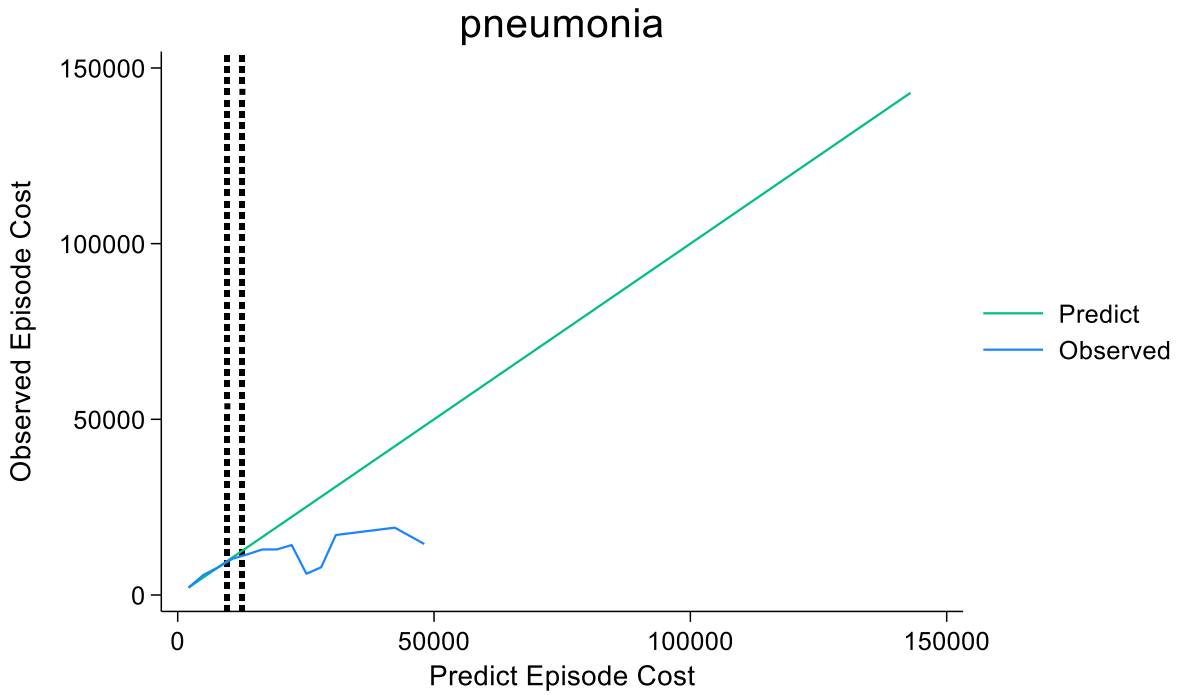

Figure E- 9 Polynomial smoothing plot of 30-day episode cost for pneumonia between actual Vs predicted

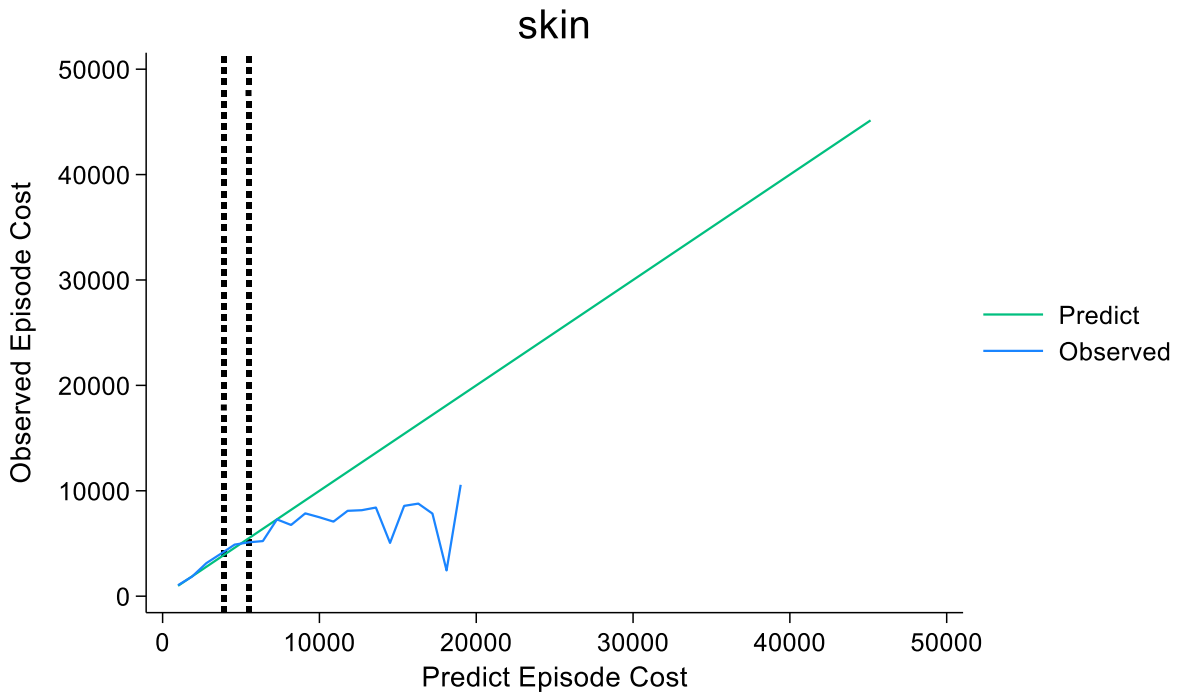

Figure E- 10 . Polynomial smoothing plot of 30-day episode cost for skin and subcutaneous infections between actual Vs predicted

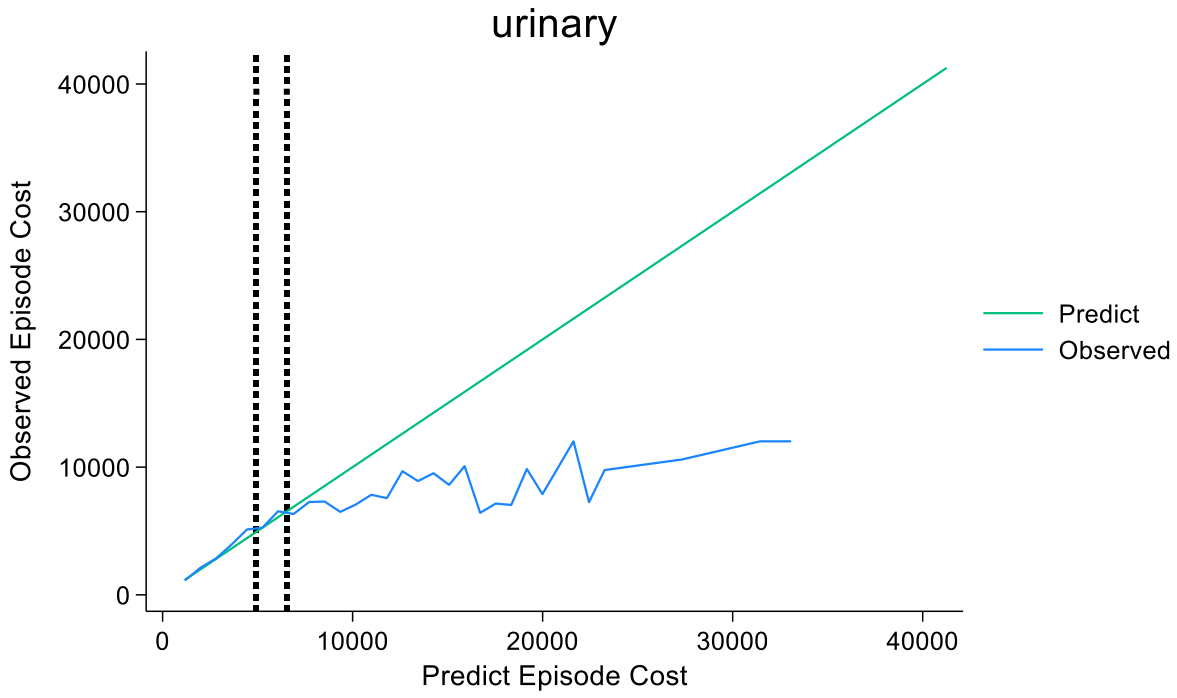

Figure E- 11 Polynomial smoothing plot of 30-day episode cost for urinary tract infections between actual Vs predicted

NOTE: Blue line denotes the unadjusted admission probabilities associated with the 30-day episode of care. Green line refers to the admission rates predicted from risk-adjustment models. A black dotted reference line refers to the 90th percentile of unadjusted admission rates.

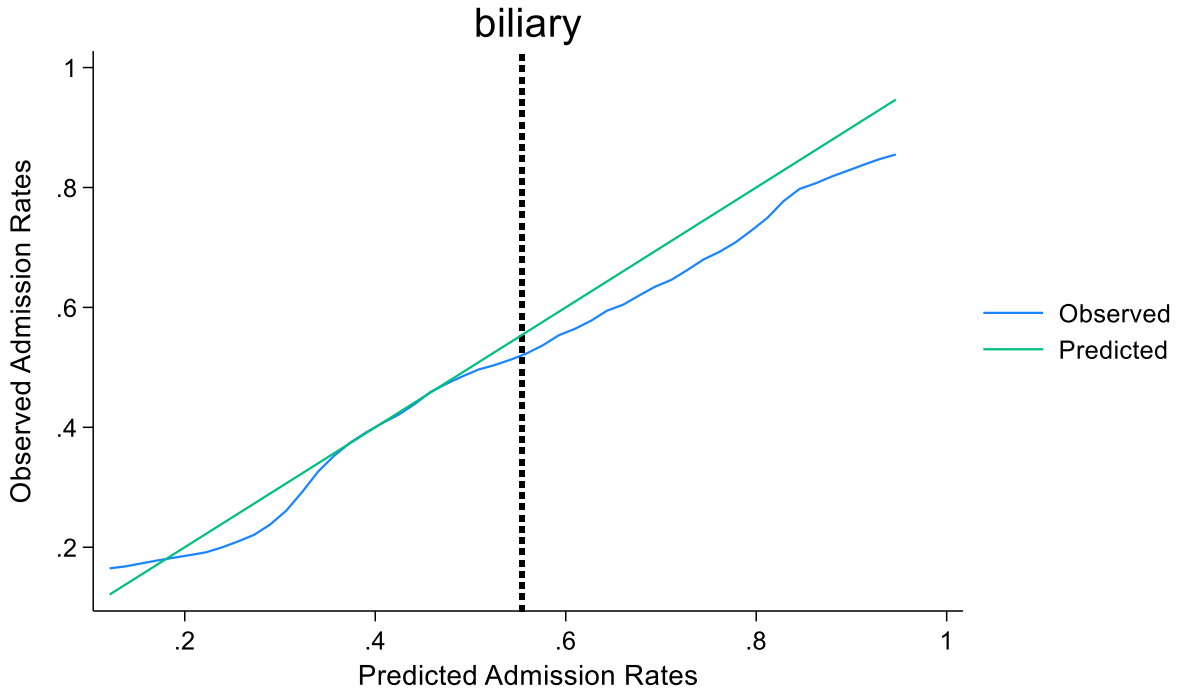

Figure E- 12 Polynomial smoothing plot of 30-day episode admission rate for biliary tract disease between actual Vs predicted

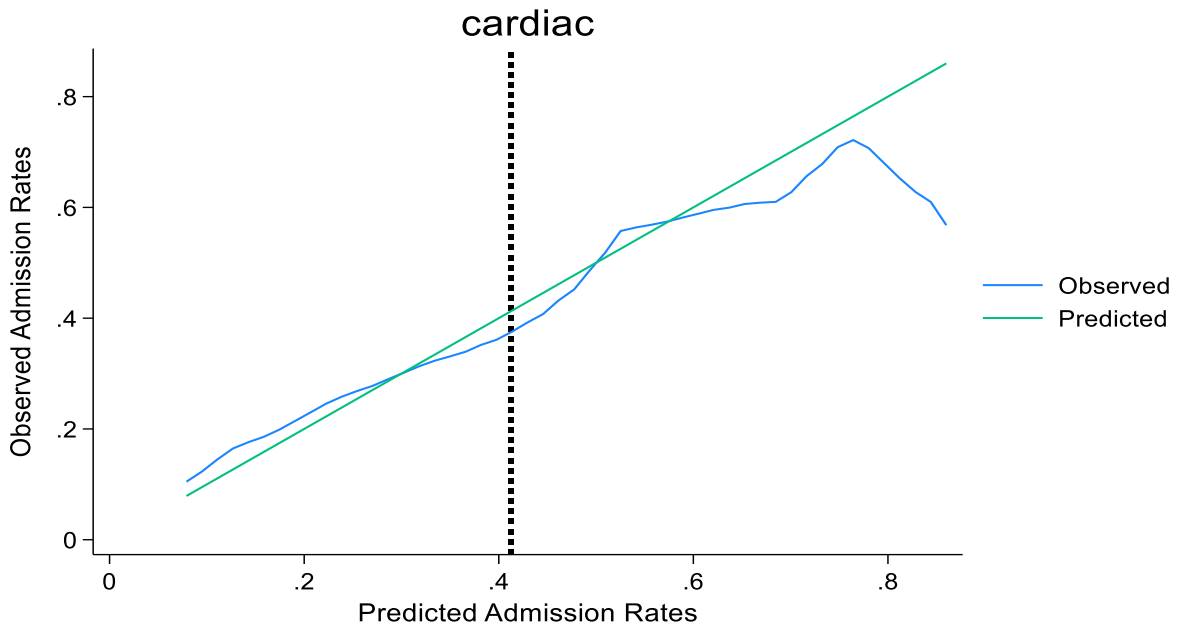

Figure E- 13 Polynomial smoothing plot of condition-specific, 30-day episode admission rate for cardiac dysthymias between actual Vs predicted

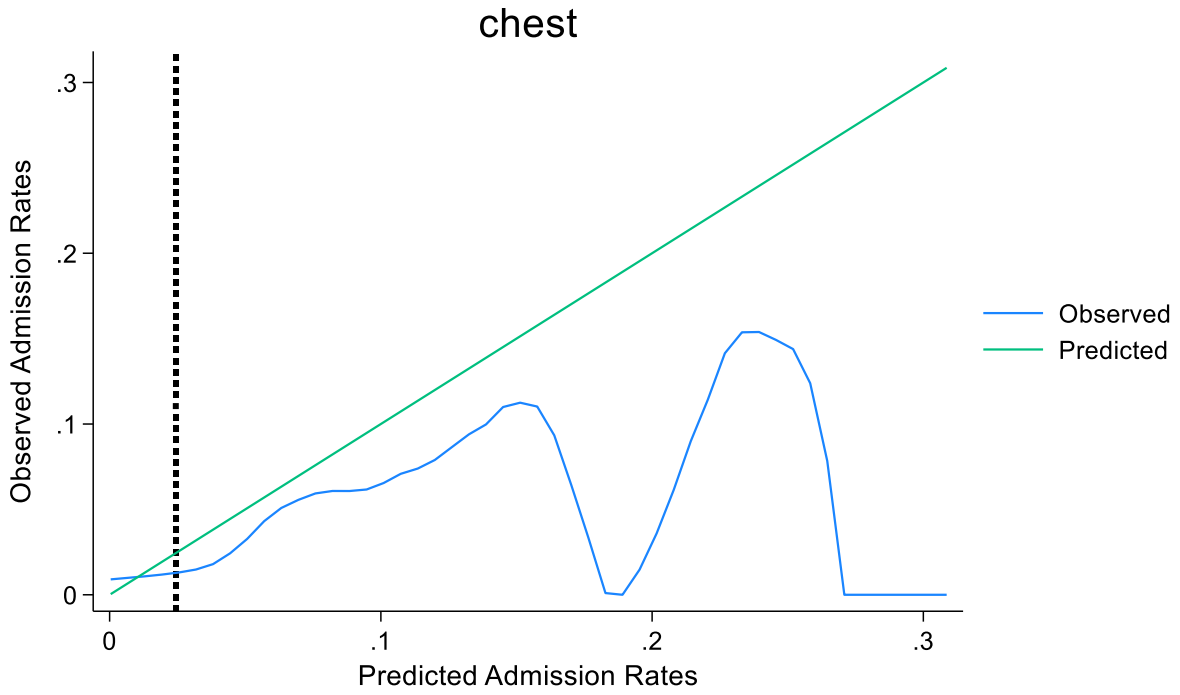

Figure E- 14 Polynomial smoothing plot of 30-day episode admission rate for chest pain between actual Vs predicted

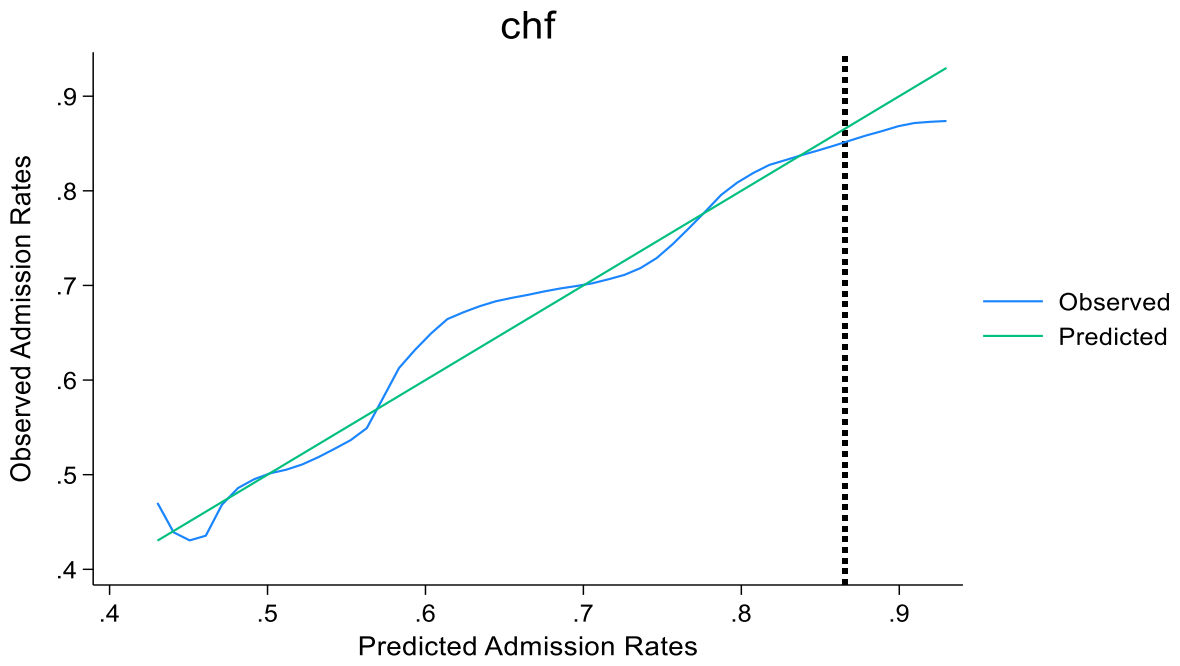

Figure E- 15 Polynomial smoothing plot of 30-day episode admission rate for congestive heart failure between actual Vs predicted

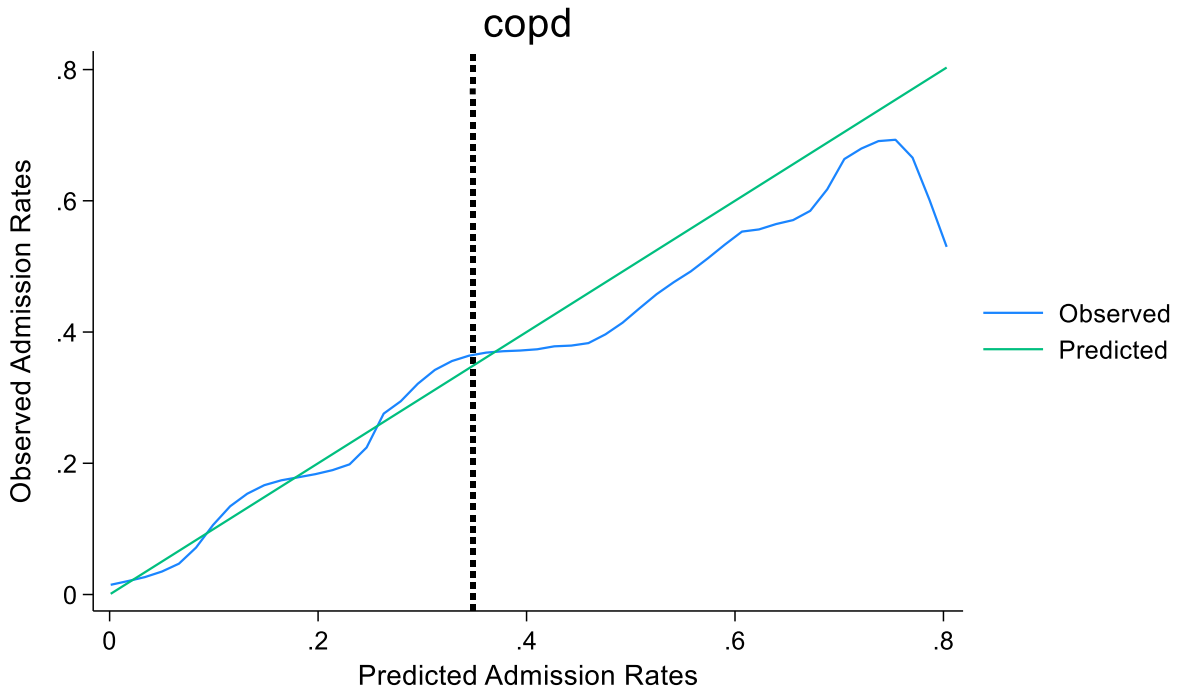

Figure E- 16 Polynomial smoothing plot of 30-day episode admission rate for chronic obstructive pulmonary disease between actual Vs predicted

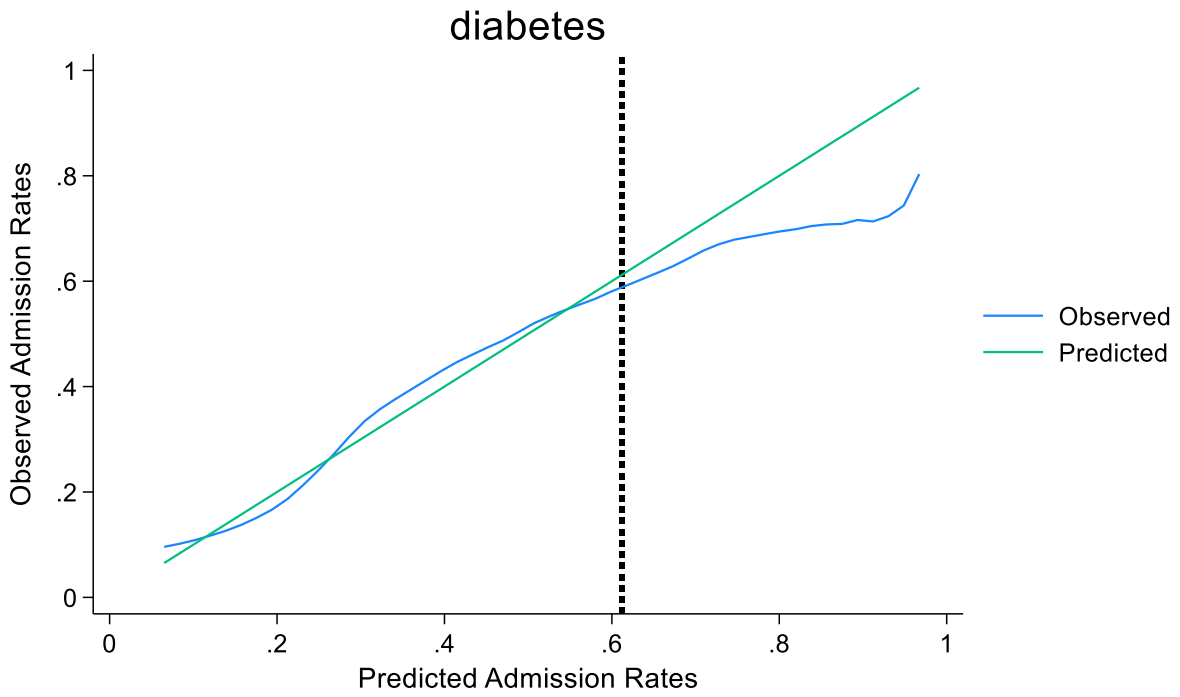

Figure E- 17 Polynomial smoothing plot of 30-day episode admission rate for diabetic mellitus between actual Vs predicted

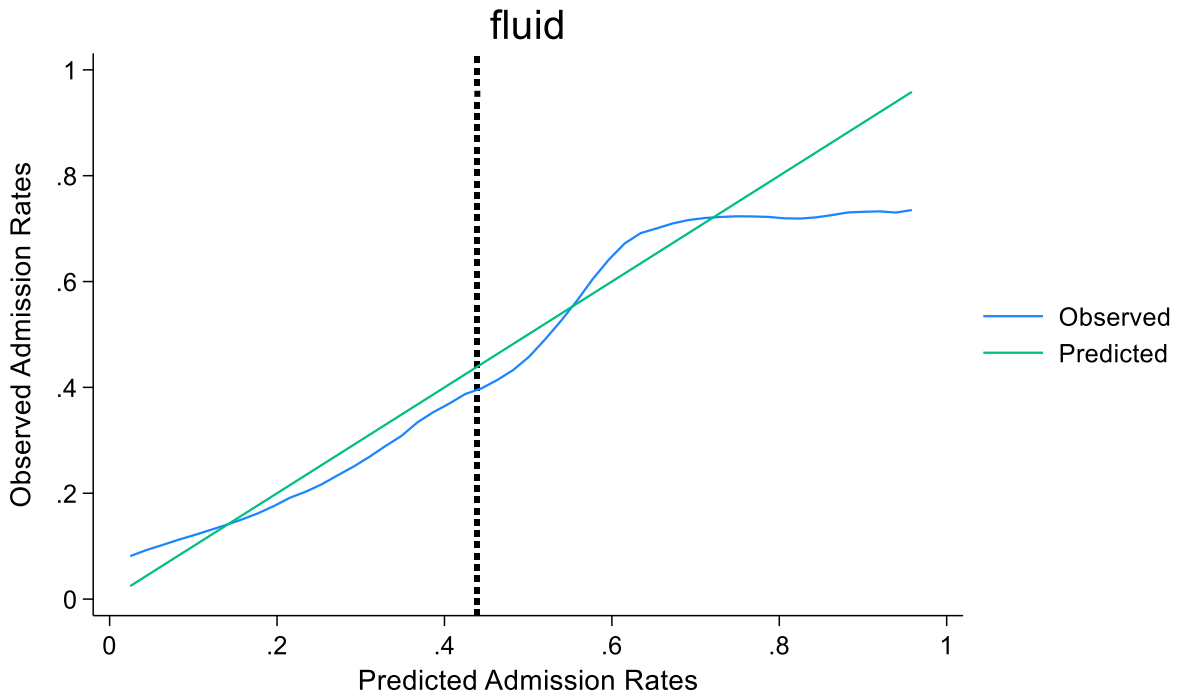

Figure E- 18 Polynomial smoothing plot of 30-day episode admission rate for fluid and electrolyte disorders between actual Vs predicted

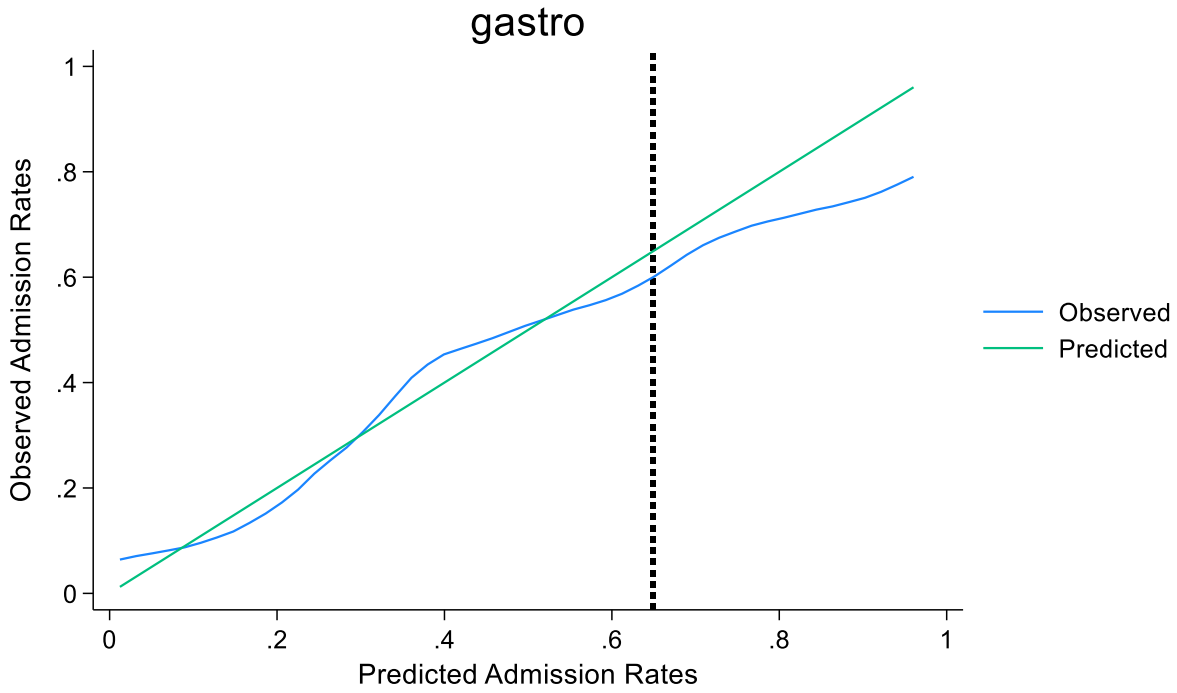

Figure E- 19 Polynomial smoothing plot of 30-day episode admission rate for gastroenteritis between actual Vs predicted

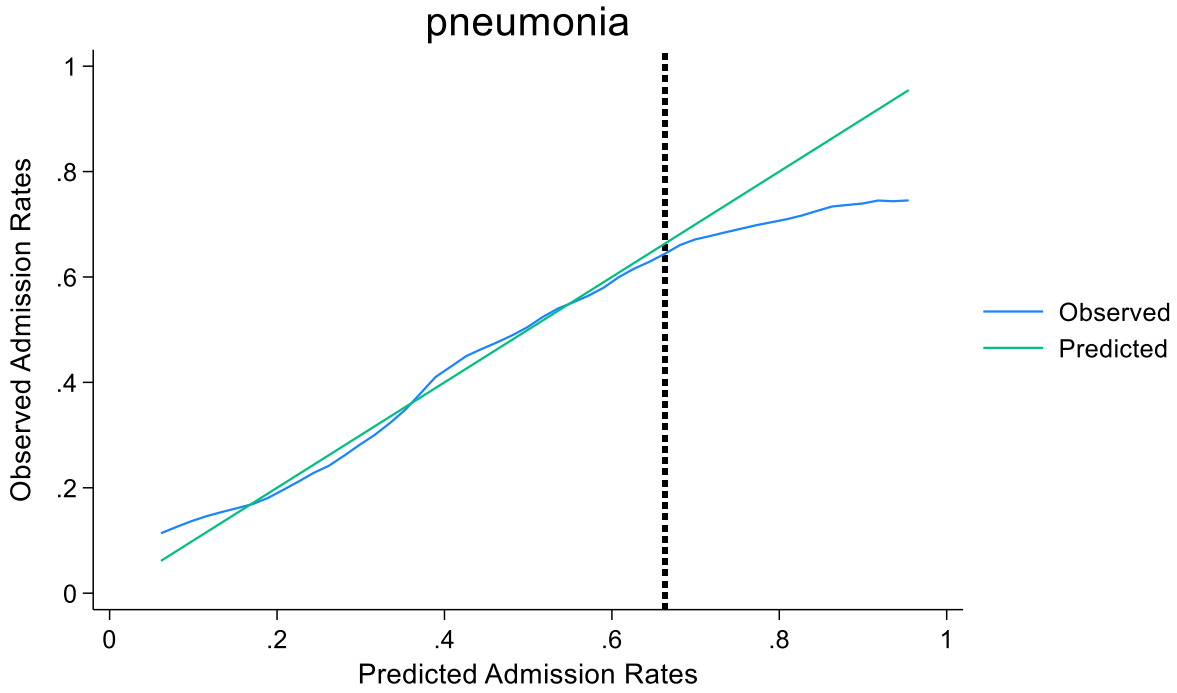

Figure E- 20 Polynomial smoothing plot of 30-day episode admission rate for pneumonia between actual Vs predicted

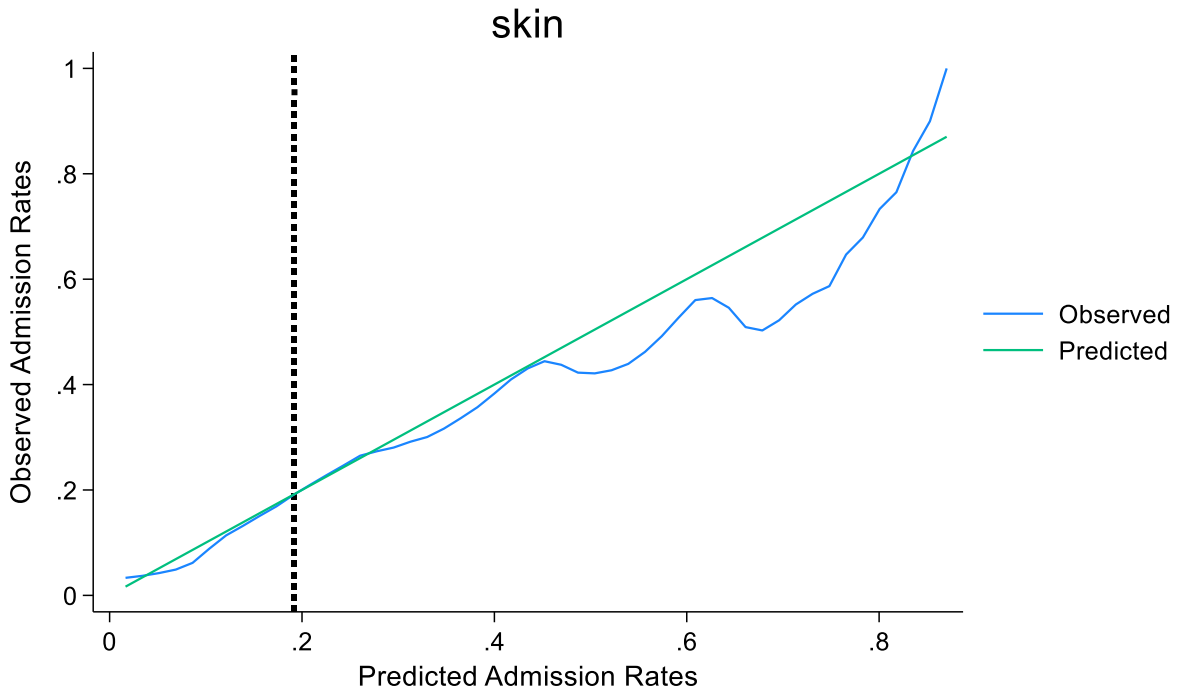

Figure E- 21 Polynomial smoothing plot of 30-day episode admission rate for skin and subcutaneous infections between actual Vs predicted

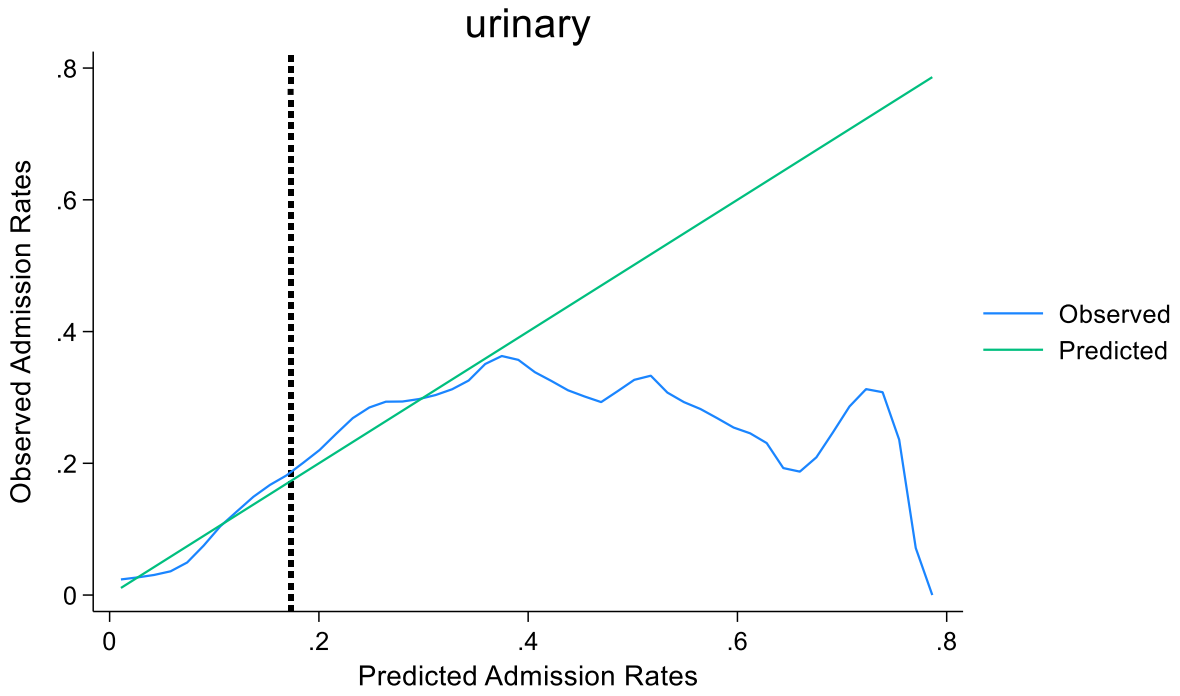

Figure E- 22 Polynomial smoothing plot of condition-specific, 30-day episode admission rate for urinary tract infetions between actual Vs predicted

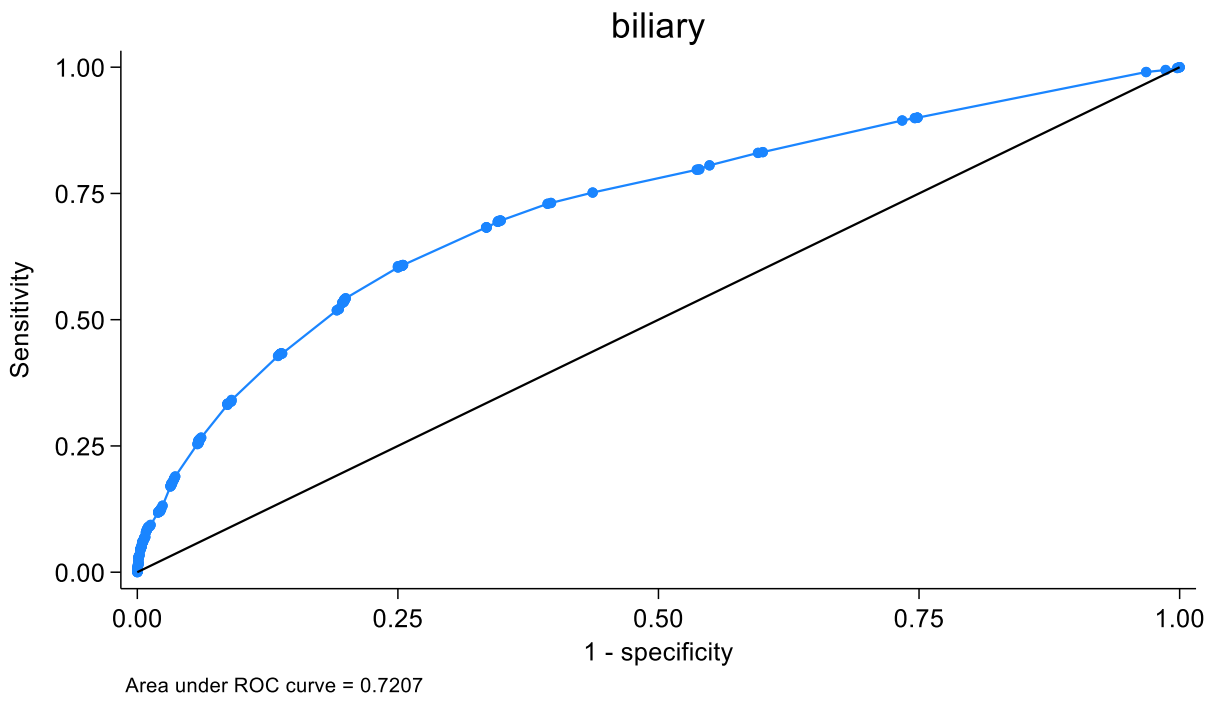

Figure E- 23 ROC/AUC of admission rate for biliary tract disease

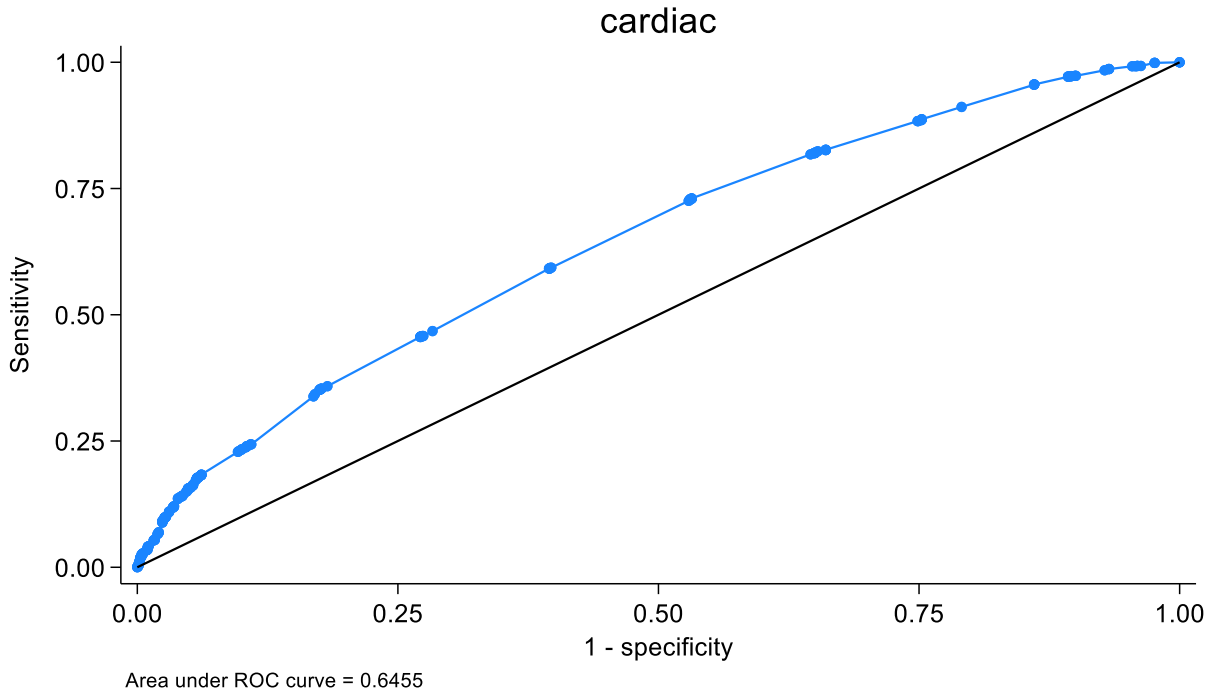

Figure E- 24 ROC/AUC of admission rate for cardiac dysthymias

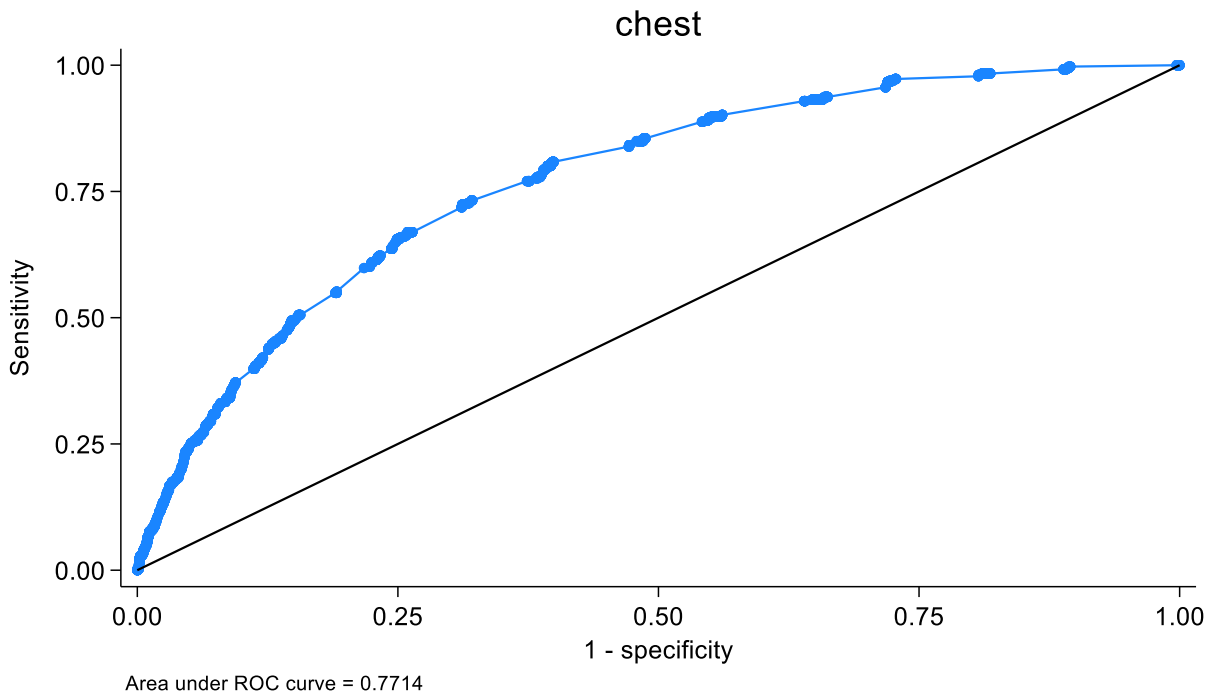

Figure E- 25 ROC/AUC of admission rate for chest pain

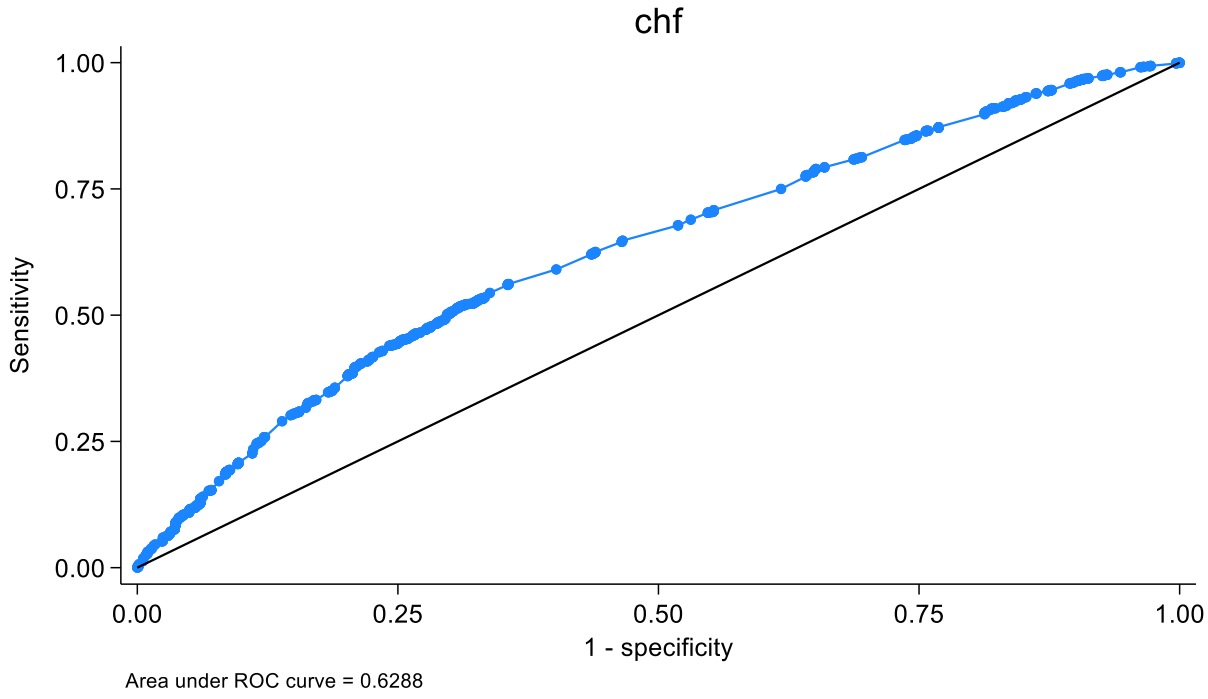

Figure E- 26 ROC/AUC of admission rate for congestive heart failure

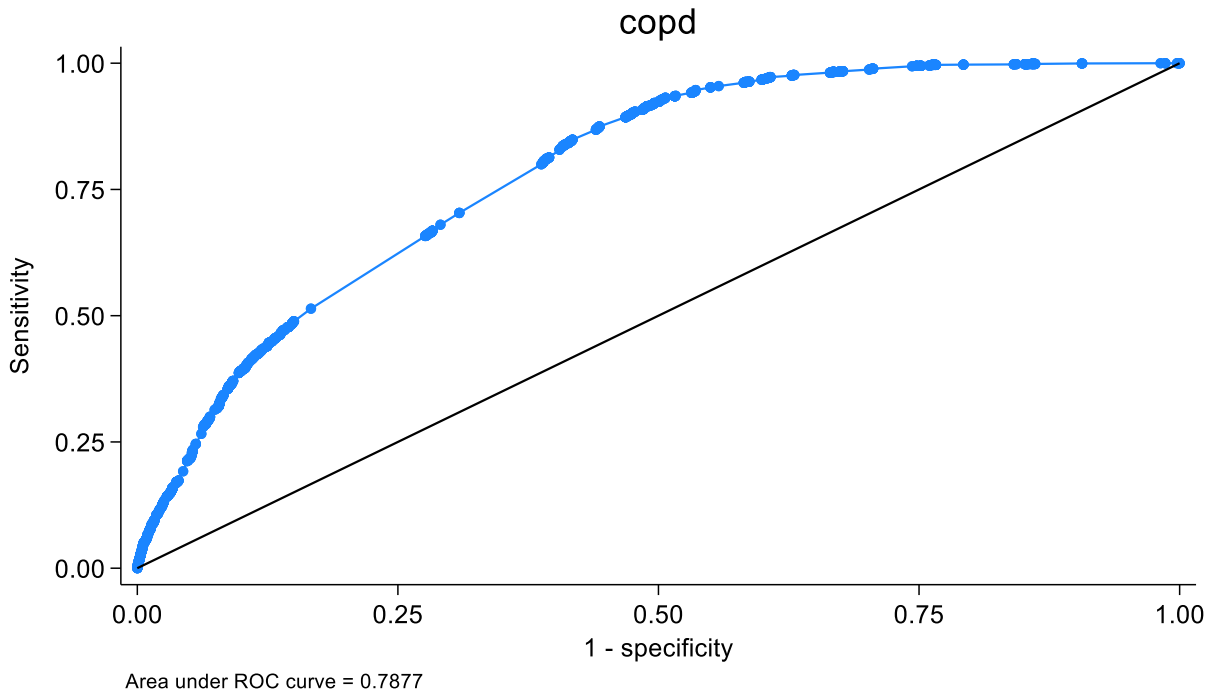

Figure E- 27 ROC/AUC of admission rate for chronic obstructive pulmonary disease

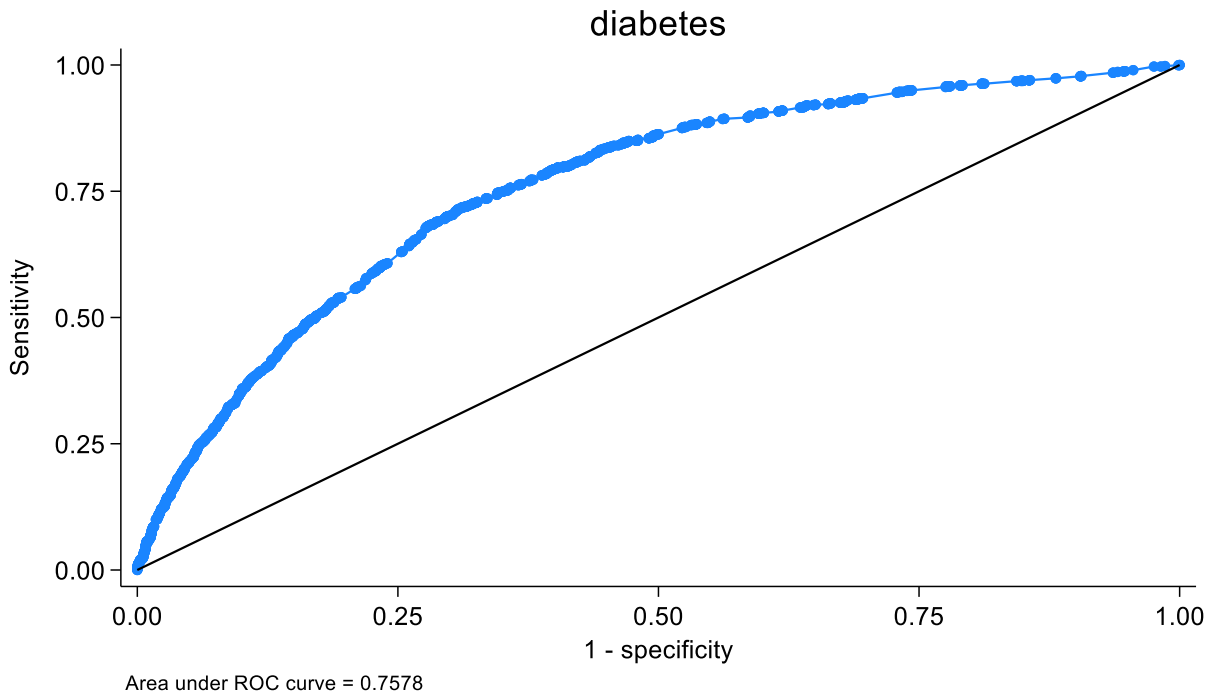

Figure E- 28 ROC/AUC of admission rate for diabetic mellitus

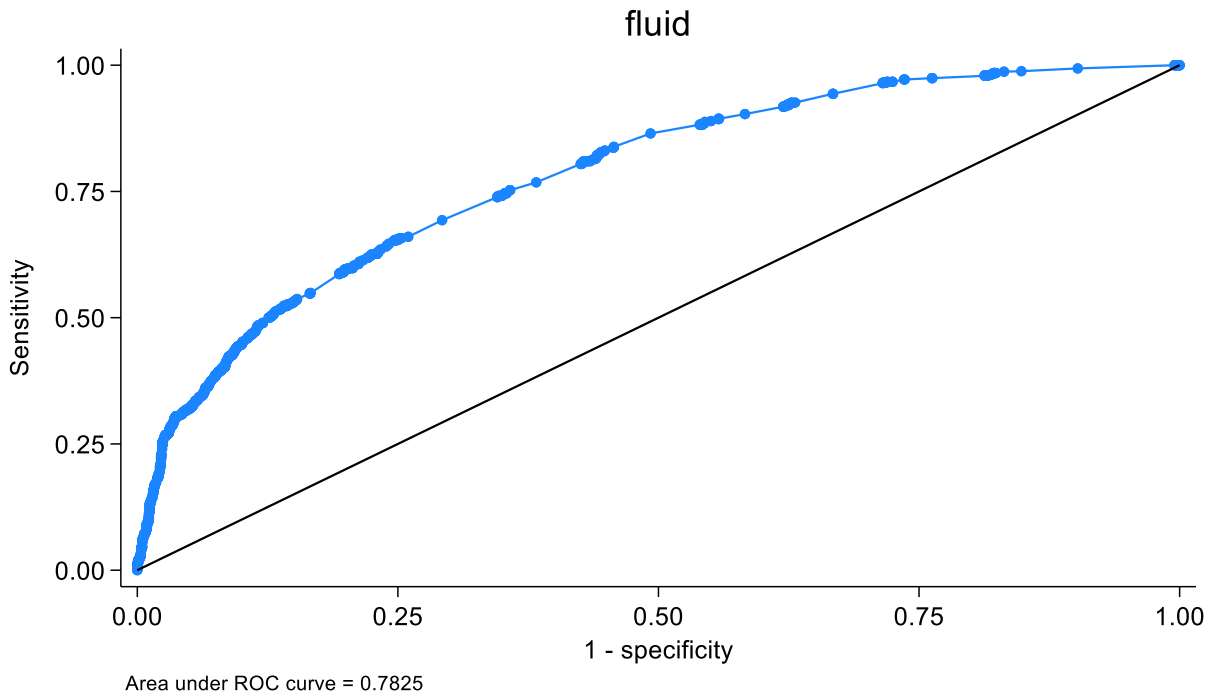

Figure E- 29 ROC/AUC of admission rate for fluid and electrolyte disorders

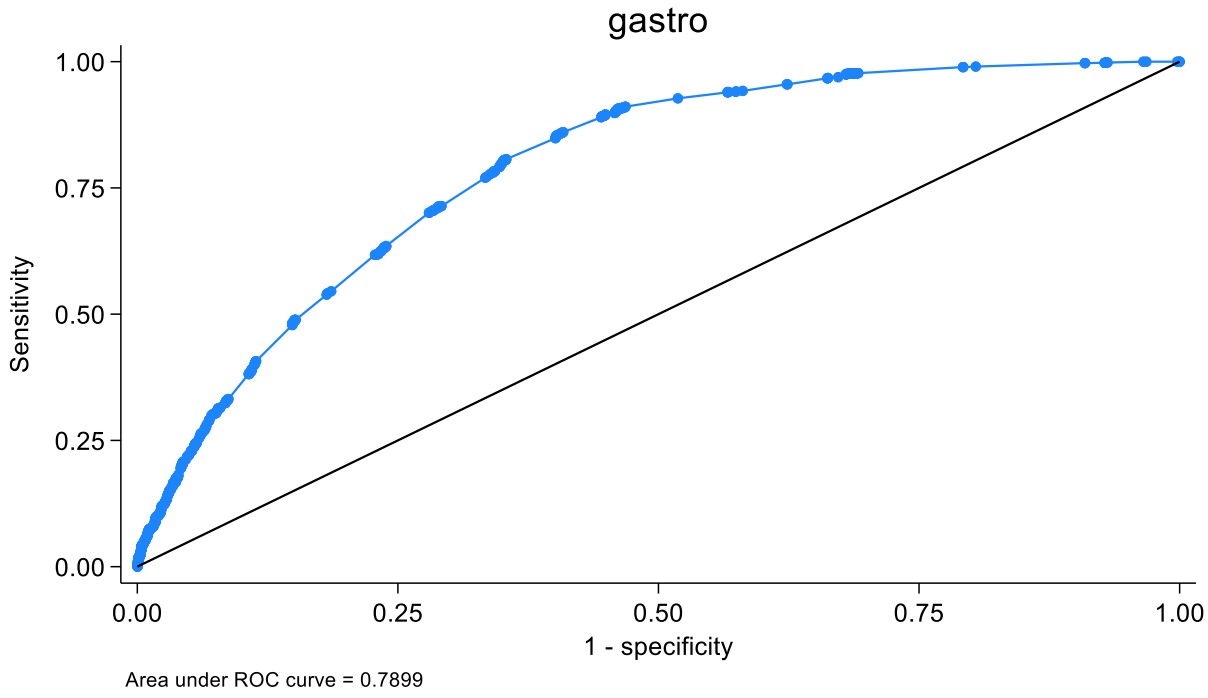

Figure E- 30 ROC/AUC of admission rate for gastroenteritis

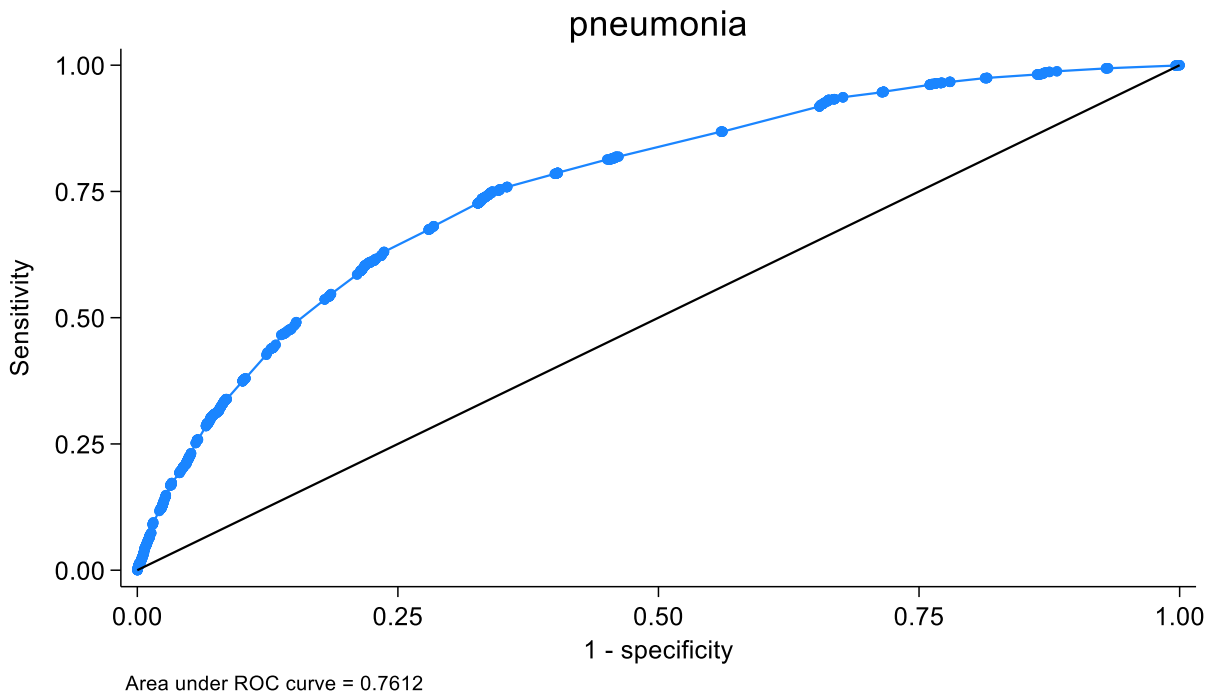

Figure E- 31 ROC/AUC of admission rate for pneumonia

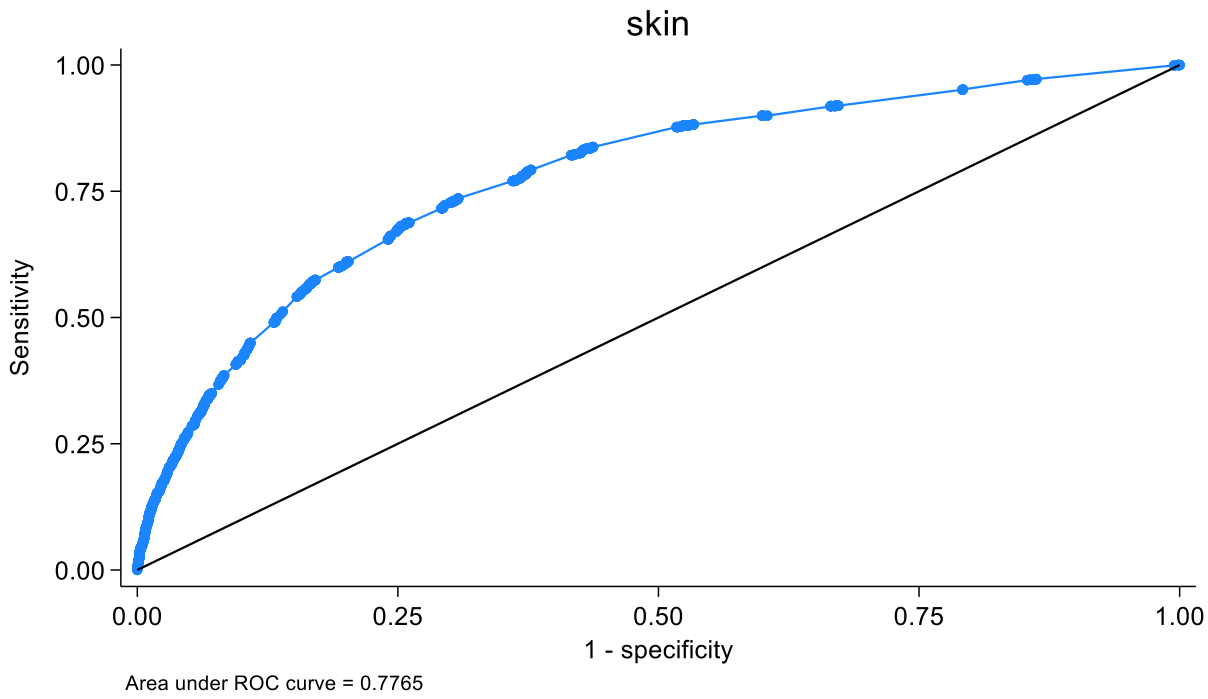

Figure E- 32 ROC/AUC of admission rate for skin and subcutaneous infections

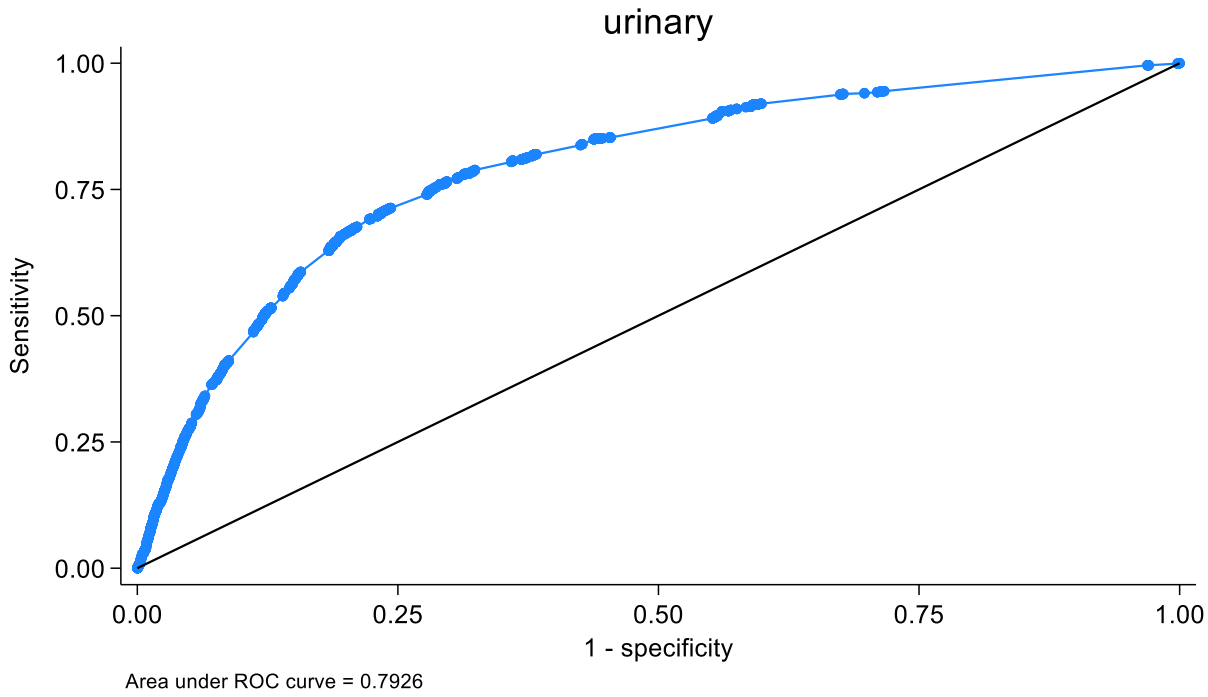

Figure E- 33 ROC/AUC of admission rate for urinary tract infections

F. ED-level, Condition-specific, 30-Day Risk-adjusted Measures Interval Plot

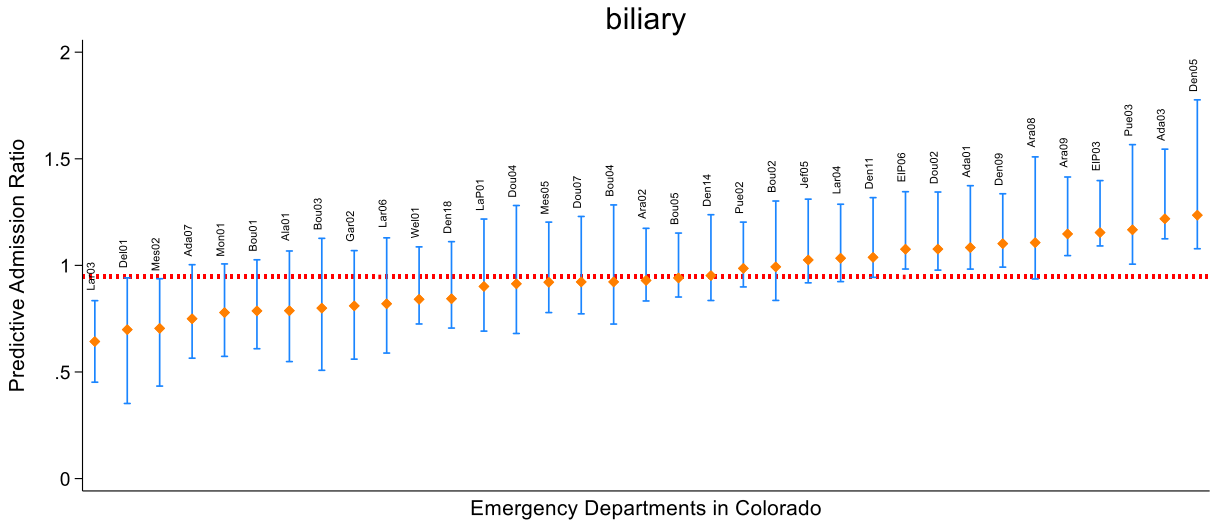

Figure F- 1 ED-level, risk-adjusted 30-day episode payment ratio for biliary tract disease pooling each ED

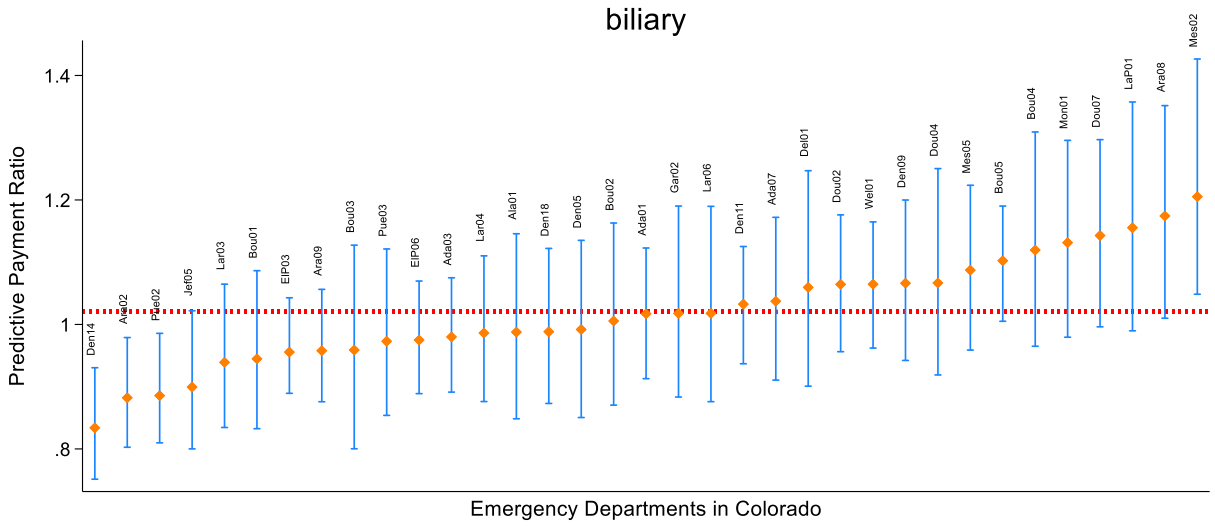

Figure F- 2 ED-level, risk-adjusted average admission ratios for biliary tract disease pooling each ED

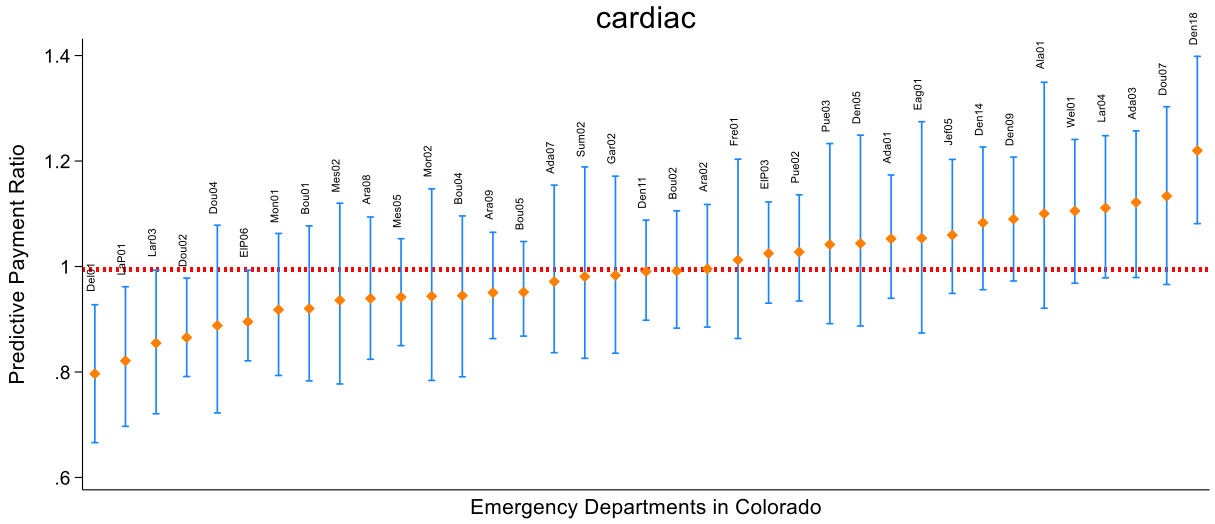

Figure F- 3 ED-level, risk-adjusted 30-day episode payment ratio for cardiac dysthymias pooling each ED

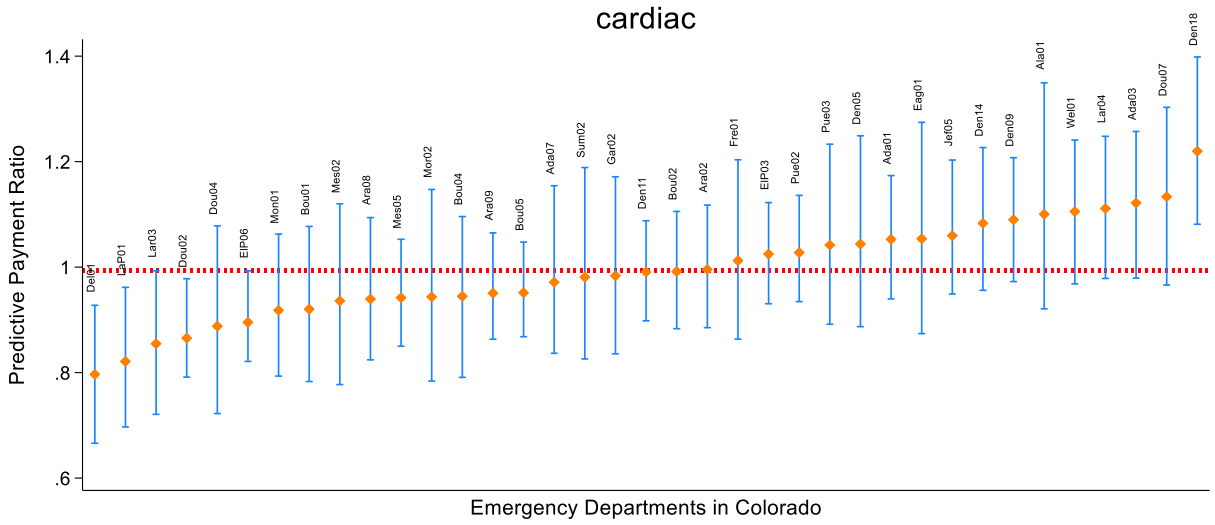

Figure F- 4 ED-level, risk-adjusted average admission ratios for cardiac dysthymias pooling each ED

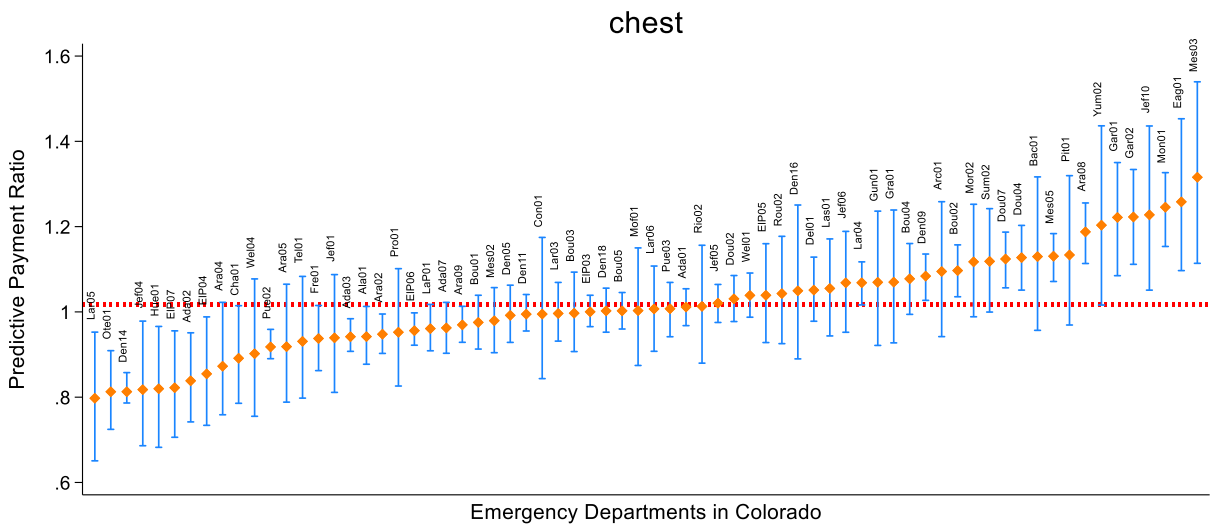

Figure F- 5 ED-level, risk-adjusted 30-day episode payment ratio for chest pain pooling each ED

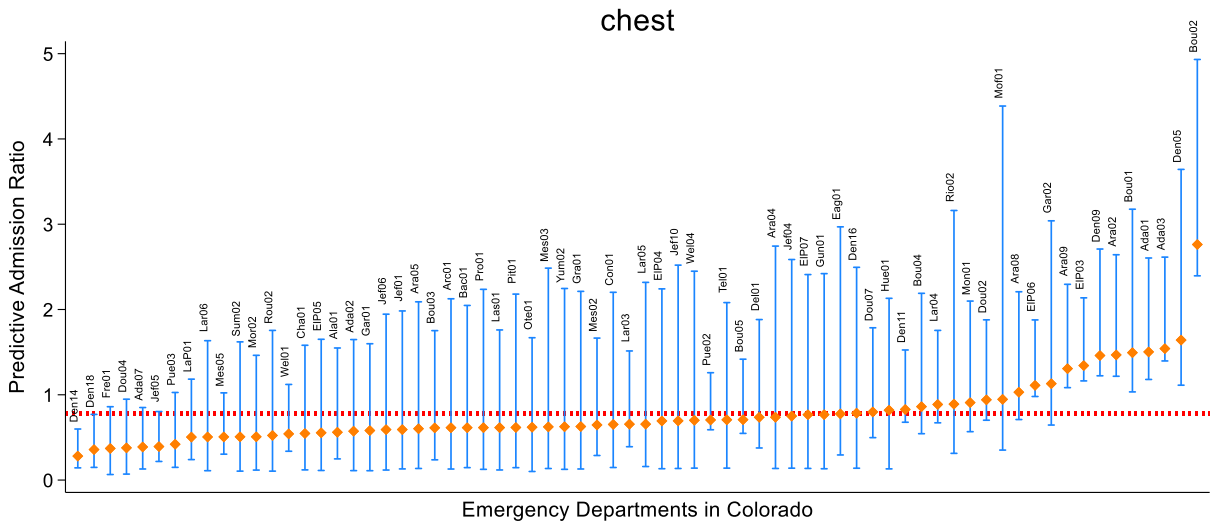

Figure F- 6 ED-level, risk-adjusted average admission ratios for chest pain pooling each ED

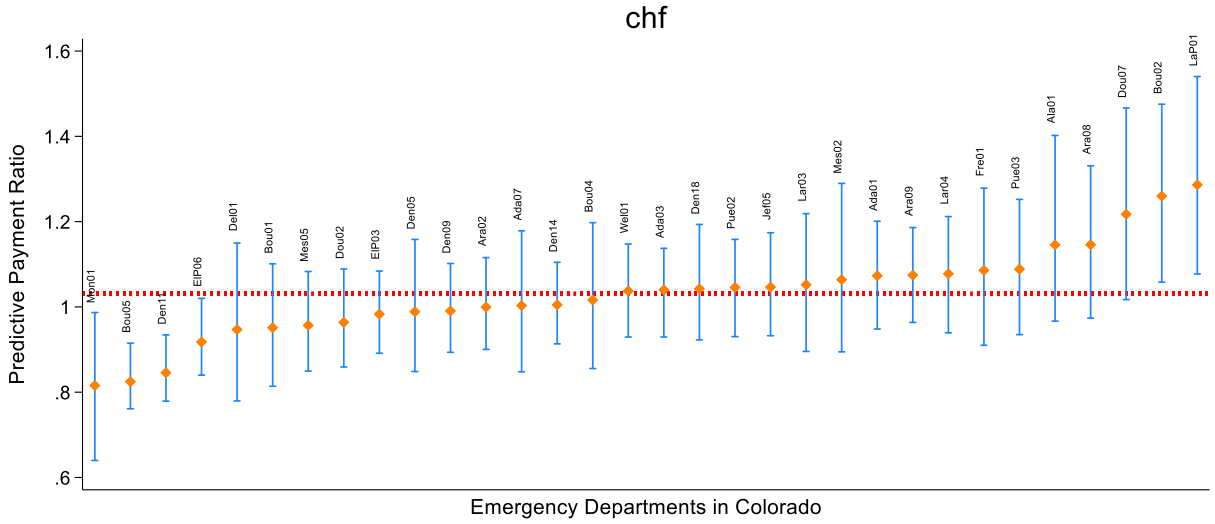

Figure F- 7 ED-level, risk-adjusted 30-day episode payment ratio for congestive heart failure pooling each ED

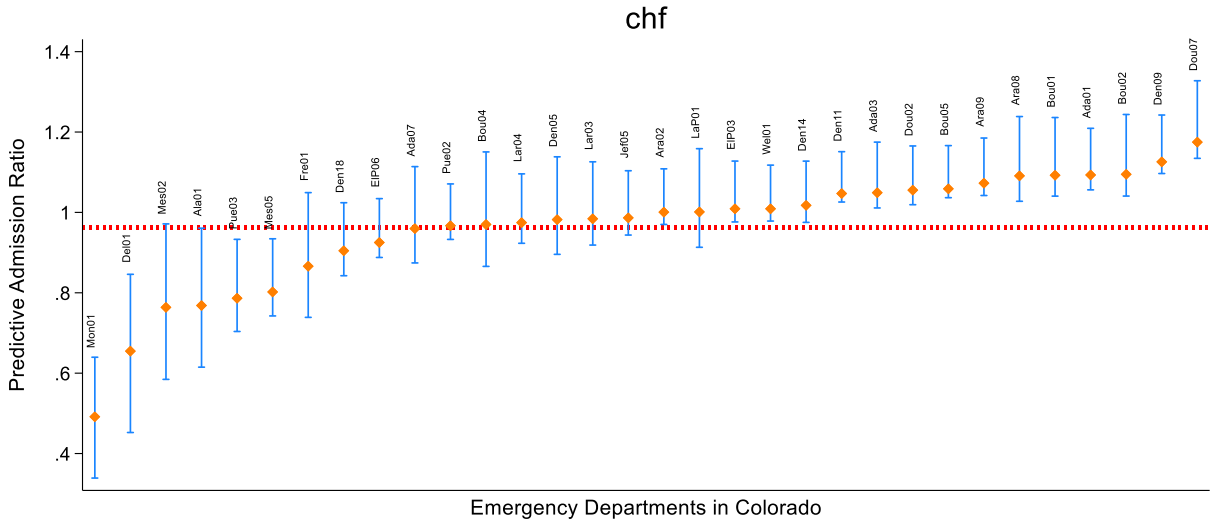

Figure F- 8 ED-level, risk-adjusted average admission ratios for congestive heart failure pooling each ED

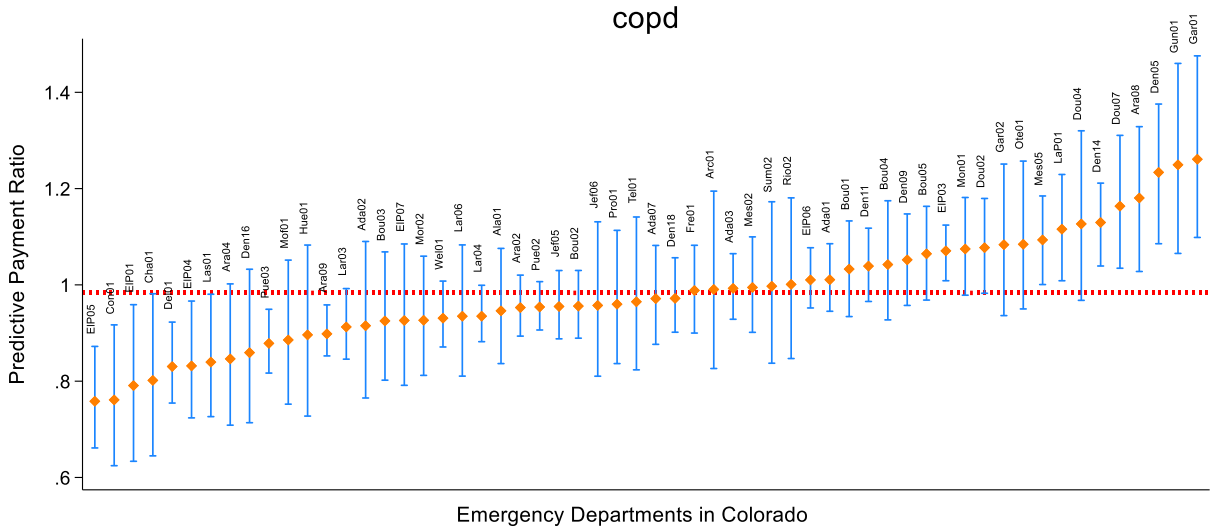

Figure F- 9 ED-level, risk-adjusted 30-day episode payment ratio for chronic obstructive pulmonary disease pooling each ED

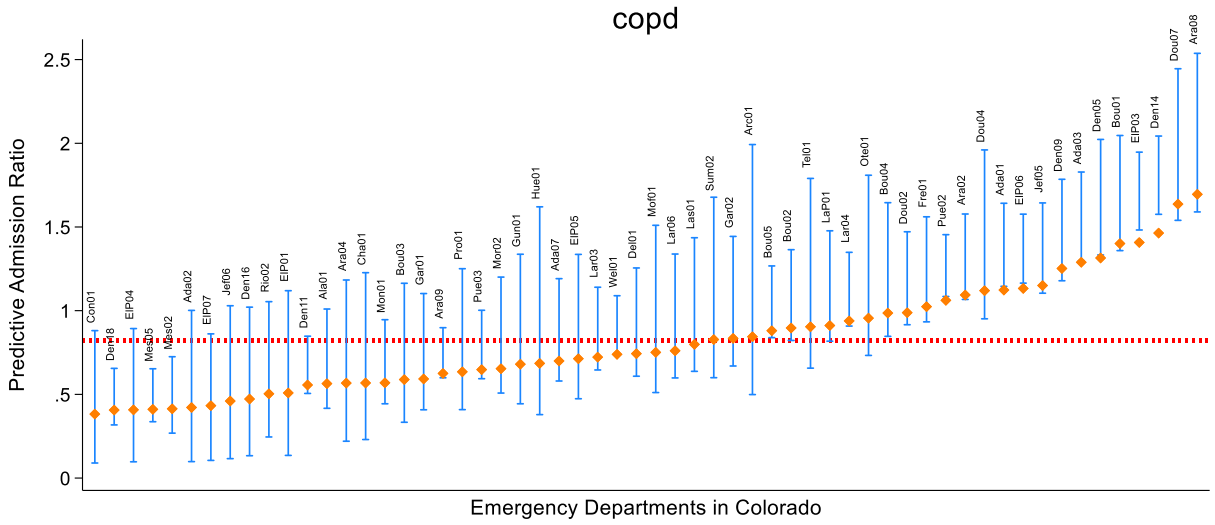

Figure F- 10 ED-level, risk-adjusted average admission ratios for chronic obstructive pulmonary disease pooling each ED

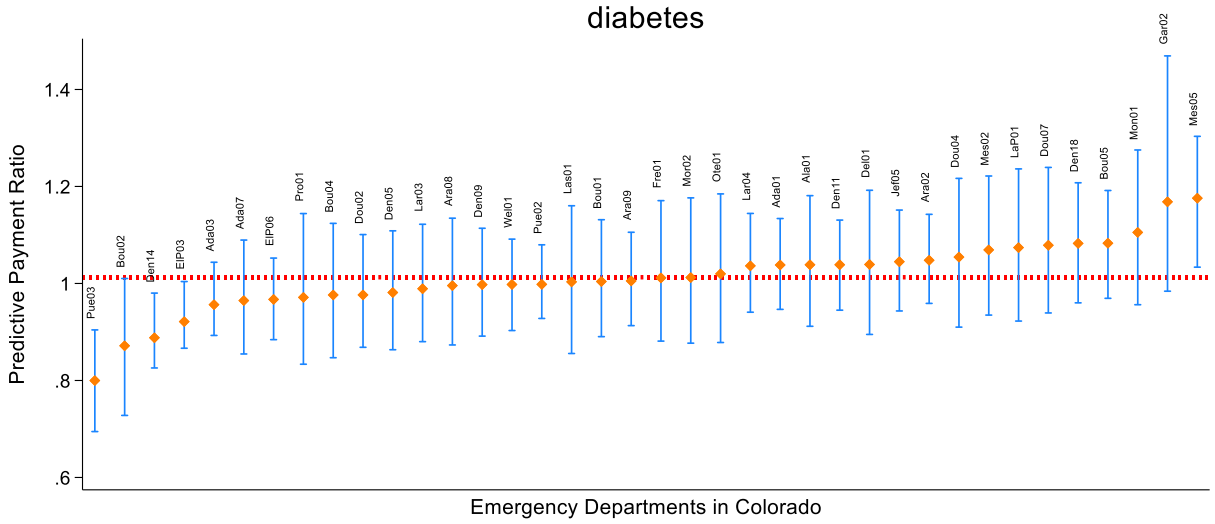

Figure F- 11 ED-level, risk-adjusted 30-day episode payment ratio for diabetic mellitus pooling each ED

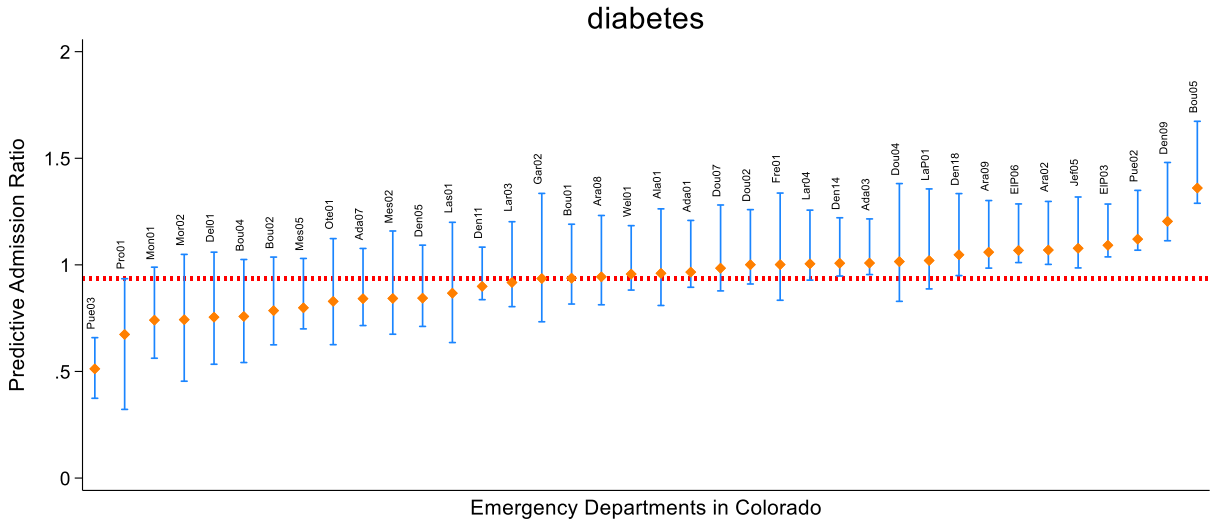

Figure F- 12 ED-level, risk-adjusted average admission ratios for diabetic mellitus pooling each ED

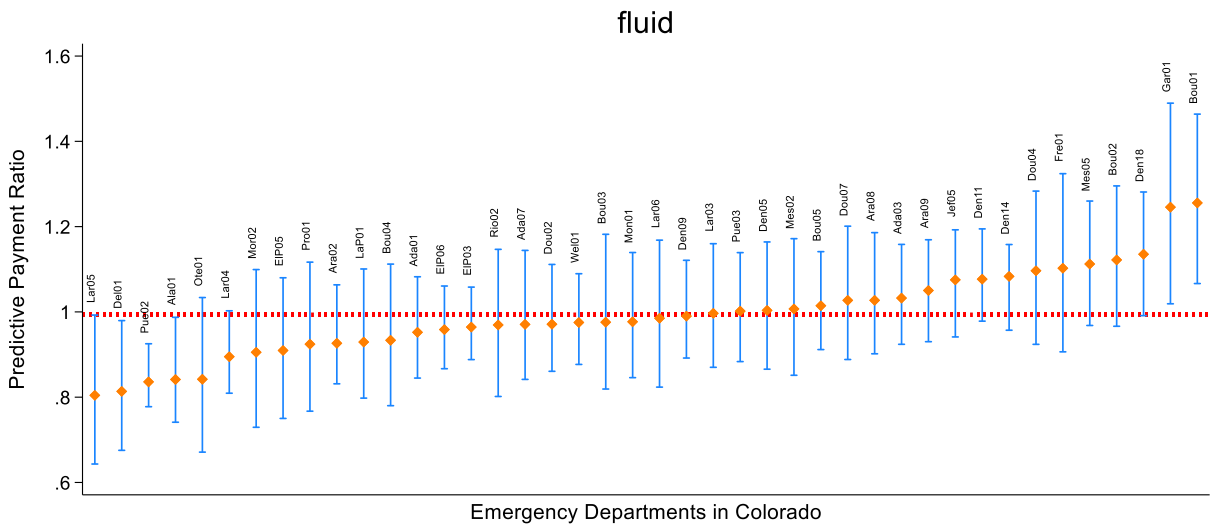

Figure F- 13 ED-level, risk-adjusted 30-day episode payment ratio for fluid and electrolyte disorders pooling each ED

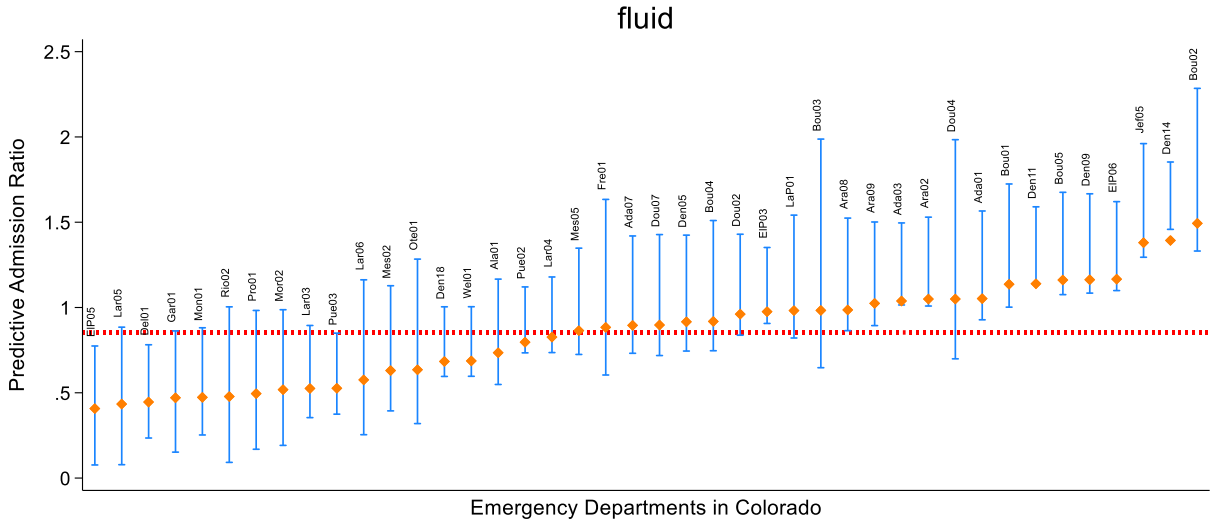

Figure F- 14 ED-level, risk-adjusted average admission ratios for fluid and electrolyte disorders pooling each ED

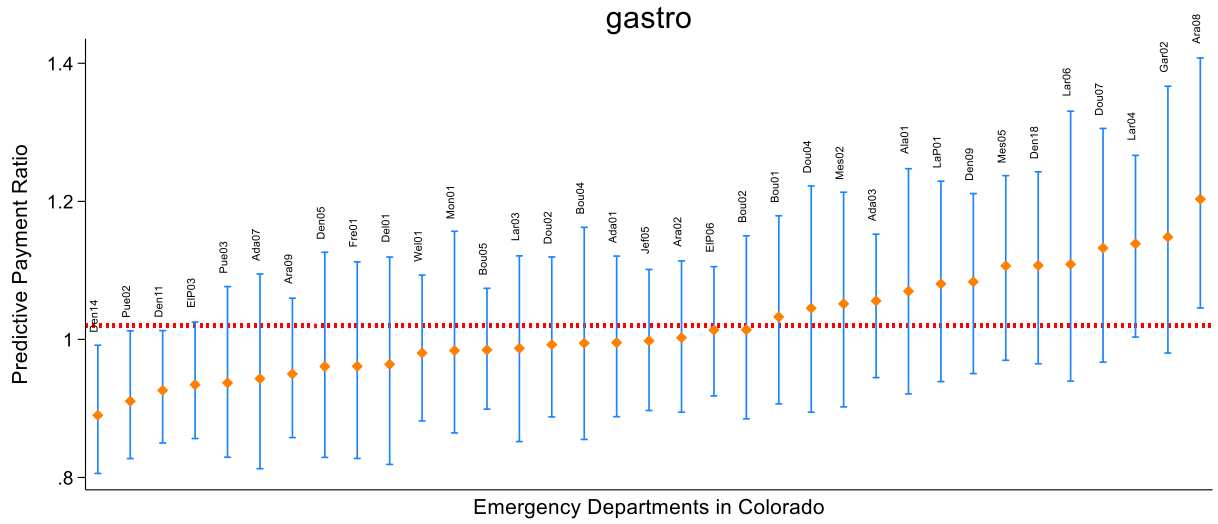

Figure F- 15 ED-level, risk-adjusted 30-day episode payment ratio for gastroenteritis pooling each ED

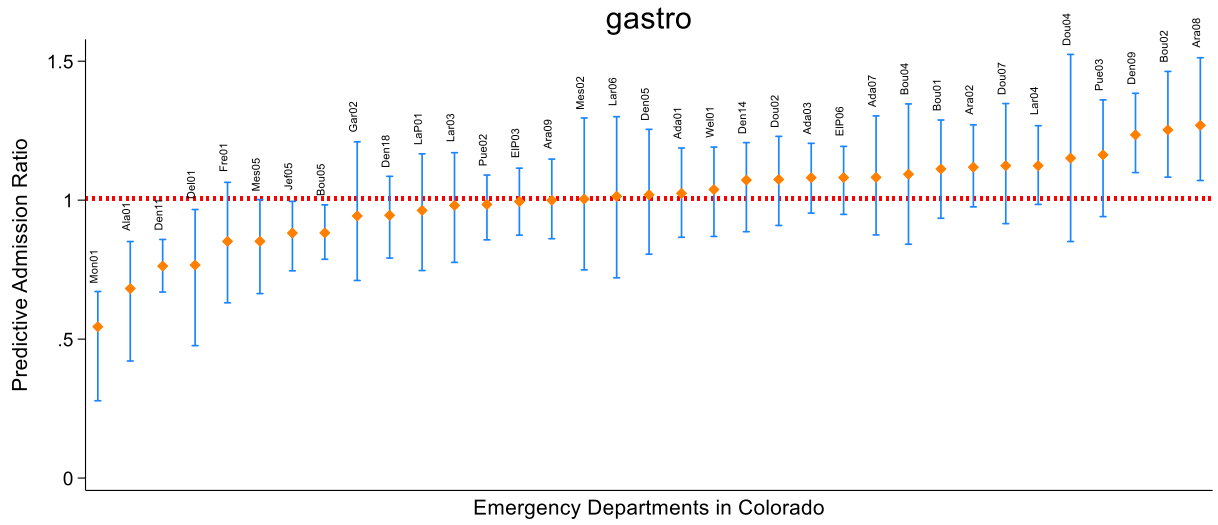

Figure F- 16 ED-level, risk-adjusted average admission ratios for gastroenteritis pooling each ED

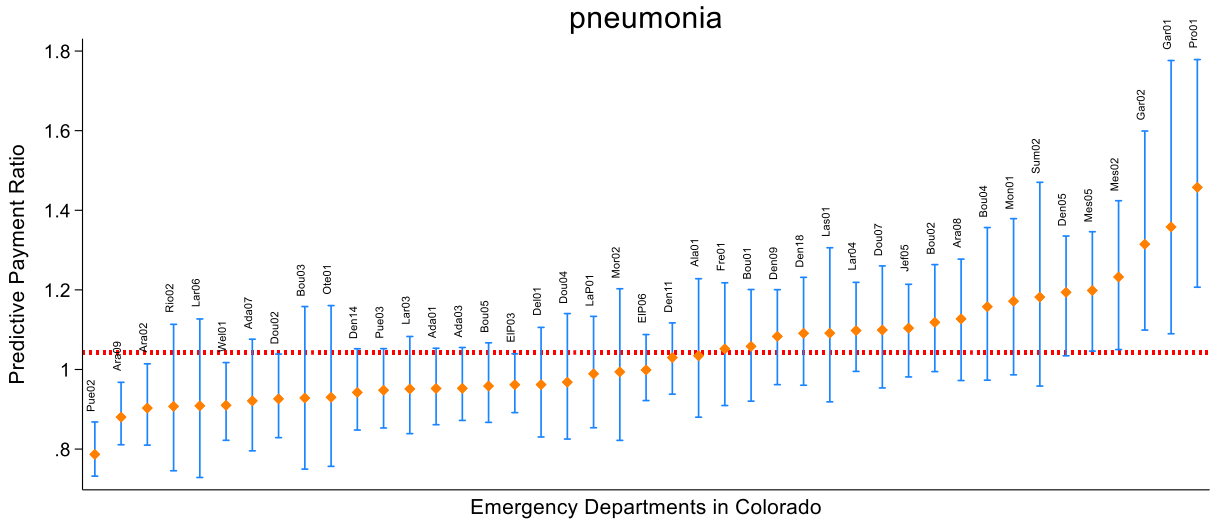

Figure F- 17 ED-level, risk-adjusted 30-day episode payment ratio for pneumonia pooling each ED

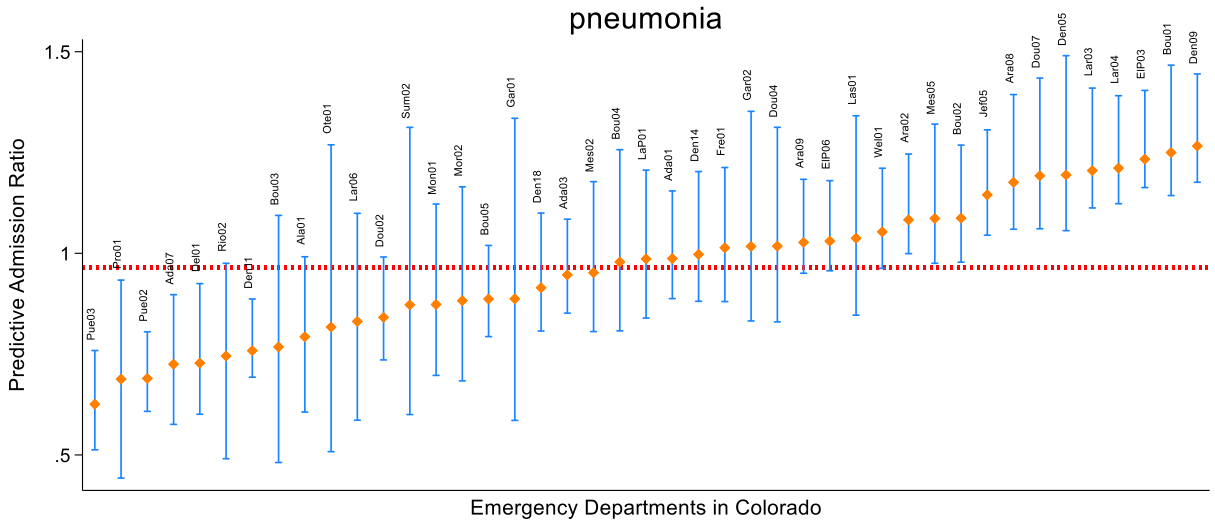

Figure F- 18 ED-level, risk-adjusted average admission ratios for pneumonia pooling each ED

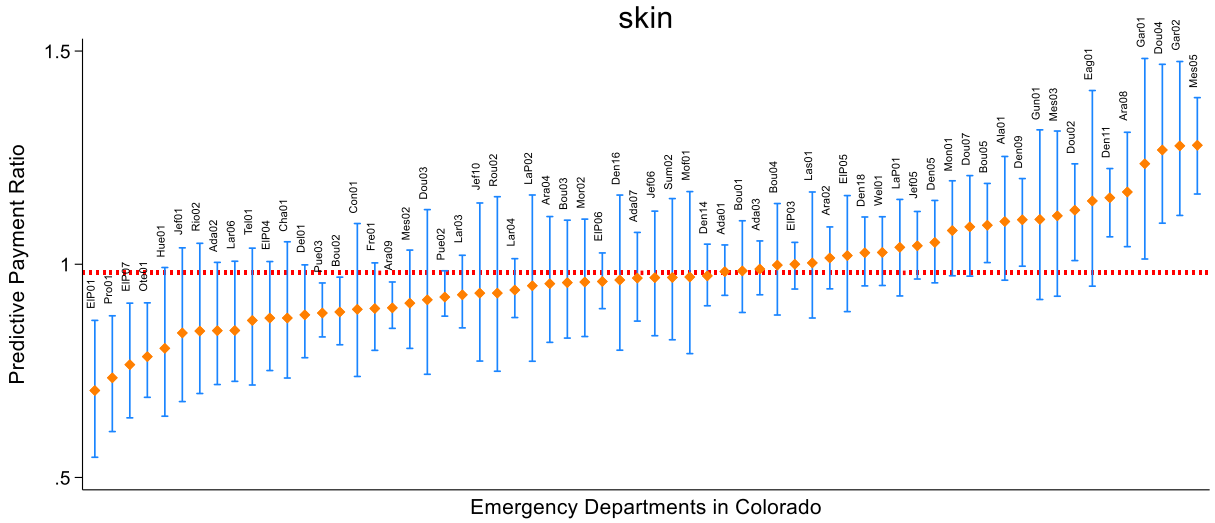

Figure F- 19 ED-level, risk-adjusted 30-day episode payment ratio for skin and subcutaneous infections pooling each ED

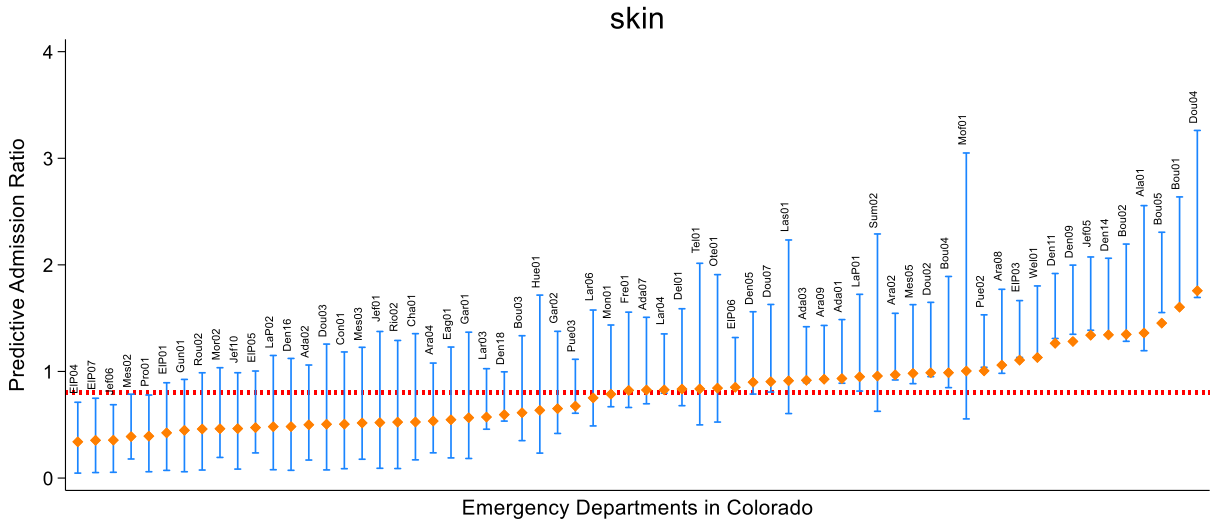

Figure F- 20 ED-level, risk-adjusted average admission ratios for skin and subcutaneous infections pooling each ED

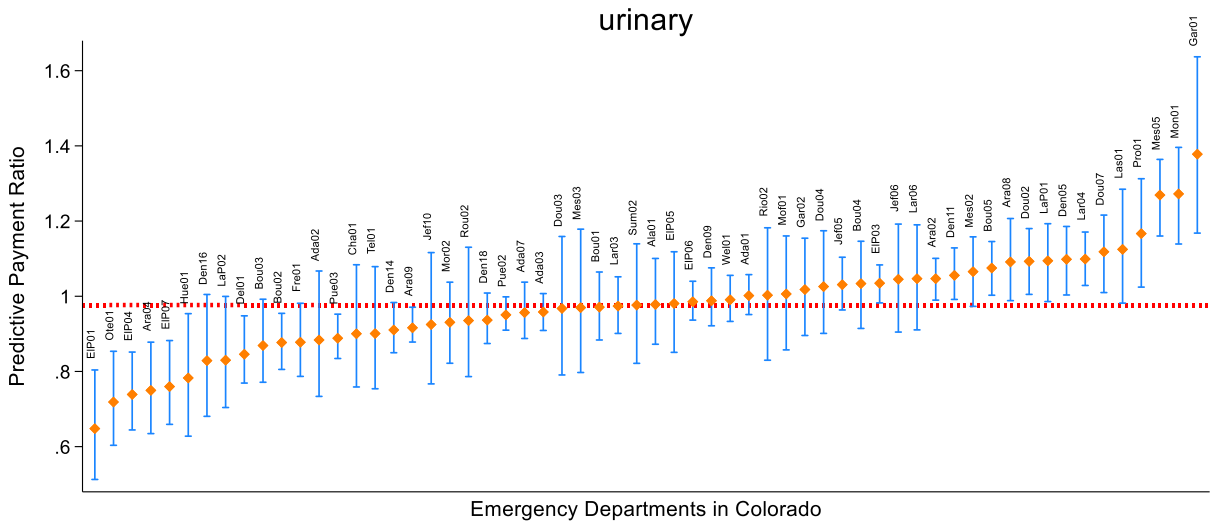

Figure F- 21 ED-level, risk-adjusted 30-day episode payment ratio for urinary tract infections pooling each ED

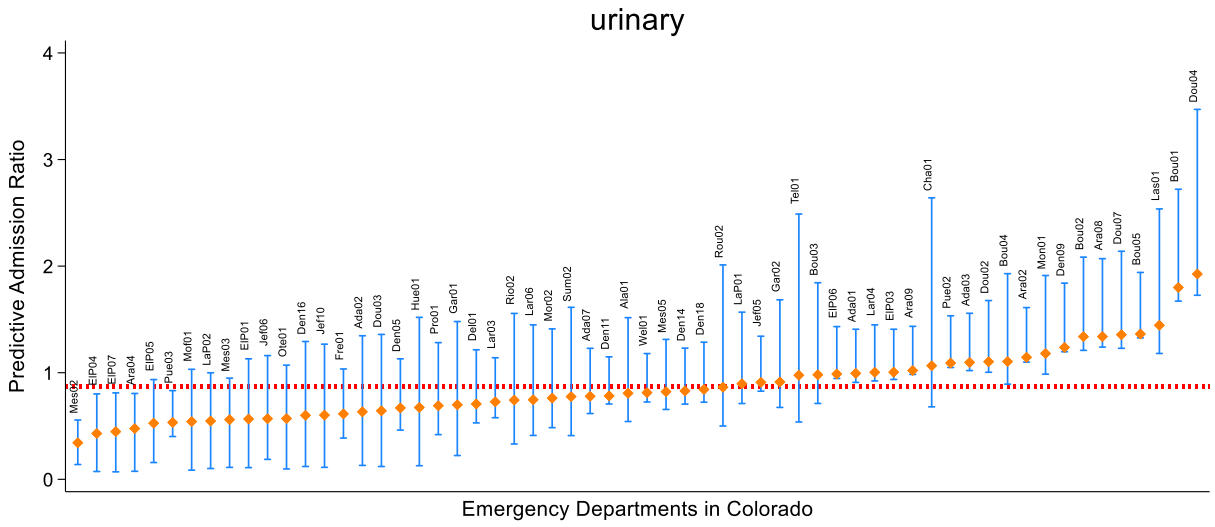

Figure F- 22 ED-level, risk-adjusted average admission ratios for urinary tract infections pooling each ED

G. Proportion and Level of Consistency by Each ED

Table G- 1 Proportion of care consistency for EDs

NPI	Abbreviated ED Identifier	Consistency Pattern			Consistency Level
		High (%)	Low (%)	Medium (%)	
1730258971	Cha01	0	100	0	Low
1528442357	Jef06	0	100	0	Low
1295225274	ElP07	0	100	0	Low
1578053567	ElP01	0	100	0	Low
1982612065	Hue01	0	100	0	Low
1154312981	Lar05	0	100	0	Low
1790162055	Ada02	0	100	0	Low
1619467412	Ara04	0	100	0	Low
1629071758	Ada07	0	100	0	Low
1417935446	Del01	0	100	0	Low
1083166623	Jef04	0	100	0	Low
1124518113	ElP04	0	100	0	Low
1720096092	Sum02	0	100	0	Low
1619351160	ElP05	0	100	0	Low
1760489470	Ote01	0	100	0	Low
1194792762	Con01	0	100	0	Low
1306857974	Pue03	10	90	0	Low
1235181744	Ala01	20	80	0	Low
1417980566	Lar03	25	75	0	Low
1497723407	Mes02	33	67	0	Mixed
1821052929	Pro01	33	67	0	Mixed
1922012350	Fre01	33	67	0	Mixed
1205822186	Mon01	43	57	0	Mixed
1104881507	Pue02	45	55	0	Mixed
1023062098	Den18	50	50	0	Mixed
1417946021	Den11	56	44	0	Mixed
1689624686	Den14	58	42	0	Mixed
1396790200	Ara09	58	42	0	Mixed
1699716027	Mes05	67	33	0	Mixed
1184616740	Las01	67	33	0	Mixed
1932112125	ElP06	70	30	0	Mixed
1720004450	Wel01	75	25	0	High
1821074196	Bou02	75	25	0	High
1659327013	Ara02	77	23	0	High
1659325629	Dou02	80	20	0	High
1083611644	LaP01	80	20	0	High
1407845035	Bou05	80	20	0	High
1144397134	ElP03	85	15	0	High
1164430567	Jef05	86	14	0	High

1477531580	Ada03	90	10	0	High
1932109048	Gun01	100	0	0	High
1992812333	Eag01	100	0	0	High
1366465866	Bou01	100	0	0	High
1982668133	Gar02	100	0	0	High
1013407865	Jef10	100	0	0	High
1689688988	Ara08	100	0	0	High
1720038946	Den05	100	0	0	High
1760492714	Lar04	100	0	0	High
1649218991	Gar01	100	0	0	High
1861496697	Mes03	100	0	0	High
1821042979	Ada01	100	0	0	High
1386651297	Dou07	100	0	0	High
1154876985	Bou04	100	0	0	High
1912249590	Dou04	100	0	0	High
1801800594	Den09	100	0	0	High
1063418424	Mof01	0	0	100	Medium
1629074182	Yum02	0	0	100	Medium
1508842964	LaP02	0	0	100	Medium
1659787554	Lar06	0	0	100	Medium
1619962321	Gra01	0	0	100	Medium
1407233778	Ara05	0	0	100	Medium
1477638971	Mor02	0	0	100	Medium
1003275553	Wel04	0	0	100	Medium
1639669435	Den16	0	0	100	Medium
1891709192	Bou03	0	0	100	Medium
1366932162	Dou03	0	0	100	Medium
1518960814	Pit01	0	0	100	Medium
1396783981	Rio02	0	0	100	Medium
1245401561	Arc01	0	0	100	Medium
1790787307	Rou02	0	0	100	Medium
1972980449	Jef01	0	0	100	Medium
1285727297	Bac01	0	0	100	Medium
1275703910	Tel01	0	0	100	Medium

H. Exploratory Factor Analysis Correlation Matrix and Figures

Table H- 1 Correlation matrix of RAPRs

	Biliary Tract Disease	Cardiac Dysrhythmias	Chest Pain	CHF	COPD	DM	Fluid and Electrolyte Disorders	Gastroenteritis	Pneumonia	Skin and Subcutaneous Tissue Infections	Urinary Tract Infections
Biliary Tract Disease	1										
Cardiac Dysrhythmias	-0.2978	1									
Chest Pain	0.6281	-0.1258	1								
CHF	0.0914	0.1864	-0.0222	1							
COPD	0.3438	0.0227	0.2032	-0.0271	1						
DM	0.4165	-0.0997	0.3252	-0.1951	0.1701	1					
Fluid and Electrolyte Disorders	-0.0793	0.1519	0.0566	-0.0628	0.2661	-0.0324	1				
Gastroenteritis	0.4917	0.1647	0.4891	0.4141	0.2565	0.4407	0.1203	1			
Pneumonia	0.508	0.0468	0.5712	0.0333	0.4261	0.3365	0.3315	0.5282	1		
Skin and Subcutaneous Tissue Infections	0.3701	0.0646	0.3968	-0.226	0.6187	0.5293	0.1954	0.4104	0.3567	1	
Urinary Tract Infections	0.4979	-0.1318	0.5495	-0.2344	0.5978	0.64	0.0391	0.3757	0.52	0.7087	1

Table H- 2 Correlation matrix of RAARs

	Biliary Tract Disease	Cardiac Dysrhythmias	Chest Pain	CHF	COPD	DM	Fluid and Electrolyte Disorders	Gastroenteritis	Pneumonia	Skin and Subcutaneous Tissue Infections	Urinary Tract Infections
Biliary Tract Disease	1										
Cardiac Dysrhythmias	0.4614	1									
Chest Pain	0.41	0.1925	1								
CHF	0.4438	0.5936	0.3738	1							
COPD	0.4535	0.5177	0.343	0.603	1						
DM	0.1838	0.4748	0.0359	0.5248	0.3324	1					
Fluid and Electrolyte Disorders	0.4526	0.3778	0.4362	0.6756	0.4971	0.455	1				
Gastroenteritis	0.398	0.3842	0.3951	0.6728	0.545	0.0765	0.3901	1			
Pneumonia	0.1686	0.1829	0.4015	0.4753	0.5305	0.3095	0.3572	0.4075	1		
Skin and Subcutaneous Tissue Infections	0.172	0.1885	0.252	0.4225	0.3832	0.384	0.6861	0.0257	0.1991	1	
Urinary Tract Infections	0.1396	0.1375	0.4835	0.4799	0.5522	0.3888	0.4617	0.285	0.3945	0.5884	1

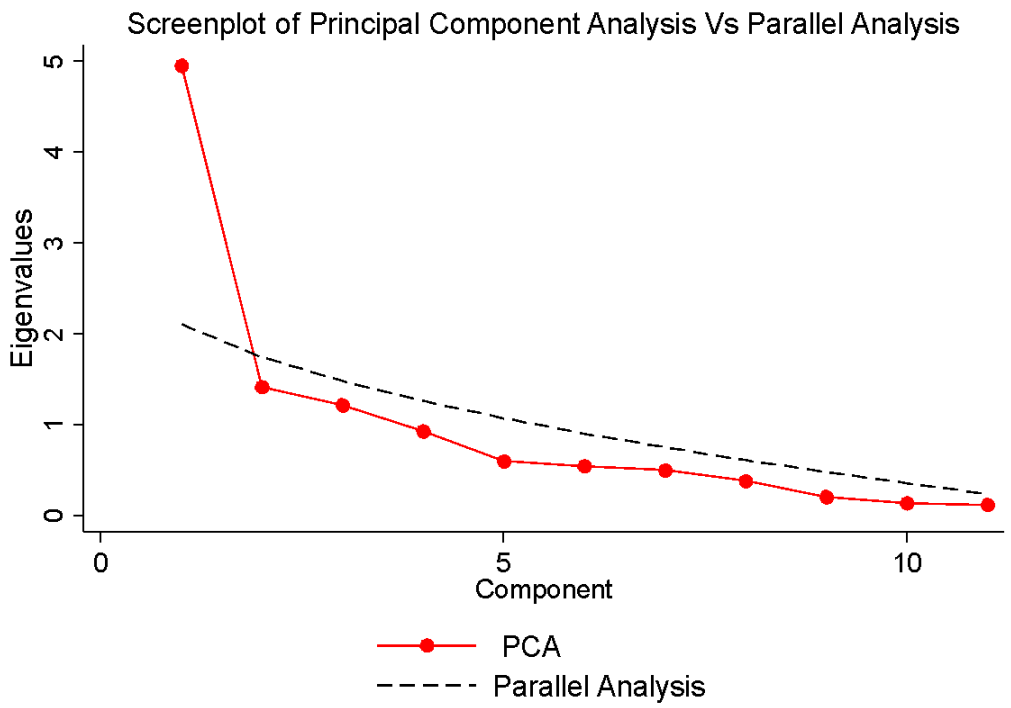

Figure H- 1 Scree Plot of PCA Vs Parallel Analysis for RAPRs

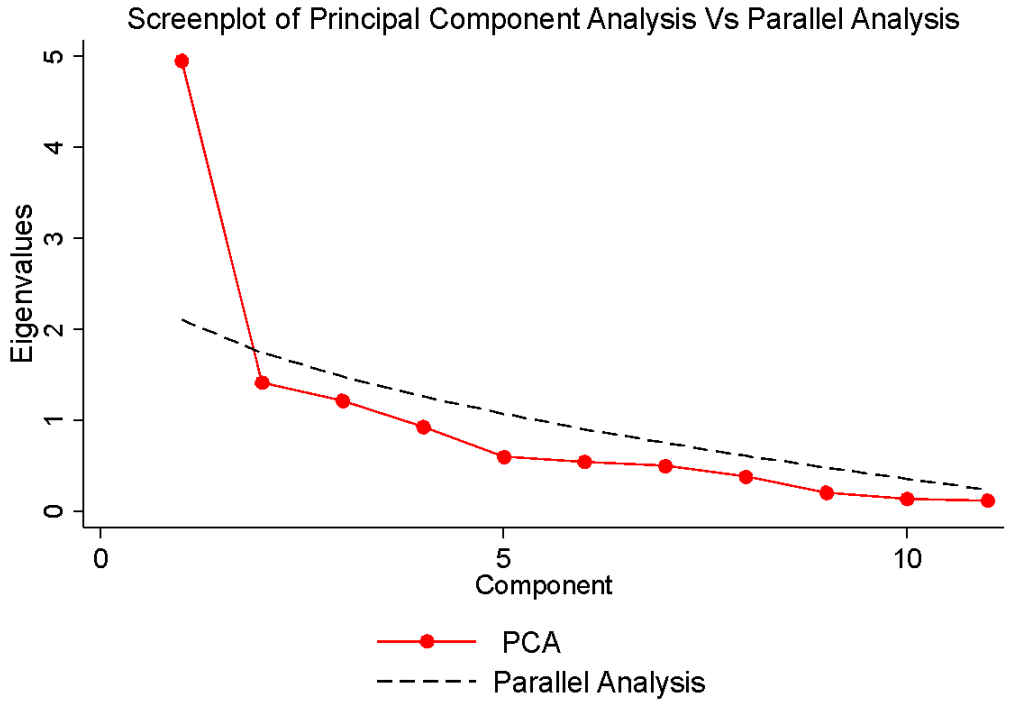

Figure H- 2 Scree Plot of PCA Vs Parallel Analysis for RAARs

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