The Impact of Hospital Characteristics on Psychiatry Readmissions: A Mediation Framework

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Abstract: We study the operational characteristics of hospitals contributing to the readmission of psychiatry patients, shortly after being discharged. We propose that the length of stay (LOS) in the inpatient ward mediates the effects of hospital characteristics on the risk of readmission. We utilize a data set of about 15,000 psychiatry patients admitted to 25 hospitals in Canada. We use a clustered-error probit model which we adjust for endogeneity through instrumental variables to conduct a causal analysis. In our mediation framework, we find that the number of patients admitted to a hospital annually, i.e., *patient volume*, increases the risk of readmission, whereas this risk reduces with the hospital specializing in certain diagnosis classes, i.e., *hospital focus*. These relationships are moderated by patients' intensity of resource usage at the emergency department. Moreover, we find a nonlinear relationship between LOS and the risk of readmission. A widely observed phenomenon in operations management is "practice makes perfect", which constitutes a positive volume-outcome relationship. The nature of this relationship, however, may change in people-centric environments, such as health systems. We provide evidence for the negative relationship among the patient volume and the risk of readmission. Our results provide insights for policy makers to manage the burden imposed on the health systems by unplanned readmissions from patients with chronic disorders. Our empirical analysis provides potentially helpful insights for managing the flow of psychiatric patients.

Key words: mental health care; readmissions; hospital characteristics; length of stay; mediation analysis

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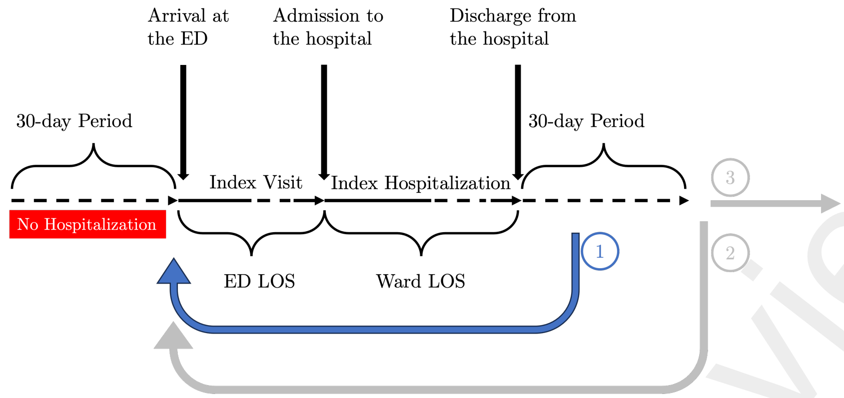
1 Introduction

Patients with mental health conditions, including major depression, bipolar disorder, schizophrenia, anxiety disorders, borderline personality disorder and post-traumatic stress disorder, account for a significant portion of healthcare expenditure. Figueroa et al. (2020) report that the presence of a mental health condition in Medicare patients in the US correlates with a tripling of total healthcare cost, largely due to increased spending on comorbidities. Canada has identified mental healthcare as a major area of investment as in excess of 70% of patient healthcare cost is covered by public insurance (Canadian Medical Association 2022). Psychiatric patients are characterized by the complexity of symptoms, higher lack of adherence to treatment as well as the risk of self-harm and/or harm to others compared to other major illnesses with physical symptoms such as cancer, cardiovascular disease, diabetes and respiratory diseases. The inherent subjectivity and potential inaccuracies in psychiatric diagnoses and the multi-faceted nature of treatment plans add to the complexity. In addition, the influence of social determinants of health —in particular, access to housing— on the patient's condition, constitutes a major differentiating characteristic of this patient population. Perhaps, most importantly, psychiatric patients often need longer hospital stays and rehospitalization than those with acute physical conditions.

A patient's rehospitalization within a short time after being discharged is more likely due to problems with inpatient care than the natural progression of the patient's condition. Hospital readmissions, in general, are strongly associated with undesirable health outcomes (Ashton et al. 1997, Zhang et al. 2016, Senot et al. 2016). They also place an extra burden on the health system, require more effort for treating returning patients, and increase staff burnout and absenteeism (Isaak et al. 2018). In the U.S., about 20% of all Medicare discharges result in readmission within 30 days (McIlvennan et al. 2015). It is estimated that at least 10% of these can be prevented, which would save Medicare over $1 billion annually (Medicare Payment Advisory Commission 2021). Similarly, one in 11 patients in Canada is readmitted within a month of leaving the hospital and readmissions cost more than $2.3 billion a year in the Canadian health system (Canadian Institute for Health Information 2021). Therefore, the reduction in hospital readmissions has attracted the attention of policy-makers and hospital administrators. For example, the U.S. 2012 Affordable Care Act launched the Hospital Readmission Reduction Program (HRRP), whereby hospitals with high 30-day readmission rates are penalized.

The hospital readmission problem is more problematic for psychiatric patients. Mental health disorders are often chronic and relapsing and so require repeated hospital admissions. This is because the underlying condition is often not treatable and psychiatric care is to monitor and control rather than to cure. The ultimate goal in psychiatric care is to increase 'quality of life' by helping the patient to cope and manage their condition. Around 40% of patients with mental disorders experience at least one readmission within one year after being discharged from hospital (this rate is around 30% for non-psychiatric disorders) (Madi et al. 2007). Moreover, care transition, a critical period after hospital discharge, is challenging for psychiatric patients. These patients often require an intensive follow-up plan to ensure medication adherence, therapy attendance, and general well-being. However, gaps in the continuity of care, such as poor discharge instructions and/or lack of coordination between the health system and the community contribute to higher

Figure 1 The Readmission Scheme.



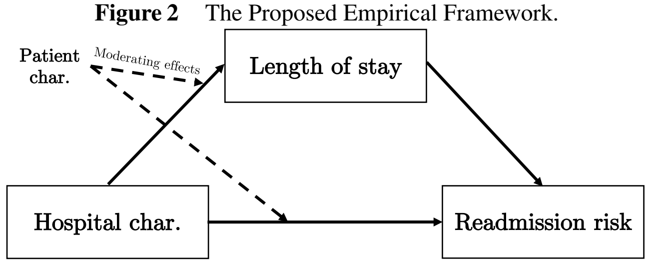
readmission rates when compared to non-psychiatric illnesses. Finally, treatment and care plans for patients suffering from mental disorders often need to be tailored to individual patients and consider their specific diagnosis and overall psychological, social, and environmental context. Patient-centered care is crucial for engaging patients (Kwame and Petrucka 2021) and improving health outcomes for individuals with mental illnesses (Dixon et al. 2016). Although the chronic and relapsing nature of mental disorders make readmissions less preventable, it highlights the need to optimize care processes. Despite the high costs of psychiatric inpatient care, the operations management literature has largely overlooked the care delivery process.

In this paper, we develop an empirical framework to answer two research questions. First, how do hospital operational characteristics impact the risk of readmission for psychiatric patients? Second, how does the length of hospital stay mediate the relation between hospital characteristics and the risk of readmission? We differentiate hospitals along two dimensions: *patient volume* and *hospital focus*. The former refers to the number of patients with a specific psychiatric disorder admitted to a hospital in a period. The latter is the proportion of admitted patients with a certain psychiatric illness.

We conceptualize a patient's readmission to the psychiatry ward as in Figure 1. The first hospitalization episode of a patient is called the *index hospitalization*, whereas the following hospital stays due to the same health condition are considered as readmissions. A patient arrives at the ED and spends time in the ED (which we refer to as ED LOS). If there is no prior hospitalization in the previous 30-day period, we refer to this visit as the *index visit*. The patient then is admitted to an inpatient ward, spends an amount of time in the hospital (which we refer to as ward LOS), and gets discharged. We refer to this episode as index hospitalization. There are three potential situations after discharge: 1) within thirty days, the patient returns to the hospital for another round of hospitalization; 2) the patient returns to the hospital after the 30-day period; 3) the patient never returns to the hospital or returns to the ED without hospitalization. We call only the first event (numbered as (1) in Figure 1) a *readmission*.

McIlvennan et al. (2015) find that, after controlling for the differences between patient populations, the readmission rates vary significantly among hospitals. This leads us to believe that the operational characteristics of a hospital could have a direct impact on its patient readmission rate. Heggestad (2001) provides

Figure 2 The Proposed Empirical Framework.



early evidence on the impact of hospital characteristics on psychiatric patients' risk of readmission. There are also studies that consider the ward LOS as an outcome variable affected by the attributes of the hospital (Newman et al. 2018, Lowell and Davis 1994, Tseng et al. 2020). Given the possible impact of the ward LOS on readmission rates, the hospital characteristics may also have an indirect effect on the risk of readmission through the *mediation effect* of the ward LOS. We also consider that these effects may be *moderated* by the characteristics of the patient population served by the hospital. These relationships are depicted in Figure 2, constituting the framework for the hypotheses we develop and test in this paper.

We use data from 25 hospitals with psychiatry wards across Canada, for our empirical study. The data set contains approximately 15,000 psychiatry patients hospitalized during a two-year period. About 8% of the patients are readmitted to the psychiatry ward within 30 days of being discharged from their index hospitalization. We deploy a clustered-error probit regression model for testing our hypotheses. Because the patient records with similar diagnosis classes at the same hospital are not independent, we cluster the records at hospital and diagnosis class levels. We use a set of simultaneous equations to estimate the effects of the hospital characteristics on the risk of readmission and the psychiatry ward LOS. This framework enables us to interpret the results based on the mediation framework we propose in Figure 2. We develop several models to capture the relations in Figure 2. We first develop a partial model for the direct effects of hospital characteristics on the risk of readmission. We then add the ward LOS to the model as a mediator. We also correct for the potential biases in our model through the use of instrumental variables. This helps us do *causal inferences* on how the hospital characteristics impact the patient outcomes.

Our mediation framework captures the impact of hospital characteristics—patient volume and hospital focus—on the risk of readmission directly as well as indirectly through the ward LOS. Although our empirical work confirms some of the findings in earlier studies on inpatient LOS and readmission risk, we identify several settings in which the earlier results do not generalize to psychiatric patients. In particular, most of the studies focusing on non-psychiatric settings find that higher ward LOS is associated with lower risk of readmission (see Section 2 for more detail). We establish, however, that the form of the relationship between LOS and readmission risk is more complex for psychiatric patients.

There is no strong evidence on the direct effects of hospital characteristics on the risk of readmission for patients with mental health conditions. This contrasts with studies in non-psychiatric settings which support direct effects of patient volume and hospital focus. In the context of psychiatric care, we find that patient volume has no direct impact on readmission rate. However, we observe strong evidence concerning indirect effects via ward LOS, i.e., higher patient volume is associated with a 7.8% decrease in the ward LOS in our data set, which increases the risk of readmission. As we detail in Section 2, earlier studies showed that a higher focus would lead to a shorter LOS, which contradicts the findings we report in this paper. This discrepancy is, arguably, due to the difference among the roles of a hospital stay in psychiatric versus non-psychiatric care settings. We find that higher hospital focus on patients with mental health conditions indirectly decreases readmission risk by extending the ward LOS by 10% in our data set.

The remainder of the paper is organized as follows. We review the most relevant literature in Section 2. We discuss our hypotheses in Section 3, and introduce our empirical setting in Section 4. The model and the results are given in Section 5. We provide the robustness checks of our empirical model in Section 6, and discuss the results in Section 7. Section 8 concludes.

2 Literature Review

We review papers on psychiatric readmissions, hospital operational characteristics, and ward LOS. We review both the clinical and the operations management studies to better position our work.

The patients served by a hospital do not constitute a uniform population in terms of the complexity of their care needs. Therefore, it is important to recognize that the patient characteristics have an impact on all three factors we review in Sections 2.1–2.3: readmission as the patient outcome and ward LOS as the mediator (mediating outcome), and the effect of hospital characteristics on the two outcomes. Several measures for evaluating *patient complexity* have been devised. The Elixhauser complexity index, for example, categorizes similar diagnoses into groups to denote specific complexity levels of patients' conditions (Elixhauser et al. 1998). Ahuja et al. (2022) point out that such indexes may not work well for patients with mental disorders. Another stream of papers assesses patient complexity based on process-related measures such as frequency of past hospitalizations (Ahuja et al. 2022) and patient resource usage (Saghafian et al. 2014). Also, Soltani et al. (2022b) measure the care intensity by the number of laboratory and radiology tests during an ED visit.

2.1 Psychiatric Readmissions

The common practice is to consider a patient "readmitted" if the hospital discharge was within 30 days and the previous hospitalization was due to the same (or similar) diagnosis. Nevertheless, other time frames for readmission are also applied in the literature. Han et al. (2020) consider both 30-day and 1-year readmission periods; Tedeschi et al. (2020) study the problem at a 1-year follow-up; Tulloch et al. (2016) create a model for 90-day readmission, and Evans et al. (2017) investigate rapid versus non-rapid readmissions. For the psychiatry ward, readmissions due to ineffective care during the hospital stay or premature discharge are most likely to occur within 30 days. Readmissions within extended time frames, e.g., 60 or 90 days, can result from the natural course of the illnesses (Heggestad 2001, Durbin et al. 2007). Thus, we focus on 30-day readmissions in this paper. We will consider 15-, 60-, and 90-day periods as robustness checks.

The medical literature is rather rich on studying the challenges of psychiatric readmissions. Donisi et al. (2016a) review the papers published until 2014 that study the readmission of psychiatry patients. Their review focuses mainly on *pre-discharge factors* such as LOS and patient diagnosis and shows mixed results on the effects of hospital LOS on readmission. We conduct further empirical analyses on this particular issue. Sfetcu et al. (2017) review papers published until 2014 that focus on *post-discharge factors*. They also observe mixed results in the literature on follow-ups in primary care, referrals to outpatient services, types of providers and loci of care, and continuity of care practices and programs. One of their interesting findings is that community follow-up is not associated with the chance of readmission within 30 days. Donisi et al. (2016b) study the relationship between pre- and post-discharge factors and early readmission in a community-based facility. They report that early readmissions can be mitigated by better managing the ward LOS rather than community follow-up. This evidence supports our choice of the readmission time window, that is, a readmission within 30 days is unlikely to be the result of a lack of community follow-up.

To the best of our knowledge, the operations management literature is silent on psychiatry readmissions. Nevertheless, the challenges associated with patient readmission to acute care facilities have garnered interest. Readmission to the intensive care units is studied by Kc and Terwiesch (2012), Kim et al. (2015), whereas Andritsos and Tang (2014), Bardhan et al. (2015), Lee et al. (2015) focus on cardiology readmissions. Also, some scholars have studied the success and failure of HRRP from different perspectives (Zhang et al. 2016, Bartel et al. 2020, Bardhan et al. 2015, Soltani et al. 2022a).

2.2 Hospital Operational Characteristics

The primary focus of clinical research on the readmission of psychiatry patients has been on patient-level factors while the impact of hospital characteristics has received less attention. The exceptions are Heggestad (2001) and Lee and Lin (2007), who show that the risk of readmission increases with patient turnover. The latter paper concludes that while in providing care for physical illnesses "practice makes perfect", in the context of psychiatric disorders this is not necessarily true. Lee et al. (2015) studies the relationship between hospital volume and patient outcomes for patients with heart diseases and points out that different definitions of hospital volume could result in significantly varied findings.

In contrast, the operations management literature has extensively studied the effects of hospital characteristics on patient outcomes (Kc et al. 2020). The most studied patient outcomes are mortality rates (Kc and Terwiesch 2011, Kuntz et al. 2019), readmission rates (Anderson et al. 2012, Soltani et al. 2022a), LOS, and their combinations (Ahuja et al. 2022). For example, Anderson et al. (2012) study the effect of the occupancy of post-operative care unit on patients' readmission rates. They conclude that early discharge is the primary reason for readmissions. Soltani et al. (2022a) consider the quality spillover mechanism caused by HRRP in non-targeted groups.

The operational characteristics can refer to a wide range of factors including patient turnover and staff management. Each characteristic refers to a specific operational aspect of a hospital. For example, Heggestad (2001) considers patient turnover as the annual number of discharges per bed to find out whether high turnover is associated with a greater risk of readmission. Kuntz et al. (2019) introduce patient volume as the annual number of hospitalized patients in a hospital and find that it increases the mortality rate of complex patients. On the other hand, Clark and Huckman (2012), Kc and Terwiesch (2011), and Soltani et al. (2022a) operationalize the concept of hospital characteristics by defining the hospital focus as the relative number of hospitalized patients to study how this characteristic can influence patient outcomes.

2.3 Length of Stay

Length of stay in an inpatient ward is often studied as a factor in health outcomes. Several studies however consider ward LOS as a patient outcome in its own right (Silva et al. 2020). Because psychiatric patients often require longer hospital stays, the impact of LOS is arguably more profound in this context. For example, the average LOS of psychiatric patients in our data is 17 days, considerably longer than other groups.

In the operations literature, LOS has been studied for several different purposes. Kc and Terwiesch (2012) considers the trade-off between discharging a patient earlier (lower LOS) and having the patient back in the cardiac intensive care unit. Shi et al. (2021) studies a similar problem to balance the care unit congestion and the quality of care patients could receive from hospitals. Kuntz et al. (2015) provides evidence that LOS increases with ward occupancy. Berry Jaeker and Tucker (2017) takes an in-depth look into the effects of ward congestion on LOS and shows that a nonlinear relationship exists. Recently, Janakiraman et al. (2023) investigate the impact of access to health information exchanges on LOS and readmission rate. However, they do not study the relationship between LOS and readmission risk, which is within our paper's focus.

3 Hypothesis Development

Hospital readmissions can be due to the natural progression of illness or a result of insufficient care (or both). Our focus is on the factors more closely related to the latter. To this end, we study how hospital characteristics affect health outcomes and, in particular, the risk of readmission either directly or indirectly through LOS. There are significant variations among hospitals in patient readmission rates (James 2013). These rates also vary with patient type, e.g., race, gender, and financial status (Pandey et al. 2020). We will illustrate similar variations in our data in Section 4.1.

3.1 Hospital Characteristics and the Risk of Readmission

We consider *patient volume* and *hospital focus* as two primary characteristics of a hospital that may impact the risk of readmission. Following the existing literature, we define patient volume in a diagnosis class as the number of patients admitted to the hospital during a specific time period (Theokary and Ren 2011).In healthcare settings, increased patient volume is positively associated with clinical quality across various conditions and procedures (Birkmeyer et al. 2002). Increased patient volume can also benefit hospitals by creating economies of scale (Kuntz et al. 2019). These economies of scale enhance operational efficiency by lowering per-unit costs and improving resource allocation, potentially improving service quality. Ultimately, higher-quality care is expected to lead to better patient outcomes. Additionally, increased patient volume fosters experience accumulation, which enhances learning. Research indicates that improved learning is positively associated with higher productivity and better performance quality (Huckman and Zinner 2008).

A high volume, however, may also deteriorate the quality of care (Heggestad 2001, Kalseth et al. 2016). A higher patient volume can introduce significant challenges in coordination, particularly for complex cases. As patient volumes increase, hospitals often adopt more "granular subdivisions" of work to manage the workload effectively (Kuntz et al. 2019). However, "hospital volume might diminish the efficiency of 'wide-ranging' coordination by reducing the level of common knowledge (through finer division of labor) and by encouraging an increasingly siloed structure (through greater structural differentiation)" (Clark 2012). Research suggests that as hospital size increases, the likelihood of errors and service failures also rises due to the added complexity in communication and coordination among staff and across functional teams (Theokary and Ren 2011, Tucker and Edmondson 2003).

Complex patients, such as those with psychiatric conditions, frequently require multidisciplinary care and access to a variety of services. The structural effects of high volume can impede the integration of knowledge and communication across these task interfaces, disproportionately affecting the quality of care for these patients. Consequently, increased structural differentiation and the resulting coordination challenges may offset the potential benefits of higher patient volumes, contributing to poorer outcomes such as higher readmission risks for complex patients. We believe this downside is more prominent for psychiatry patients.

HYPOTHESIS 1a *Higher patient volume increases the risk of readmission for psychiatric patients.*

Hypothesis 1a tests whether there is a direct relationship between patient volume and readmission risk. The effect however may be indirect and mediated by other variables. Our focus is then to study a mediation framework where we hypothesize that hospital characteristics impact ward LOS which in turn affects readmission risk.[1] Psychiatric illnesses are often multifaceted and require extended monitoring and control when compared to non-psychiatric ailments. Comprehensive treatment plans for psychiatric patient can extend their stay in inpatient care units. On average, psychiatric patients stay longer in hospitals than non-psychiatric patients. Moreover, psychiatric conditions are diverse and we observe a wider range of LOS among psychiatric patients. So it is reasonable to expect that the impact of hospital characteristics on the risk of readmission among psychiatric patients may be mediated by the length of stay in the psychiatry

[1] We note that the effects of hospital characteristics on ward LOS cannot be mediated by readmission risk. This is because readmission happens after the conclusion of the index hospital stay.

ward. A high patient volume may lead to premature discharges from the inpatient ward to free up beds for those boarding in the ED. That is, a higher patient volume may reduce the ward LOS. We next look into how ward LOS may affect the risk of readmission.

There are mixed results in the healthcare literature on the effect of ward LOS on the risk of readmission. Although most studies find that higher ward LOS is associated with a lower likelihood of readmission, there are several studies that detect a positive or no association; see Donisi et al. (2016a) for a review. A close examination of these studies reveals that the paradoxical effect of LOS on readmission risk emerges under specific circumstances. For instance, Zhou et al. (2014) found no significant relation between LOS and risk of readmission in a setting where the average LOS was 64 days. Also, Ono et al. (2011) observed an elevated readmission risk for female dementia patients with longer ward stays and attributed it to an "increased likelihood of complications." The majority of studies however find longer LOS reduces readmission risk. To allow flexibility in our empirical analysis, we stipulate that the relation can be non-linear.

HYPOTHESIS 1b *The ward LOS mediates the relationship between patient volume and risk of readmission: a higher patient volume reduces the ward LOS which in turn increases the risk of readmission for psychiatric patients.*

Hospital focus on a diagnosis class refers to the proportion of hospitalized patients who belong to that category. Hospital focus measures the relative frequency of admitted patients with similar diagnoses (Soltani et al. 2022a). Narayana Hrudayalaya Heart Hospital in India and Shouldice Hospital in Canada specializing in hernia operations are examples of high-focus hospitals. The higher the focus, the higher the number of similar patients the hospital serves. A high-focus hospital's operations and services are tuned toward specific diagnosis classes which in turn results in higher efficiency and an enhanced quality of care. On the other hand, high focus limits the spectrum of a hospital's services (Kuntz et al. 2019) that can negatively affect the quality of care provided to complex patients (Clark and Huckman 2012). Psychiatric disorders are often interrelated and usually accompanied with non-psychiatric comorbidities. So, a high-focus hospital may leave patients with complex conditions worse off. However, we believe that the benefits of focus overcome its downsides and so should potentially lead to a lower risk of readmission.

HYPOTHESIS 2a *Higher hospital focus reduces the risk of readmission for psychiatric patients.*

Hypothesis 2a is to test for a direct relationship between hospital focus and readmissions. However, ward LOS may mediate the relation. Non-psychiatric patients in a high-focus hospital often have shorter ward LOS. Care providers in such hospitals amass experience and expertise that are likely to lead to faster discharge (Huckman and Zinner 2008). For instance, the average post-operative stay at the Nayarana Heart Hospital is half as long as that in similar surgery classes in Canada's general hospitals. In other words, non-psychiatric disorders benefit from operations and process standardization. This rationale may not apply to multifaceted psychiatric disorders. One may argue that hospital focus is likely to help achieve better outcomes for psychiatric patients by extending their ward LOS so that the hospital staff can develop a comprehensive care plan that also considers their comorbidities. A higher ward LOS may in turn reduce the risk of readmission.

HYPOTHESIS 2b *The ward LOS mediates the relationship between hospital focus and risk of readmission: a higher hospital focus increases the ward LOS which in turn decreases the risk of readmission for psychiatric patients.*

We next argue that the effects we intend to test in Hypotheses 1 and 2 may be moderated by patient characteristics. Our approach is similar to Ahuja et al. (2022), Kuntz et al. (2019) that focus on the impact of operational factors on health outcomes and argue that patient characteristics moderate the impact.

3.2 Patient Characteristics as Moderators.

We presuppose that the impact of hospital characteristics on the risk of readmission is moderated by patient characteristics. We use *patient complexity* and *patient history* as the two patient-level moderators. Psychiatry patients are typically admitted to inpatient beds after being seen in the ED. We determine patient complexity at the time of hospital admission based on the number of laboratory tests, radiological examinations, and consultations with non-psychiatric specialists in the ED. The resulting *ED resource usage intensity* serves as an indicator of the patient's physical condition, which is closely linked to their psychiatric complexity (Sprah et al. 2017). This is also supported by the "care complexity" concept developed by the European Consultation Liaison Workgroup in their Biomed1 Risk Factor Study (Herzog et al. 1997). Ahuja et al. (2022) provide references to highlight that "nearly half of those with a mental disorder have an associated comorbidity, and an additional 35% have undiagnosed medical conditions, implying that only a small proportion are free of comorbidities."

Patient complexity may lead to different outcomes in hospitals varying in volume or focus. A hospital with a high focus may afford patients with high resource-usage intensity a more thorough treatment, necessitating extended stays in the inpatient ward. Alternatively, a high-volume hospital might accommodate these patients for a shorter stay due to treatment challenges or a potential inability to fully treat them.

ED visits do not necessarily lead to hospitalization and, in majority of the cases, the patient is sent home. However, over 90% of psychiatric hospital admissions occur through the emergency department (ED). (Aflalo et al. 2015). A hospitalized patient may have a set of prior ED visits (with no hospital admission) and so be a *revisiting patient*. Else, the patient is a *new patient* with no history. The *patient history* plays an important role in treatment planning. A revisiting patient may benefit from a more precise diagnosis and treatment due to the availability of prior medical records. However, frequent visits might lead healthcare professionals to view a patient's condition as chronic or 'difficult to treat'. In hospitals with high patient volume, where there is a constant pressure for bed availability, there could be an operational inclination to discharge these revisiting patients as soon as their conditions stabilize, potentially overlooking the comprehensive care they might need. We suggest that a patient's history may influence how hospital characteristics impact the risk of readmission. Though we consider patient characteristics as moderators in the relation between hospital characteristics and the risk of readmission, we do conduct a robustness check where we treat patient characteristics only as control variables.[2]

4 Empirical Model

In this section, we describe the data set and define the variables and outcome measures.

4.1 The Data

We gathered data on 18,594 psychiatry patients during a two-year period from 28 hospitals across Canada. One hospital did not record the patients' ward LOS, and another had missing values in the diagnosis codes entered for most of its patients. A third hospital recorded the diagnosis codes of most of its patients as "unspecified mental disorders". The removal of these three hospitals shrank our data to 16,661 records.

We observe that 30% of the patients are readmitted, at least once, during the two-year study period. Given the chronic nature of some of the more severe mental illnesses, this is not surprising. Our focus however is on the 30-day readmissions after the first hospitalization, which are likely due to shortcomings in the quality of care. With a 30-day focus, we observe an 8% rate of readmission. This rate increases to 11.5%, and 14% with 60-day and 90-day readmission periods, respectively.

Our focus on 30-day readmissions renders the first and last months' data unusable. For admission during the first month, we are unable to ascertain whether it is an index admission or readmission of the patient who was originally admitted during the prior 30 days. Similarly, for discharges during the 24^{th} month, we are not able to observe the associated readmissions–if any–within the data set. So, we remove the first and the 24^{th} months of the records from our data.

Figures 3 and 4 show the variations in the risk of readmission and ward LOS across the 25 hospitals in our data set. Figure 3 shows the annual hospital readmission rates which are risk-adjusted, i.e., they are estimated by controlling for age, gender, acuity level, arrival mode, chief complaint, diagnosis class, discharge day (weekend versus weekday), and discharge destination. In this figure, we follow Gupta (2021) to measure standardized variations between hospitals and calculate readmission rates (see equations (EC.1)–(EC.3) in the appendix). Figure 3 shows that the risk-adjusted hospital readmission rates are stable over time and that there are variations in readmission rates across hospitals that may not be explained by differences in patient mix or the quality of care provided. Figure 4 illustrates the distribution of psychiatry ward LOS.

4.2 Diagnosis Classes and Chief Complaints

Our data contains the diagnosis code for each patient recorded by the hospital staff at the end of a patient's stay in the ED based on the ICD-10-CM coding system (World Health Organization 2023). An ICD code is

[2] Our results are robust to this alternative specification and available upon request.

Figure 3 Average risk-adjusted standardized risk of readmission (RSRR)

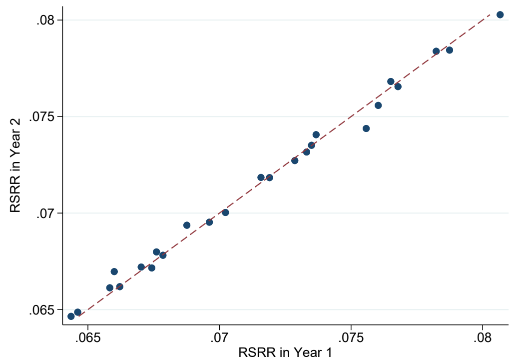
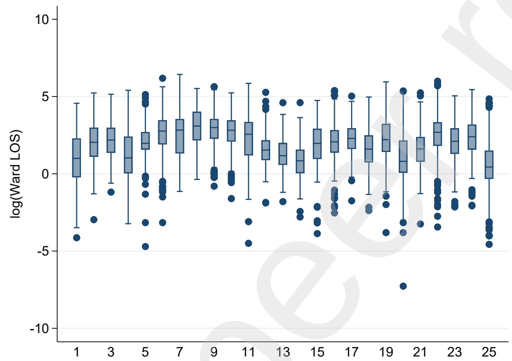


Figure 4 Boxplots of log(Ward LOS) for the 25 hospitals listed on the x-axis



a number that represents a medical diagnosis and is often used for billing purposes. The ICD coding system provides a tool for hospital staff to report their diagnosis of a patient in a systematic framework. This diagnosis can be precise (e.g., schizoaffective disorder F25.9), a syndrome (e.g., frontal lobe syndrome F07.0), or a symptom (e.g., psychotic symptoms of depression F32.2). The diagnosis usually is either 'provisional' or 'definitive' (Wagner et al. 2006).

For ease of implementation, we aggregate similar codes into diagnosis/disorder categories to build the variable $DiagnosisICD10Class$ and assign each patient to a category of disorders. The details of how we create this variable are in Table EC.1. Our data also include the chief complaint recorded at the beginning of the ED visits. The complaint is in text format and based on what patients describe to triage nurses about their condition and in that sense do not follow a structure similar to diagnosis codes. Nonetheless, the complaints can be categorized with accuracy by machine learning algorithms. We use topic modeling which is an unsupervised natural language processing (NLP) technique to identify the underlying patterns in text corpora. A topic model learns and extracts topics from volumes of text. We use Latent Dirichlet Allocation (LDA) to extract the topics of the unstructured textual records in our data set. We obtain eight topics to categorize the chief complaints with the highest performance measure in our data set. The details of these categories are in Table EC.2 in the appendix. We add these topics as fixed effects of patient conditions to our empirical model. We believe these categories help to reduce patients' heterogeneity in our analysis.

4.3 Independent Variables: Hospital Operational Characteristics

We define two measures to capture the operational discrepancies among hospitals: patient volume and hospital focus. We use the convention proposed by Kuntz et al. (2019) to create the measures.

4.3.1 Patient Volume.

We define an indicator variable $n_{idh} = 1$ if patient-visit $i \in \{1, \ldots, N\}$ belongs to diagnosis class $d \in \{1, \ldots, D\}$ and is admitted to hospital $h \in \{1, \ldots, H\}$, and 0 otherwise. Given the two-year worth of data, we calculate the annualized volume (separate volume values for each year) of patients-visits in diagnosis class d and hospital h as $\mathrm{PtVol}_{dh} = \sum_{i=1}^{N} n_{idh}$. This variable has a high variance which is a common problem when incorporating continuous variables in empirical models. To deal with this issue, we standardize the variable PtVol_{dh} for each diagnosis class d across hospitals (by subtracting the mean and dividing by the standard deviation). The standardized PtVol ranges from -1 to 5.

4.3.2 Hospital Focus.

We calculate a continuous focus measure for diagnosis class d in hospital h as the annualized relative volume of patients in that disease category and hospital:

$$\mathrm{HospFoc}_{dh} = \frac{\sum_{i=1}^{N} n_{idh}}{\sum_{d' \in \mathcal{D}} \sum_{i=1}^{N} n_{id'h}}. \tag{1}$$

The variable $\mathrm{HospFoc}_{dh}$ also suffers from the problem of high variance and so we standardize it similar to PtVol. The standardized HospFoc ranges from -2 to 3.

4.4 Moderator Variables: Patient-Level Characteristics

To study the moderating effects of patient characteristics on the relation between hospital characteristics and health outcomes, we develop patient-level measures in this section.

4.4.1 The Patient Resource Usage Intensity Measure.

One common approach to assess the complexity of a patient's condition is to use the Elixhauser index of comorbidities (Elixhauser et al. 1998). For instance, Kuntz et al. (2019) considers a patient complex if she has at least three Elixhauser comorbidities. These indexes are also used to assess the severity score of a patient's condition (Berry Jaeker and Tucker 2017). However, these scores are mostly for non-psychiatric complications and as such not suitable for psychiatric patients.[3] We instead apply three diagnostic variables: *Consult*, *LabTest*, and *RadioTest* to identify a complex patient. Our approach assumes that higher numbers of laboratory tests, radiology tests, and consultations with non-psychiatric specialists (or a combination of

[3] Moreover, our data does not contain the necessary fields to create and use these scores.

these) indicate a complex patient. We consider three variables $HighConsult$, $HighLab$, and $HighRadio$ to develop a measure for patients' resource usage intensity. The definitions of all the above variables are given in Section EC.5.1 of the appendix.

$$RSC\_INT_{id} = \begin{cases} \text{HRI}, & \text{if } HighConsult_{id} = 1 \text{ or } HighLab_{id} = 1 \text{ or } HighRadio_{id} = 1; \\ \text{LRI}, & \text{otherwise.} \end{cases} \quad (2)$$

This two-level measure differentiates patients based on their conditions as high resource-intensive (HRI) or low resource-intensive (LRI). This binary variable RSC_INT_{id} splits patients in the fixed diagnosis class d. As a robustness check, we developed a three-level resource usage intensity measure (HRI, benchmark, LRI). This approach did not yield additional insights or alter our results.[4]

4.4.2 Patient History.

The variable NUM_Visits denotes the number of times a patient visited the ED as of the index visit (inclusive). We then dichotomize NUM_Visits to differentiate between patients based on the history of their visits. Our rationale is that a patient who has been in the ED at least two times prior to the index visit is a "revisiting" patient for the hospital, while a patient in her first visit or with only one prior visit is a "new" case. Our approach in defining a revisiting patient as one with two visits prior to the index visit avoids including a patient with irrelevant previous ED visits as revisiting and in that sense is *conservative*. Our analysis is nonetheless robust if we define a revisiting patient to have one prior visit and results do not change.

$$History_i = \begin{cases} \text{Revisiting}, & \text{if } NUM\_Visits_i >= 3; \\ \text{New}, & \text{otherwise.} \end{cases} \quad (3)$$

4.5 Control Variables

We provide a description of the variables in Table EC.3 in the appendix. The $ArrivalMode$ captures whether the patient arrived in the ED in an ambulance or walked in. We also consider the chief complaint categories to account for the heterogeneity in patients' conditions in our data set.

Our data offers evidence on the effect of the discharge day of the week on the risk of readmission and LOS in the inpatient ward (i.e., the *weekend effect*; see Bartel et al. 2020). Patients discharged on weekends have significantly lower ward LOS and higher readmission rates. Therefore, we include a dummy variable to control for the weekend effect. Also, we define patient severity as a dichotomous measure to categorize a patient's condition after triage as severe or otherwise. The details are in Section EC.5.2 in the appendix.

5 The Effect of Hospital Characteristics

We develop a probit model to study the effects of hospital characteristics on the risk of readmission.

[4] The results are available from the authors upon request.

5.1 The Partial Model: Clustered-Error Probit

A patient returns to the hospital as her overall mental health condition deteriorates after discharge. One may think of readmission as a result of a marginal benefit/cost analysis from a patient's perspective based on the utility attributed to each option. Readmission offers the benefit of receiving appropriate care. However, returning to the hospital incurs both financial expenses and an emotional toll of another hospitalization on the patient. We model the difference between the perceived benefit/cost as an unobserved (latent) variable $Readmission^*$ such that:

$$\begin{aligned} Readmission^* &= \mathcal{X}'\boldsymbol{\beta} + \varepsilon; \\ Readmission &= \mathbb{1}\{Readmission^* > 0\}, \end{aligned}$$

where $\mathbb{1}\{.\}$ is the indicator function, $\mathcal{X}$ is the set of all independent variables in the model, and ε is $\mathcal{N}(0,1)$ random error. Our model then is a probit regression model in which the binary outcome variable indicates whether a patient is readmitted within thirty days of discharge from her index hospitalization ($Readmission = 1$) or not ($Readmission = 0$). To construct a general framework that links the binary patient outcome to a set of factors, we use a probability model as follows:

$$\Pr(\text{Readmission} = 1|\mathcal{X}) = \Phi(\mathcal{X}'\boldsymbol{\beta}),$$

where Φ is the cumulative distribution function of the standard normal distribution. This model estimates the probability of readmission for each patient.

Our model needs to account for the structural differences among hospitals and diagnosis classes. To this end, we introduce fixed effects of hospitals and diagnosis classes to the model. Also, we add the year fixed effect to capture any variations across years. Moreover, patients' records in each hospital and diagnosis class cannot be assumed to be independent hence violating the assumption of independence of residuals. To remedy this issue, we cluster patients within each diagnosis class and each hospital using the cluster-specific probit model (Wooldridge 2010, chap. 15) which allows error distributions to vary among clusters. We assume that readmission within thirty days of discharge for patient i in diagnosis class d, hospital h, and year t (i.e., the binary variable $Readmission_{idht}$) is linked to an unobserved health index $Readmission^*_{idht}$ for that patient which is a linear function of the variables of interest, the interactions required to test our hypotheses, and the control variables:

$$\begin{aligned} Readmission^*_{idht} &= \beta_0 + \beta_1 PtVol_{idht} + \beta_2 PtVol_{idht} RSC\_INT_{id} \\ &+ \beta_3 PtVol_{idht} History_i + \beta_4 HospFoc_{idht} \\ &+ \beta_5 HospFoc_{idht} RSC\_INT_{id} + \beta_6 HospFoc_{idht} History_i \\ &+ \beta_7 RSC\_INT_{id} + \beta_8 History_i + \boldsymbol{X}_i \boldsymbol{\theta} \\ &+ DiagnosisClass_d + Hospital_h + Year_t + \nu^r_{dh} + \varepsilon_{idht}; \\ Readmission_{idht} &= \mathbb{1}\{Readmission^*_{idht} > 0\}. \end{aligned} \tag{4}$$

The cluster-specific effects are denoted by ν^r_{dh}. The hospital-level independent variables of interest are $PtVol_{idht}$ and $HospFoc_{idht}$ that show patient volume and hospital focus (of hospital h where patient i in diagnosis class d is hospitalized in year t), respectively. The moderators are the dichotomous variables RSC_INT_{id}, indicating if patient i in diagnosis class d is of type HRI or LRI (which serves as the reference category) patient, and $HISTORY_i$ denoting whether a patient is revisiting. The matrix $\boldsymbol{X}_i$ contains the control variables for patient i: the patient's gender (male or female), linear and squared terms of the patient's age, the severity of the patient's health condition at the time of presence at the ED as severe or not severe, the topic of the patient's chief complaint, whether the patient is discharged from hospital on a weekday (Monday to Friday) or weekend, and whether the patient is discharged to her home, a nursing home, or leaves the hospital against medical advice (A patient does not have to stay in the hospital or receive treatment against her will unless a court order is issued. Our data does not contain court orders).

5.2 Partial Model Results

In our results, a factor is said to have a positive effect on the risk of readmission if it has a negative coefficient in the regression model with the risk of readmission as the dependent variable. Table 1 shows the coefficients of regression for the model specified in equation (4). We observe no significant effect of the patient volume on the risk of readmission. Moreover, there is no significant moderation effect of the patient resource usage intensity and patient history on the relationship between hospital characteristics and the risk of readmission. The coefficient of hospital focus is insignificant. However, the coefficient of its interaction term with HRI patients is positive and significant at the 5% level. This implies that an increase in hospital focus leads to a higher risk of readmission for HRI patients while it does not affect LRI patients' risk of readmission.

The partial model does not provide evidence for the direct effects of hospital characteristics on the risk of readmission. Thus, Hypotheses 1a and 2a are not supported. We next test for the mediation effect of ward LOS on the relation between hospital characteristics and risk of readmission.

The classic literature on mediation studies frames the mediation analysis into three steps: first, testing the effect of the independent variable on the dependent variable when the mediator is excluded from the model (so called total/zero-order effect); second, adding the mediator to the model and testing the effect of the independent variable on the dependent variable (direct effect); and third, testing the mediator's effect on the dependent variable (mediation effect) in the presence of the independent variable (Baron and Kenny 1986, Preacher and Hayes 2004). By this framework, we cannot proceed to a step if we do not find a significant effect in the previous step. In our analysis, we could not find significant effects for all the hospital characteristics on the readmission risk and so one may think that we need to stop our analysis of the mediation effects. However, recent literature shows that this is neither true nor practical in mediation analysis and one does not need to find a significant zero-order effect to establish mediation (Zhao et al. 2010, Hayes 2022). So we continue our analysis by adding the ward LOS to the current regression model to simultaneously

Table 1 Total Effects of Hospital Characteristics on Risk of Readmission in Probit.

	Dependent Variable
	Readmission Risk
Patient Volume	−0.000 (0.028)
Patient Volume × HRI Patient	−0.007 (0.029)
Patient Volume × Revisiting Patient	0.013 (0.027)
Hospital Focus	−0.010 (0.031)
Hospital Focus × HRI Patient	0.091** (0.040)
Hospital Focus × Revisiting Patient	0.009 (0.033)
Constant	−1.817*** (0.178)
Observations	14956

Standard errors are given in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

incorporate the direct and indirect effects of hospital operational factors on the risk of readmission. We first incorporate ward LOS as a mediator into our regression model in Section 5.3. Then, in Section 5.4, we discuss the endogeneity of the ward LOS and the instrumental variable approach we adopt to address it. Section 5.5 presents the results of the regression model.

5.3 The Full Model with Ward LOS

The variable *WardLOS* is the number of days a patient stays in a hospital's psychiatric inpatient care unit. We use the log transformation of ward LOS as its distribution is highly skewed (Kc and Terwiesch 2012). The log-transformed distribution is approximately normal (see Figures Figures EC.1-EC.2 in the appendix). We include the variable *WardLOS* in our full model as an independent variable to obtain equation (5). We also include a square term to account for the potential nonlinear impact of the ward LOS on the risk of readmission. These two terms, i.e., ward LOS and its square, are the patient-level independent variables in our model. Ward LOS is itself dependent on hospital characteristics as we model in equation (6).

$$
\begin{aligned}
Readmission^*_{idht} = \; & \beta_0 + \beta_1 PtVol_{idht} + \beta_2 PtVol_{idht} RSC\_INT_{id} \\
& + \beta_3 PtVol_{idht} History_i + \beta_4 HospFoc_{idht} \\
& + \beta_5 HospFoc_{idht} RSC\_INT_{id} + \beta_6 HospFoc_{idht} History_i \\
& + \beta_7 RSC\_INT_{id} + \beta_8 History_i \\
& + \alpha_1 \log(WardLOS_i) + \alpha_2 (\log(WardLOS_i))^2
\end{aligned}
$$

$$
\begin{aligned}
&+ \boldsymbol{X}_{idh}\boldsymbol{\theta} + DiagnosisClass_d + Hospital_h + Year_t + \nu^r_{dh} + \varepsilon_{idht};\\
Readmission_{idht} &= \mathbb{1}\{Readmission^*_{idht} > 0\}; \qquad (5)\\
\log(WardLOS_{idht}) &= \eta_0 + \eta_1 PtVol_{idht} + \eta_2 PtVol_{idht} RSC\_INT_{id}\\
&+ \eta_3 PtVol_{idht} History_i + \eta_4 HospFoc_{idht}\\
&+ \eta_5 HospFoc_{idht} RSC\_INT_{id} + \eta_6 HospFoc_{idht} History_i\\
&+ \eta_7 RSC\_INT_{id} + \eta_8 History_i\\
&+ \boldsymbol{X}_i \boldsymbol{\theta}' + DiagnosisClass_d + Hospital_h + Year_t + \nu^l_{dh} + \varepsilon_{idht}. \qquad (6)
\end{aligned}
$$

Table 2 shows the estimation results of the simultaneous equations of the clustered-error probit model, using the user-written command `cmp` in STATA 17. The second column reports the estimation coefficients from equation (5), and the third column reports the estimation coefficients from equation (6). The second column illustrates that hospital characteristics' effects on the readmission risk are similar to what we observed from the partial model (equation (4)) in Table 1.

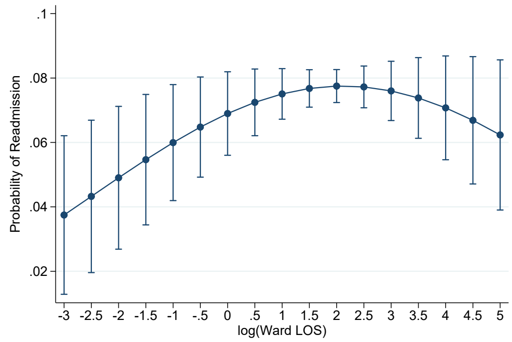
Table 2 The Indirect Effects of Hospital Characteristics on Risk of Readmission Through Ward LOS.

	Dependent Variable	
	30-day Readmission Risk	log(Ward LOS)
Patient Volume	0.001 (0.028)	-0.085^{**} (0.039)
Patient Volume × HRI Patient	-0.007 (0.029)	-0.036^{*} (0.022)
Patient Volume × Revisiting Patient	0.013 (0.027)	0.019 (0.032)
Hospital Focus	-0.010 (0.030)	0.017 (0.033)
Hospital Focus × HRI Patient	0.090^{**} (0.040)	0.087^{***} (0.032)
Hospital Focus × Revisiting Patient	0.010 (0.033)	-0.037 (0.026)
log(Ward LOS)	0.060^{**} (0.026)	
log(Ward LOS)^2	-0.014^{***} (0.005)	
Constant	-1.801^{***} (0.178)	0.013 (0.161)
ρ_{los_rr} (eq. (5) & eq. (6))		-0.003 (0.018)
Observations	14956	14956

Standard errors are given in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 5 Predicted risk of readmission by Ward LOS from the probit model in equations (5)–(6)



The effects of the ward LOS on the risk of readmission are captured by the coefficients of the linear and squared terms of the log of ward LOS in the second column of Table 2. Both terms are strongly significant and so support a nonlinear relation ($\alpha_1 = 0.060$, $p < 0.05$ and $\alpha_2 = -0.014$, $p < 0.01$). However, we cannot interpret the results from a nonlinear probit model similar to a linear model. We instead use the *average marginal effects*. We estimate the risk of readmission by calculating the average marginal effects of the ward LOS. Figure 5 shows the results. It shows a clear concave effect with two segments. In the left segment, a higher ward LOS increases the risk of readmission for patients who stay in the inpatient ward for about a week or less ($\exp(\log(WardLOS) = 2) \approx 7$). Interestingly, the opposite holds for patients who stay in the hospital longer than a week. We deduct that higher ward LOS reduces the risk of readmission for patients who stay long enough in the index hospitalization. We elaborate more on this relationship in Section 5.5.

From the third column in Table 2, we observe that patient volume has a negative impact on the ward LOS, i.e., the higher the patient volume, the lower the ward LOS. Therefore, a higher patient volume is associated with a higher risk of readmission through ward LOS. Moreover, hospital focus positively affects the ward LOS for the high resource-intensive patients, i.e., the higher the hospital focus, the higher the ward LOS for this patient group. Here, we observe that hospital focus affects the risk of readmission in different ways through different channels, that is, higher hospital focus is associated with a higher risk of readmission in the direct channel. At the same time, it lowers the risk of readmission by increasing the ward LOS resulting in a lower risk of readmission in the indirect channel. We elaborate more on this in Section 5.5 after correcting the model for biases caused by the endogeneity. We note here that the value ρ_{los_rr} in Table 2 is the correlation between the error terms of equations (5)–(6) for $\log(WardLOS)$ and *ReadmissionRisk*. This correlation is not significantly different from zero ($\rho_{los\_rr} = -0.003(0.018)$) which suggests that our two equations could be estimated separately without loss of efficiency.

Endogeneity is a critical concern in causal analysis that attenuates the validity of the results in empirical models. We believe the existence of unobserved factors in our model can bias our results. Section 5.4 provides an analysis of this concern. In Section 5.5, we correct our model for endogeneity by using an instrumental variable (IV) approach and report the unbiased estimates.

5.4 Ward LOS as Source of Endogeneity

The presence of endogenous variables on the right-hand side of equation (5) could bias the coefficient estimates including α_1 and α_2. Disregarding omitted or unobservable patient-level risk factors tends to affect *WardLOS* and simultaneously affect the likelihood of an adverse outcome requiring readmission. The medication used by a patient during her hospitalization is an example of such risk factors. A medication that reduces the risk of readmission may require the patient to be in the care unit for a more extended time period (higher ward LOS); this however is unobservable to us. Unobserved variables attenuate the estimates of α_1 and α_2; that is, α_1 and α_2 underestimate the effect of a shorter ward LOS on the risk of readmission. An instrumental variable (IV) approach can be applied to circumvent such endogeneity concerns and to generate consistent estimates for α_1 and α_2. We investigated a few candidates that can potentially satisfy the conditions for an instrumental variable. The details are provided in the Appendix (Section EC.7).

The time a patient spends in the ED between an admission request to the hospital until she is accommodated in an inpatient ward is called the *ED boarding time*. Long ED boarding time is associated with higher ward LOS (Singer et al. 2011). We could potentially use this for estimating ward LOS, but the ED boarding time in our data set contains a notable amount of missing values. Our data set however offers an alternative. ED LOS is the time (in hours) from a patient entering into the ED to when she is admitted into the ward. In our data, the ED boarding time constitutes about 80% of the ED LOS and so the two are strongly positively correlated in our sample. We believe that ED LOS is a satisfactory IV choice for ward LOS. As we discuss next, ED LOS meets both the relevance and exclusion (exogeneity) criteria (Greene 2018). We apply a log-transformation to *EDLOS* as its distribution is skewed. The ED LOS satisfies the relevance condition as it is correlated with ward LOS and the exclusion condition as it is not associated with the risk of readmission in 30 days (correlation≈ -0.004). However, the exclusion condition is not technically verifiable and often presumed.

One may argue that this assumption is not satisfied as a patient's ED LOS is also associated with her condition's severity (which in turn affects the risk of readmission). Admittedly, some levels of association may exist but the patient's hospitalization after her stay in the ED will blunt the effects of her ED stay including the amount of time she spent in the ED. Moreover, we observe that the correlation between ED LOS and the risk of readmission is practically zero in our data. No association between ED LOS and risk of readmission has been reported in the medical literature on psychiatric readmissions; see the review by Donisi et al. (2016a). Therefore, we choose ED LOS as the IV for ward LOS. We also perform a set of robustness checks by using alternative IVs in Section 6 to showcase the robustness of our results.

Our IV specification modifies the simultaneous equations in equations (5)–(6) as follows[5]:

$$\begin{aligned}
Readmission^*_{idht} = {} & \beta_0 + \beta_1 PtVol_{idht} + \beta_2 PtVol_{idht} RSC_INT_{id} \\
& + \beta_3 PtVol_{idht} History_i + \beta_4 HospFoc_{idht} \\
& + \beta_5 HospFoc_{idht} RSC_INT_{id} + \beta_6 HospFoc_{idht} History_i \\
& + \beta_7 RSC_INT_{id} + \beta_8 History_i + \boldsymbol{X}_i \boldsymbol{\theta} \\
& + \alpha_1 \log(\widehat{WardLOS_i}) + \alpha_2 (\log(\widehat{WardLOS_i}))^2 \\
& + DiagnosisClass_d + Hospital_h + Year_t + \nu^r_{dh} + \varepsilon_{idht}; \\
Readmission_{idht} = {} & \mathbb{1}\{Readmission^*_{idht} > 0\}; \qquad (7) \\
\log(WardLOS_{idht}) = {} & \eta_0 + \gamma_1 \log(EDLOS_i) + \gamma_2 \log(EDLOS_i)^2 \\
& + \eta_1 PtVol_{idht} + \eta_2 PtVol_{idht} RSC_INT_{id} \\
& + \eta_3 PtVol_{idht} History_i + \eta_4 HospFoc_{idht} \\
& + \eta_5 HospFoc_{idht} RSC_INT_{id} + \eta_6 HospFoc_{idht} History_i \\
& + \eta_7 RSC_INT_{id} + \eta_8 History_i + \boldsymbol{X}_i \boldsymbol{\theta}' \\
& + DiagnosisClass_d + Hospital_h + Year_t + \nu^l_{dh} + \varepsilon_{idht}. \qquad (8)
\end{aligned}$$

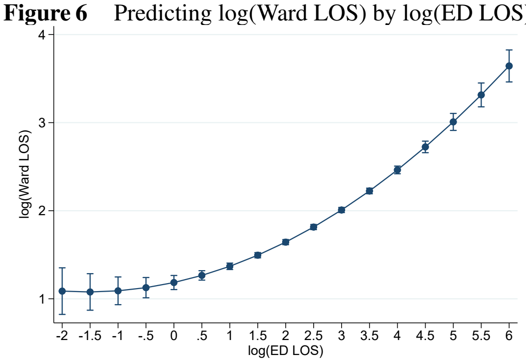
Here, ν^r_{dh} and ν^l_{dh} accounts for unobserved heterogeneity that impacts the dependent variables.

Because a higher ED LOS could lead to a longer hospital length of stay ($WardLOS_i$), while (arguably) having no impact on the unobserved factors underlying a patient's readmission in 30 days, $EDLOS_i$ provides exogenous variation in $WardLOS_i$ that is unrelated to the patient's underlying conditions. This allows us to generate a consistent estimate for α_1 and α_2 in equation 6. Figure 6 shows that the relation between ED LOS and ward LOS is curvilinear.

One might argue that the benefits of hospital characteristics on the risk of readmission are due to 'cherry picking' rather than operational excellence. For example, high-focus hospitals might admit patients with less severe conditions which would result in a selection bias in the empirical estimates hence compromising the validity of our causal analysis. Kuntz et al. (2019) address this issue by introducing distance-based instrumental variables. However, we do not need to revert to this approach as this source of endogeneity does not exist in our data. Each hospital in our data set has a *catchment area*, that is, psychiatry patients living in a predetermined geographical area cannot get admitted to hospitals other than the one assigned to that area. If patients refer to a different hospital, they will be transferred to the one assigned to their living area. This prevents hospitals from cherry-picking among patients. So, we do not develop IVs for hospitals.

[5] Some references such as Wooldridge (2010) suggest introducing IV for the squared term of the endogenous variable as well. In a robustness check, we incorporated that suggestion and obtained similar results. The results are available upon request. Moreover, Wooldridge (2015) concludes that it is sufficient to include IV for only the linear terms as the residuals from the first stage adjust for the endogeneity of the quadratic terms.

Figure 6 Predicting log(Ward LOS) by log(ED LOS).



5.5 Full Model Results

Table 3 reports the estimation results of the simultaneous equations from the endogeneity-corrected clustered-error probit model in equations (7)–(8). The second column of Table 3 shows the effects on the risk of readmission, and the third column illustrates the results for the log of ward LOS. From the second column, we observe that the patient volume has no significant effect on the risk of readmission directly, regardless of patient characteristics, and from the third column, patient history has no moderation effect on the ward LOS. Therefore, a higher patient volume reduces the ward LOS for the low resource-intensive patients ($\eta_1 = -0.081$, $p < 0.05$), and its effect becomes more substantial for the high resource-intensive patients ($\eta_1 + \eta_2 = -0.118$, $p < 0.01$). We observe that the new patients in the same diagnosis class who are low resource-intensive have 7.8% shorter average ward LOS in hospitals with one unit increase in patient volume ($(\exp^{-0.081} - 1) \times 100 = -7.8\%$, $p < 0.05$). Moreover, this effect intensifies for high resource-intensive patients by 3.3%. So we do not reject Hypothesis 1b. It is evident from the second column that an increase in the ward LOS reduces the risk of readmission. Hence, we conclude that patient volume indirectly increases the risk of readmission by lowering the ward LOS. We conclude that Hypothesis 1a is supported.

We observe that hospital focus does not significantly affect the risk of readmission for low resource-intensive patients. However, it increases the risk of readmission for high resource-intensive patients ($\beta_5 = 0.117$, $p < 0.01$). On the other hand, hospital focus has no significant effect on the ward LOS of low resource-intensive patients while significantly increasing the ward LOS of high resource-intensive patients ($\eta_5 = 0.085$, $p < 0.05$). We observe that high resource-intensive and new patients in the same diagnosis class have 10.3% longer average ward LOS in hospitals with one unit increase in hospital focus ($(\exp^{\eta_4+\eta_5=0.085+0.013} - 1) \times 100 = 10.3\%$, $p < 0.05$). This evidence supports Hypothesis 2b, so we do not reject this hypothesis. Therefore, hospital focus indirectly reduces the risk of readmission for high resource-intensive patients by increasing their ward LOS. To this end, the direct and indirect effects of hospital focus on high resource-intensive patients contradict. We compute the value of the mediation effect of ward LOS by multiplying the corresponding coefficients from the two equations as follows: $(\alpha_1 \times (\eta_4 + \eta_5) + \alpha_2 \times (\eta_4 + \eta_5)^2 = -0.427 \times 0.098 + (-0.011) \times 0.098^2 = -0.042$, $p < 0.1$. We now compare these two effects:

Table 3 The Indirect Effects of Hospital Characteristics on Risk of Readmission Through Ward LOS with Endogeneity-corrected IV.

	Dependent Variable	
	Readmission Risk	log(Ward LOS)
Patient Volume	-0.039 (0.031)	-0.081^{**} (0.039)
Patient Volume × HRI Patient	-0.023 (0.027)	-0.037^{*} (0.022)
Patient Volume × Revisiting Patient	0.020 (0.021)	0.017 (0.032)
Hospital Focus	-0.000 (0.028)	0.013 (0.034)
Hospital Focus × HRI Patient	0.117^{***} (0.036)	0.085^{**} (0.034)
Hospital Focus × Revisiting Patient	-0.010 (0.031)	-0.036 (0.025)
log(Ward LOS)	-0.427^{***} (0.120)	
log(Ward LOS)^2	-0.011^{***} (0.004)	
log(ED LOS)		-0.239^{***} (0.036)
log(ED LOS)^2		0.050^{***} (0.008)
Constant	-1.488^{***} (0.238)	0.222 (0.163)
ρ_{los_rr} (eq. (7) & eq. (8))		0.634^{***} (0.203)
Observations	14956	14956

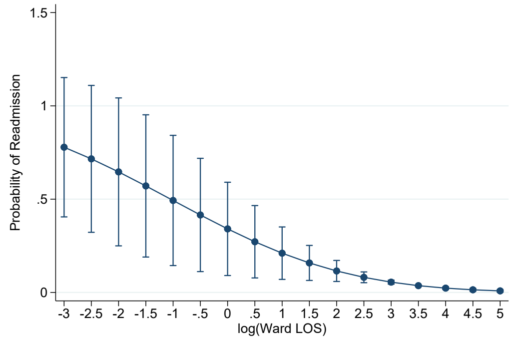
Standard errors are given in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$-0.042 + 0.117 = 0.075$, $p = 0.14$. Although the mediation effect attenuates the significance and magnitude of hospital focus' effect on the risk of readmission for high resource-intensive patients, this characteristic is still associated positively with the risk of readmission. However, note that the comparing value (0.075) is not significant (p-value=0.14). We conclude that Hypothesis 2a is supported, so we do not reject it.

Table 3 shows that the impact of ward LOS on the risk of readmission is significant and nonlinear. Both coefficients of the linear and squared terms of the ward LOS are strongly significant ($\alpha_1 = -0.427$ and $\alpha_2 = -0.011$, $p < 0.01$), indicating higher ward LOS causes a lower risk of readmission and their relationship is nonlinear. Figure 7 shows the predicted risk of readmission calculated by the average marginal effects of $\log(WardLOS)$ on the risk of readmission. The curvilinear shape of the figure indicates higher ward LOS causes a lower risk of readmission in a nonlinear way.

Figure 7 Predicted risk of readmission by Ward LOS from the IV-probit model in equations (7)–(8).



Moreover, we observe from Table 3 that the correlation coefficient of equations (7)–(8) for $\log(WardLOS)$ and *ReadmissionRisk* is significantly positive ($\rho_{los\_rr} = 0.634$). This observation supports the existence of endogeneity in our empirical model that is corrected by using an IV, as discussed in Section 5.4. Interestingly, after this correction, the left segment depicted in Figure 5 no longer exists, and the concave form of the right segment is preserved.

6 Robustness and Limitation of the Results

This section conducts a series of robustness checks on our model's features including alternative instrumental variables, the time to readmit a patient, hospital fixed effects, and dichotomized hospital characteristics.

6.1 Alternative IVs for Ward LOS

We conduct two robustness checks on the choice of instrumental variables for the ward LOS.

6.1.1 ED Boarding Time.

Longer ED boarding time is associated with higher ward LOS. In our data, the two variables have a positive correlation of approximately 0.20. On the other hand, ED boarding time is not affected by a patient's condition's severity as it is an operational factor depending on the occupancy of the inpatient care units and the availability of hospital staff to proceed with the admission paperwork. Moreover, no association between ED boarding time and risk of readmission has been reported in the medical literature on psychiatric readmissions; see Donisi et al. (2016a) for a review. These properties make the ED boarding time a plausible choice as an IV for ward LOS. However, around 10% of the ED boarding time values in our data set are missing or are negative values. We address this issue by imputing the problematic records with the average ED boarding times of other psychiatry patients. The details are in the appendix (Section EC.8.1). We then use the ED boarding time as as alternate IV for the ward LOS as a robustness check. The results are in Table EC.5 in the appendix and show no departure from Table 3 results.

Although imputation is commonly used to address the issue of missing variable values, we do not use the ED boarding time as the IV in our main empirical analysis to avoid introducing potential measurement errors to the model. Instead, we use it as an alternate IV in our robustness check.

6.1.2 Average ED LOS of Other Patients.

Our original model uses a patient's ED LOS as an instrumental variable for ward LOS. A plausible alternative is to use the average ED LOS of other patients present in the same ED on the same day as the focal patient. This variable does not correlate with the severity of the patient's unobserved condition, yet it does correlate with the ED LOS of the focal patient (correlation is positive and approximately 61%). The regression results with this IV are in Table EC.6 in the appendix. The results do not differ significantly from the original results and so our results are robust to this IV as well.

6.2 Readmission Periods

Our analysis focuses on 30-day readmissions which is a widely used time frame in the literature. However, we consider 15-, 60- and 90-day periods as a robustness check. Each time frame can capture certain types of clinical and operational problems such that more extended periods tend to magnify the effects of clinical problems and attenuate operational issues. We observe from Table EC.7 in the appendix that the results of our original model are robust.

6.3 Dichotomized Hospital Characteristics

We have incorporated hospital characteristics as continuous variables in our original model. As a robustness check, we replace these variables with dichotomous regressors. The dichotomization details are in Equations (EC.9)–(EC.10) in the appendix. Table EC.8 contains the results of replacing the continuous variables with their dichotomized counterparts. We observe that the impact of patient volume on the ward LOS disappears for the low resource-intensive patients while it becomes more substantial for high resource-intensive patients, the same way as in the original model. Moreover, hospital focus directly reduces the risk of readmission and ward LOS for low resource-intensive patients, while its effects for high resource-intensive patients are identical to the original model. Besides these few discrepancies, the estimates are similar to the original model. Thus, our model is robust to the specification of the main dependent variables.

6.4 Hospital Mixed-Effects

Our model so far includes hospital fixed effects. Hospitals' contextual unobserved heterogeneity can be captured by mixed-effect models, that is, a mix of random and fixed effects. We believe adding random (or in general, mixed) effects of hospitals is not justified in our study because the hospitals are not selected randomly. Nonetheless, as a robustness check, we incorporate hospital random effects by adding random intercepts to the model using the user-written command `cmp` in STATA 17. The results are in Table EC.9. We observe that the values and signs of the hospital characteristics are the same as those given in Table 3, except that the patient volume directly reduces the risk of readmission. We conclude that our results are robust to the use of hospital random (or mixed) effects.

6.5 Regional Characteristics

Socioeconomic factors can influence the risk of readmission for patients with mental disorders. To analyze this possibility, we include controls for patient demographics, patient characteristics, and hospital fixed effects in our study. Hospital fixed effects account for all time-invariant differences across hospitals. Nonetheless, unobserved regional heterogeneity may still affect our results. To address this issue, we include regional characteristics in our model as an additional robustness check. The results are in Table EC.10. We observe that the values and signs of the hospital characteristics remain consistent with those in Table 3, with the exception that higher patient volume directly reduces the risk of readmission. Our results are then robust to the inclusion of regional characteristics.

6.6 Link Function

We use probit as the link function to capture the binary outcome of whether the patient is readmitted in a 30-day time period. Other link functions such as logit and linear probability model (LPM) may also be plausible choices. We cannot implement the logit model given our choice of instrumental variables because of technical difficulties. So, we only consider the LPM here. All variables across different models have similar coefficients in sign and significance level.[6]

6.7 Fewer Diagnosis Classes

Table EC.1 shows the description and frequency of diagnosis codes. We grouped these codes based on their similarities in a handful number of classes. Nonetheless, there are still classes with relatively low number of observations. So as a robustness check, we remove all classes with less than 20 observations and rerun our analyses. We observe no deviations in our results.

6.8 Subsample Analysis

By Table EC.1, the most frequent diagnosis classes relevant to mental care are “F20-F29”, “F30-F39”, and “F40-F48”. We test our hypotheses on these classes by analyzing the original model on each subsample separately. We show the results in Table EC.11 and provide a thorough discussion in Section EC.13 of the appendix. The results from our original model are robust and reliable.

[6] The results are available upon request.

7 Discussion

We study the effects of hospital operational characteristics on the risk of readmission of psychiatric patients whose chronic disorders are difficult to treat in acute care. Although there exist other works in the literature that study hospital characteristics and their impact on different patient outcomes, none considers psychiatric patients and the unique context of mental healthcare. So whether and how hospital characteristics impact psychiatric care outcomes remain open questions. To address this gap, we propose a mediation framework in which these characteristics affect the risk of readmission through two channels: a direct channel and an indirect channel through ward LOS. The latter is a crucial part of this study, as we observe that the average ward LOS of psychiatric patients is higher than that of other patients with non-mental disorders. Thus, our framework suggests that even if hospital characteristics do not affect the patient outcomes directly, they still affect the ward LOS, and then ward LOS affects the risk of readmission. We disentangle these effects and provide a more detailed map of how hospital operations influence the quality of care that psychiatric patients receive. Our partial model—without the ward LOS—reveals weak evidence for the zero-order effects of the hospital operational characteristics on the risk of readmission. However, by adding the ward LOS to the model, we find strong evidence for the impact of hospital characteristics on readmission risk through LOS.

7.1 A Unique Patient Population

At the outset of this paper, we highlighted the differentiating characteristics of patients with mental health conditions in order to point out the need for focusing on this patient group. Empirical findings concerning other patient groups, such as those admitted to intensive care units or cardiology wards, cannot be generalized to psychiatry patients. These unique characteristics are also reflected in our data set. For example, we had emphasized the significance of pre-admission and post-discharge care for the psychiatry patients. More than 25% of the psychiatry inpatients, in our data, were discharged to nursing homes and long-term care facilities. The limited bed availability at these facilities, however, causes the patients with mental health conditions boarding in psychiatry inpatient wards, directly contributing to their extended LOS. In our data, 50% of the patients spend more than a week in the hospital, with an average length of stay of 31 days. Considering the $4,503 daily average cost of staying in a Canadian psychiatry inpatient unit[7], the hospitalization of each patient in this sub-group leads to an average expenditure of $139,500. This underscores the importance of focusing on psychiatric patients in our research.

Due to the unique nature of mental health disorders -–including (i) the treatment complexity, requiring long-term management to prevent relapse, (ii) the significant impact of social determinants, and (iii) pivotal role of community-based care and support—- psychiatric patients' reasons for hospital admissions and readmissions can differ significantly from those with other medical conditions. Our findings suggest that

[7] `https://www.jgh.ca/about-us/fees-for-medical-services/`

the extant empirical findings regarding different medical conditions cannot be generalized to the psychiatric patient population. A solid understanding of the differentiating characteristics of mental health care is crucial for developing targeted interventions to reduce readmission rates and improve the quality of care.

Psychiatry patients admitted to hospitals with a *high focus* on mental health care typically have access to multidisciplinary teams and receive more comprehensive treatment, which may include psychiatric evaluations, adjustments to medication, and psychotherapy sessions. At the time of discharge, these hospitals often coordinate with community-based services, and facilitate outpatient follow-up visits. To ensure that patients are fully stabilized, and a suitable discharge plan is prepared, the LOS could be longer. This could reduce the risk of readmission due to premature discharge.

7.2 Positioning of Our Findings

There is no consensus among researchers regarding the definitions of several metrics. For example, Birkmeyer et al. (2002) used Medicare claims to study the surgical mortality rate associated with cardiovascular procedures and cancer resections. They defined hospital volume as the total number of procedures performed annually at the procedure level. In contrast, we define patient volume at the patient level. Therefore, in comparing our empirical findings with those of other papers, it is crucial to dig deeper into how the metrics are defined. In the remainder of this section, we provide an assessment of our findings in the context of the extant literature. Perhaps the most relevant paper to ours is Kc and Terwiesch (2011). The authors studied the effect of hospital focus on two patient outcomes: LOS and mortality rate. They showed that *a higher focus would lead to a shorter LOS* which contradicts the findings we report in this paper. This discrepancy is, arguably, due to the difference among the roles of a hospital stay in psychiatric versus non-psychiatric care settings. Given that Kc and Terwiesch (2011) is focused on a dataset of *cardiac patients*, it is understandable that their results would not apply to patients with mental health conditions. From a methodology perspective, they studied LOS and mortality rate via two separate regression equations, while our study analyzes LOS and readmission risk in an integrated mediation framework.

Another relevant study is Bartel et al. (2020) reporting that an increase in LOS is associated with a decrease in 30-day mortality rates. The authors, however, stated that hospital operational characteristics were not included in their analysis. Perhaps more importantly, they did not consider LOS as a patient outcome. In this paper, we consider LOS as a *mediator* to depict how it affects the relationship between hospital operational characteristics and quality of care. Recent literature on mediation analysis (see e.g., Hayes 2022) emphasizes that the "step method" is neither valid nor useful. In other words, the absence of a total (zero-order) effect should not stop researchers from analyzing the mediation effects of variables. We use this new approach in our analysis to provide evidence for the complex effects of the ward LOS as the mediator on the relationship between hospital operations and patient readmission risk.

7.3 Methodological Issues

It is common practice to control for hospitals' contextual discrepancies by adding fixed or random effects to an empirical model according to the sample's characteristics. A random-effects model is suitable if the data contains records of hospitals sampled randomly. On the other hand, if hospitals are included in the sample data set non-randomly, as in our case, a fixed-effects model is more appropriate. Nevertheless, using fixed-effects can lead to the problem of incidental parameter bias because of the limited number of hospitals in our data set. Thus, we caution against the generalizability of our findings beyond the Canadian mental health system as we cannot claim our data set is representative of all types of hospitals. Our analysis controls for fixed-effects of hospitals, diagnosis classes, chief complaints, and years to account for heterogeneity across patients, locations, and times. Moreover, we cluster the errors within hospital-diagnosis levels to account for the dependency of records in each diagnosis class at each hospital.

We introduce the patient's resource usage in the ED and ED visit history as the potential moderators of the effects of hospital characteristics on the risk of readmission. We observe that the effects of hospital characteristics on the risk of readmission and the ward LOS do not vary significantly between new patients and those revisiting the ED. This implies that patient ED visit history does not moderate the effects of hospital operational characteristics on patient outcomes. Note that patients revisiting the ED have a significantly lower ward LOS and higher risk of readmission than new patients. In other words, revisiting patients are more susceptible to return to the hospital, regardless of the type of hospital where they are admitted. Overall, of the two patient characteristics we include in our model, the effects of hospital characteristics on patient outcomes are moderated only by the intensity of the patient's resource usage in the ED.

7.4 Policy Insights

Our results have important implications for hospital administrators, care providers as well as policy makers. We show that LOS impacts the relationship between hospital characteristics and readmission rates. Therefore, there is a need for clear standards and metrics for LOS at all three levels mentioned above. Our findings also suggest that measuring resource usage intensity in the ED can be an effective means to estimate the acuity level of psychiatric patients. This metric can be considered by physicians dealing with trade-offs while making patient discharge decisions or by hospital administrators for capacity and resource planning.

We observe that patients requiring high levels of resources benefit significantly from receiving care at focused hospitals. Policymakers should consider implementing policies and initiatives that support the development and implementation of regional networks for mental health services, which include (strategically located) focused hospitals. Such networks have been successful in the context of stroke care and trauma care. They enable transferring high resource intense patients to focused hospitals following their assessment and care in a general hospital ED. Among the alternative policies are financial incentives for inter-hospital transfers, remote patient care systems, and guidelines for patient transfers to different types of hospitals within regional networks. To the extent that these policies are effective, the policymakers can improve patient outcomes, reduce hospital readmissions, and improve care coordination.

The integration of mental health services with community-based care services –including primary care– is a potentially fruitful next step. Collaborative care models and care coordination programs have been shown to be effective in non-psychiatric care settings. This integration is essential to ensure a smooth transition of care at the time of hospital discharge.

8 Concluding Remarks

In this paper, hospital characteristics are based on patient-volume measures. Therefore, the psychiatry patients housed off-service (i.e., in other inpatient wards) could jeopardize the validity of our insights. Nevertheless, less than 10% of the patients are off-service in the hospital that has the largest number of psychiatry patients among the 25 hospitals in our data set. Also, patients without mental health conditions are almost never housed in the psychiatry inpatient wards. Therefore, our analyses pertaining to the accumulation of expertise and experience that can benefit patient outcomes are on solid ground.

There are several avenues for further research. First, the relevant hospital characteristics go beyond the two we study in this paper. In particular, the incorporation of the demographics and socioeconomic status of the patient population in the hospital's catchment area could further improve our understanding of the readmission phenomenon. Second, the clinical notes taken by the physicians during the patient's hospital stay include a wealth of information that could be included in the analysis if one takes advantage of the latest developments in natural language processing. Finally, an integrated study of the mental healthcare ecosystem including EDs, hospitals, out-patient clinics, community-based care, and home-care would be a significant step towards improving the health outcomes of psychiatry patients.

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E-Companion for The Impact of Hospital Characteristics on Psychiatry Readmissions: A Mediation Framework

EC.1 Risk-adjusted Standardized Risk of Readmission

We use equation (9) and provide more details on the calculation of the risk-adjusted readmission rate:

$$r_h = \frac{\hat{Y}_h}{\tilde{Y}_h}\bar{y}, \tag{EC.1}$$

in which,

$$\hat{Y}_h = \frac{1}{N_h}\sum_{i=1}^{N_h}\Phi(\hat{\alpha}_h + \boldsymbol{X}'_{ih}\boldsymbol{\beta}), \tag{EC.2}$$

$$\tilde{Y}_h = \frac{1}{N_h}\sum_{i=1}^{N_h}\Phi(\boldsymbol{X}'_{ih}\boldsymbol{\beta}), \tag{EC.3}$$

where Φ is the cumulative density function of the standard normal distribution.

To calculate the risk-adjusted readmission rate for hospital h, i.e., r_h, equation (EC.1) divides the predicted readmission rate for hospital h ($\hat{Y}_h$ in equation (EC.2)) by the expected readmission rate for hospital h ($\tilde{Y}_h$ in equation (EC.3)). Here, $\bar{y}$ is the observed average readmission rate from our data. Also, $\tilde{Y}_h$ is the average predicted readmission probability across all hospitals using the probit model. The calculation of $\hat{Y}_h$ is similar except for a mixed-effect term (i.e., $\hat{\alpha}_h$) that captures the structural differences between hospitals. Therefore, by dividing $\hat{Y}$ by $\tilde{Y}$, we normalize the readmission risk and can compare different hospitals in terms of their normalized readmission rates.

EC.2 Ward LOS

We draw the histogram and QQ-plot of the log of the ward LOS to illustrate why we log-transform this variable in our empirical model. Figures EC.1-EC.2 shows these two plots.

Figure EC.1 Histogram of log(Ward LOS)

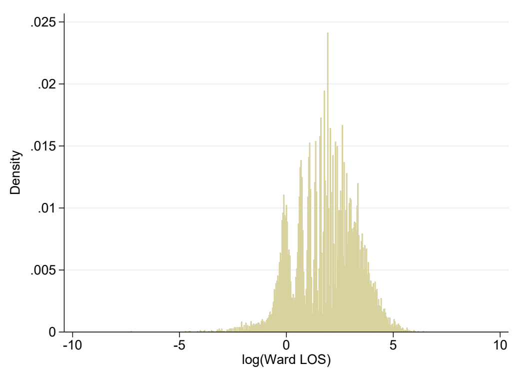
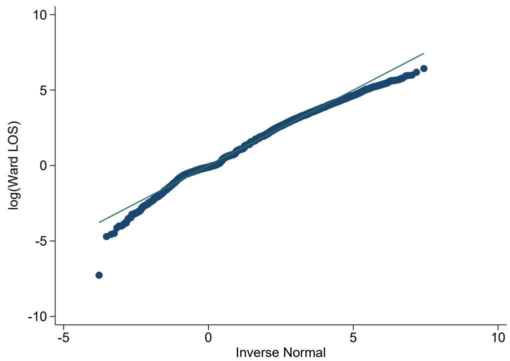


Figure EC.2 QQ-plot of log(Ward LOS)



EC.3 Diagnosis Codes

We create the variable *DiagnosisICD*10*Class* in two steps. First, we create a variable *DiagnosisICD*10*Code* to categorize the ICD codes at one level and then implement further categorization to create *DiagnosisICD*10*Class*. We categorize non-psychiatric disorders into one broad category ('S00-T88' which includes injury, poisoning, and others due to external causes). We apply a finer categorization when dealing with diagnoses that are psychiatric in nature. For instance, all records with diagnostic codes "F01" (vascular dementia), "F01.50" (vascular dementia without behavioral disturbance), "F06.3" (mood disorder due to known physiological condition), and "F09" (unspecified mental disorder due to a known physiological condition) are grouped as "F01-F09" (mental disorders due to known physiological conditions). Table EC.1 shows the name, description and frequency of these categories in our data set. The variable *DiagnosisICD*10*Code* still contains numerous categories which we aggregate into fewer diagnosis classes to build the variable *DiagnosisICD*10*Class* distinguishing between the main mental disorders and other diagnoses that are not our main concern based on the feedback of the psychiatric expert involved in our study. This variable classifies the diagnosis codes into classes "F10-F19" "F20-F29", "F30-F39", "F40-F48", "F60-F69", lumps other psychiatric codes as "Others (Psych)", and treats the rest of them as "Others."

EC.4 Chief Complaints

The topics of chief complaints are reported in Table EC.2. The first and second columns of the table show the absolute and relative frequency of each topic, respectively. Each topic is represented by a set of the most relevant and frequent keywords which are given in the last column. The keywords here are stemmed and lemmatized. Further, we use the original data set encompassing all 28 hospitals (with 18,594 admission records) to implement the chief complaint analysis.

Table EC.1 The Diagnosis Classes Created Based on the ICD-10-CM Codes.

Diagnosis Codes	Description	Frequency
A00-B99	Certain infectious and parasitic diseases	6
C00-D49	Neoplasms	3
D50-D89	Diseases of the blood and blood-forming organs and certain disorders involving the immune mechanism	2
E00-E89	Endocrine, nutritional and metabolic diseases	27
F01-F09	Mental disorders due to known physiological conditions	125
F10-F19	Mental and behavioral disorders due to psychoactive substance use	383
F20-F29	Schizophrenia, schizotypal, delusional, and other non-mood psychotic disorders	3,729
F30-F39	Mood [affective] disorders	4,369
F40-F48	Anxiety, dissociative, stress-related, somatoform and other nonpsychotic mental disorders	1,133
F50-F59	Behavioral syndromes associated with physiological disturbances and physical factors	11
F60-F69	Disorders of adult personality and behavior	676
F70-F79	Intellectual disabilities	8
F90-F98	Behavioral and emotional disorders with onset usually occurring in childhood and adolescence	8
F99-F99	Unspecified mental disorder	1,079
G00-G99	Diseases of the nervous system	19
H00-H95	Diseases of the eye and adnexa, and ear and mastoid process	2
I00-I99	Diseases of the circulatory system	25
J00-J99	Diseases of the respiratory system	22
K00-K95	Diseases of the digestive system	10
L00-L99	Diseases of the skin and subcutaneous tissue	4
M00-M99	Diseases of the musculoskeletal system and connective tissue	133
N00-N99	Diseases of the genitourinary system	8
O00-O9A	Pregnancy, childbirth and the puerperium	1
R00-R99	Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified	1,829
S00-T88	Injury, poisoning and certain other consequences of external causes	896
V00-Y99	External causes of morbidity	1
Z00-Z99	Factors influencing health status and contact with health services	243

EC.5 Variables

EC.5.1 Resource Usage Intensity

The variable *Consult* shows the number of non-psychiatric consultations, i.e., counts the number of consultations the patient received from specialists rather than psychiatrists during her stay in the ED. The *LabTest* is the number of laboratory tests performed for the patient during her stay in the ED. Finally, the *RadioTest* is the number of radiology imaging done for the patient during her stay in the ED. These variables are non-negative integer quantities. We dichotomize them so a patient has either a high or low value.

Table EC.2 The Topics of Chief Complaints Extracted from the LDA Topic Model.

Counts	Rel. Freq.	Topic Keywords (in French)
3525	0.1896	suicidair, ide, plan, prci, concret, projet, noir, ideat, prec, suicidal
3068	0.165	dpression, intox, automutil, tentat, suicid, douleur, psychiatr, substanc, troubl, valuat
2814	0.1513	comport, bizarr, hallucin, confus, drogu, toxiqu, usag, urgenc, spcial, mdecin
2317	0.1246	anxit, situationnel, cris, inquitud, patient, fac, scur, vertig, fivr, saut
2268	0.122	cris, anxit, situationnel, homicidair, violent, palpit, irrguli, poul, fill, emploi
1747	0.094	sant, mental, psychosocial, hallucin, agit, illus, fuit, actif, dang, insomn
1734	0.0933	suicidair, ide, rfrenc, consult, mineur, gnral, problm, plaint, faibless, social
1121	0.0603	risqu, collabor, modr, calm, symptm, prendr, dpressif, tat, vouloir, dlir

The variable $HighConsult_{id}$ is a dichotomization of $Consult$ at the diagnosis class level via a median split across patients for each disease category d as follows.

$$HighConsult_{id} = \begin{cases} 1, & \text{if } Consult_{id} \geq \text{median}\{Consult_{i'd} | i' \in \{1, \ldots, N\}, \\ & Consult_{i'd} > 0\}; \\ 0, & \text{otherwise.} \end{cases} \tag{EC.4}$$

The binary variable $HighConsult_{id}$ splits the patients into high- and low-usage of non-psychiatric consultations for the fixed disease category d.

The variable $HighLab_{id}$ is a dichotomization of $LabTest$ at the diagnosis class level via a median split across patients for each diagnosis class d as follows:

$$HighLab_{id} = \begin{cases} 1, & \text{if } LabTest_{id} \geq \text{median}\{LabTest_{i'd} | i' \in \{1, \ldots, N\}, LabTest_{i'd} > 0\}; \\ 0, & \text{otherwise.} \end{cases} \tag{EC.5}$$

This binary variable $HighLab_{id}$ splits the patients into high- and low-usage patients in terms of lab tests for the fixed disease category d.

The variable $HighRadio_{id}$ is a dichotomization of $RadioTest$ at the diagnosis class level via a median split across patients for each diagnosis class d as follows.

$$HighRadio_{id} = \begin{cases} 1, & \text{if } RadioTest_{id} \geq \text{median}\{RadioTest_{i'd} | i' \in \{1, \ldots, N\}, RadioTest_{i'd} > 0\}; \\ 0, & \text{otherwise.} \end{cases} \tag{EC.6}$$

The binary variable $HighRadio_{id}$ splits the patients into high- and low-usage patients in terms of radiology imaging for the fixed disease category d.

Now, we consider the three variables $HighConsult$, $HighLab$, and $HighRadio$ to develop a measure for patients' resource usage intensity. This two-level measure differentiates patients based on their conditions as high resource-intensive (HRI) or low resource-intensive (LRI).

$$RSC\_INT_{id} = \begin{cases} \text{HRI}, & \text{if } HighConsult_{id} = 1 \text{ or } HighLab_{id} = 1 \text{ or } HighRadio_{id} = 1; \\ \text{LRI}, & \text{otherwise.} \end{cases} \tag{EC.7}$$

This binary variable RSC_INT_{id} splits patients in the fixed diagnosis class d. As a robustness check, we also developed a three-level resource usage intensity measure (HRI, benchmark, LRI). This approach did not yield additional insights or alter our results.[1]

EC.5.2 Patient Severity.

Patient severity is a dichotomous measure to categorize a patient's condition after triage as severe or otherwise. The triage score has five levels: (1) life-threatening ('Resuscitation'), (2) potential threat to life or function ('Emergent'), (3) severe conditions requiring emergency intervention ('Urgent'), and levels (4) and (5) for non-urgent cases. According to the Canadian triage and acuity scale (CTAS), 98% of level 1 patients need to be treated immediately without any delay, 95% of level 2 patients should be visited within 15 minutes, and 90% of level 3 patients should be seen within 30 minutes. These three levels are 'priority'. We dichotomize the five-level triage scores to obtain a binary indicator of a patient's condition's severity.

$$Severity_i = \begin{cases} \text{Severe}, & \text{if TriageLevel} \in \{\text{Resuscitation, Emergent, Urgent}\}; \\ \text{Not-severe}, & \text{if TriageLevel} \in \{\text{NotUrgent}\}. \end{cases} \tag{EC.8}$$

The two-level discrete variable $Severity_i$ splits the patients into severe and not-severe patients.[2]

EC.5.3 Control Variables

A short description of the control variables in our empirical model is in Table EC.3.

EC.6 Correlation

The correlation matrix of the independent variables is in Table EC.4.

[1] The results are available from the authors upon request.

[2] For robustness, we also use the original five-level triage scores to capture severity. The results are similar and so not reported in the paper.

Table EC.3 Descriptions of Variables.

Variables	Description
Age	patient's age
Gender	whether patient is male (1) or female (0)
TriageLevel	patient's severity (resuscitation, emergent, urgent, not urgent)
ArrivalMode	patient's arrival type (Ambulance, Police, or Walk-in)
EDLOS	length-of-stay of patient in the ED
WardLOS	length-of-stay of patient in hospital's inpatient care unit
NUM_Visits	number of times patient had been at the ED as of the index visit
Consult	number of non-psychiatric consultation patient received in the ED
LabTest	number of laboratory tests patient had in the ED
RadioTest	number of radiology imaging patient had in the ED
*DiagnosisICD*10*Code*	patient's diagnosis category based on ICD-10-CM coding system

EC.7 IV Analysis

We check a few candidates that can potentially satisfy the conditions for an instrumental variable. Our first IV is the peak ward occupancy during the period a patient is hospitalized in the inpatient care unit. We contemplate that ward occupancy can affect the amount of time a patient is hospitalized while it does not impact the risk of readmission. Kc and Terwiesch (2012) use a similar IV to estimate bounceback to ICU for cardiac patients based on the occupancy level at the time of patient's discharge. Ward occupancy can be measured at several time stamps, such as at the time of admission or discharge, or the average or maximum occupancy levels during a patient's hospital stay. Each of these measures can affect the patient outcome differently. To this end, we develop several versions of the measure: (1) *WardUtilMax* denotes the maximum occupancy (utilization) level of the inpatient care unit in which the patient was hospitalized during her stay; (2) *WardUtilAdmission* denotes the occupancy level of the inpatient care unit when the patient is admitted; (3) *WardUtilDischarge* denotes the occupancy level of the inpatient care unit when the patient is discharged; (4) *WardUtilLag*1 refers to a similar quantity as (3), but instead, is measured one day prior to the patient's discharge; (5) *WardUtilMean* represents the average occupancy (utilization) rate of the inpatient care unit where the patient is hospitalized during her stay. But we believe the peak occupancy level is the best choice because while other measures (for example, occupancy at the time of admission) illustrate the ward's situation in a one-day time frame, the peak occupancy level accounts for the whole period a patient is hospitalized. Moreover, the peak occupancy is monotonically non-decreasing over the stay of a patient and so captures the fact that the effect of a high occupancy level on the quality of care a patient receives during her hospitalization cannot be undone (Kuntz et al. 2015). That is to say, the high occupancy level on a day affects the quality of care the patient receives over the remaining days of her hospitalization.

Kuntz et al. (2015) show that the impact of peak occupancy level on the ward LOS has a tipping point when modeled using linear splines with one dot. They find a positive association between occupancy level and ward LOS in hospitals that becomes stronger beyond a threshold. Berry Jaeker and Tucker (2017)

Table EC.4 Cross-correlation Table.

Num	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
0	Hospital ids	0.357	-0.131																	
1	PatientVol	1.000																		
2	HospitalFoc	0.358	1.000																	
3	ResInstensPt	-0.057	0.067	1.000																
4	HighVisitNumIdx	-0.035	0.002	-0.003	1.000															
5	RegionEmployment	0.039	0.013	-0.027	-0.032	1.000														
6	PopDensity	-0.064	0.160	0.359	-0.064	0.008	1.000													
7	Age	-0.069	-0.063	0.124	0.028	-0.006	0.059	1.000												
8	Age^2	-0.061	-0.057	0.140	0.033	-0.000	0.055	0.978	1.000											
9	Gender	-0.001	0.005	-0.027	-0.045	-0.019	-0.004	-0.073	-0.086	1.000										
10	SeverePatient	0.072	0.026	-0.052	-0.038	0.099	0.007	-0.109	-0.119	0.023	1.000									
11	DischargeWeekday	-0.019	-0.006	0.080	-0.016	-0.012	0.083	0.035	0.035	-0.017	-0.029	1.000								
12	ArrivalMode	-0.031	-0.035	-0.062	0.016	-0.017	-0.040	-0.078	-0.072	-0.057	-0.091	0.028	1.000							
13	DestinationType	0.065	0.008	0.036	0.009	0.095	-0.166	0.021	0.047	-0.011	-0.032	0.026	-0.030	1.000						
14	ChiefComplaint	-0.039	0.055	0.068	0.029	0.027	0.010	0.021	0.029	-0.028	-0.151	0.052	0.003	0.057	1.000					
15	DiagnosisClass	0.131	0.212	-0.098	0.060	-0.095	-0.241	-0.018	0.001	-0.044	0.049	-0.086	-0.059	-0.027	0.055	1.000				
16	log(WardLOS)	-0.084	-0.022	0.199	-0.059	0.011	0.277	0.258	0.265	-0.038	-0.137	0.271	0.013	0.068	0.069	-0.238	1.000			
17	$\log(WardLOS)^2$	-0.063	-0.020	0.164	-0.059	0.008	0.281	0.257	0.266	-0.041	-0.123	0.187	-0.021	0.064	0.033	-0.203	0.853	1.000		
18	log(EDLOS)	-0.068	0.103	0.402	-0.012	-0.048	0.401	0.146	0.143	-0.029	-0.011	0.123	-0.076	0.061	0.049	-0.196	0.275	0.242	1.000	
19	$\log(EDLOS)^2$	-0.082	0.103	0.406	-0.020	-0.030	0.449	0.137	0.133	-0.019	-0.019	0.115	-0.082	0.036	0.041	-0.191	0.278	0.255	0.958	1.000

propose a nonlinear association modeled by a spline with two dots representing two tipping points. Their rationale in using the model is that they observed an N-shape association providing support for two effects: a congestion effect and a saturation effect. We check both of these models with our data set. Although we observe a slightly inverted-U-shaped association between ward occupancy and ward LOS, we do not confirm the existence of two tipping points. Instead, we find that the spline model with one tipping point works well for our data.[3]

Kc and Terwiesch (2012) find a negative impact of occupancy on the LOS (i.e., higher occupancy leads to shorter LOS), while Kuntz et al. (2015) and Berry Jaeker and Tucker (2017) report the opposite (i.e., higher occupancy leads to longer LOS). Although the ward occupancy is a plausible IV choice (as it satisfies the relevance and exclusion criteria), the mixed results in the literature and its strong positive association with ward LOS make it an unsuitable choice in our setting. Thus, we check another IV candidate for ward LOS.

EC.8 Alternative IVs

EC.8.1 ED Boarding Time

In our data set, around 10% of the values recorded for the ED boarding time are either missing or negative. For each patient with a problematic ED boarding time value, we impute her record by replacing it with the average ED boarding times of other psychiatry patients who were in the same ED on the same day. If there was no other patient in the ED on the same day, we use records of patients from the closest previous and next days. We then use the ED boarding time as the alternate IV for the ward LOS. Table EC.5 reports the results.

EC.8.2 ED LOS of Other Patients

We calculate an average ED LOS for each patient in our sample by using the ED LOS of other patients who were at the same ED on the same day as the focal patient. For patients who were the only psychiatry visitors of an ED on a specific day (around 33% of patients in our data set), we use the ED LOS of patients who were in the same ED in the nearest previous and following days. We then use the average ED LOS as an alternate IV for the ward LOS. Table EC.6 shows the results.

EC.9 Readmission Periods

Table EC.7 shows the results of the model given in equations (7)–(8) for different readmission periods.

[3] The results with two tipping points are available upon request.

Table EC.5 The Indirect Effects of Hospital Characteristics on Risk of Readmission Through Endogeneity-corrected Ward LOS with ED Boarding Time as IV.

	Dependent Variable	
	Readmission Risk	log(Ward LOS)
Patient Volume	-0.012	-0.080^{**}
	(0.033)	(0.037)
Patient Volume × HRI Patient	-0.012	-0.035
	(0.030)	(0.022)
Patient Volume × Revisiting Patient	0.015	0.017
	(0.025)	(0.032)
Hospital Focus	-0.007	0.011
	(0.030)	(0.032)
Hospital Focus × HRI Patient	0.101^{**}	0.085^{***}
	(0.044)	(0.033)
Hospital Focus × Revisiting Patient	0.004	-0.034
	(0.033)	(0.025)
log(Ward LOS)	-0.089	
	(0.238)	
log(Ward LOS)^2	-0.014^{***}	
	(0.005)	
log(EDBT)		0.005
		(0.008)
log(EDBT)^2		0.013^{***}
		(0.003)
Constant	-1.773^{***}	0.222
	(0.205)	(0.163)
ρ_{los_rr}		0.174
		(0.283)
Observations	14956	14956

Standard errors are given in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

EC.10 Dichotomization of Hospital Characteristics

We dichotomize the variable PtVol_{dh} at the diagnosis class level via a median split across hospitals for each diagnosis class d as follows.

$$\overline{PtVol}_{dh} = \begin{cases} 1, & \text{if PtVol}_{dh} \geq \text{median}\{\text{PtVol}_{dh'} | h' \in \{1,\ldots,H\}, \text{PtVol}_{dh'} > 0\}; \\ 0, & \text{otherwise.} \end{cases} \tag{EC.9}$$

Also, we dichotomize the variable HospFoc_{dh} at the diagnosis class level via a median split across hospitals for each diagnosis class d as follows.

$$\overline{HospFoc}_{dh} = \begin{cases} 1, & \text{if HospFoc}_{dh} \geq \text{median}\{\text{HospFoc}_{dh'} | h' \in \{1,\ldots,H\}, \text{HospFoc}_{dh'} > 0\}; \\ 0, & \text{otherwise.} \end{cases} \tag{EC.10}$$

Table EC.6 The Indirect Effects of Hospital Characteristics on Risk of Readmission Through Endogeneity-corrected Ward LOS with Other Patients' ED LOS as IV

	Dependent Variable	
	Readmission Risk	log(Ward LOS)
Patient Volume	-0.005	-0.083^{**}
	(0.049)	(0.039)
Patient Volume × HRI Patient	-0.009	-0.037^{*}
	(0.033)	(0.022)
Patient Volume × Revisiting Patient	0.014	0.019
	(0.027)	(0.032)
Hospital Focus	-0.008	0.015
	(0.031)	(0.033)
Hospital Focus × HRI Patient	0.095	0.088^{***}
	(0.058)	(0.032)
Hospital Focus × Revisiting Patient	0.007	-0.037
	(0.036)	(0.026)
log(Ward LOS)	-0.009	
	(0.480)	
log(Ward LOS)^2	-0.014^{***}	
	(0.005)	
log(ED LOS of Others)		0.044^{***}
		(0.016)
Constant	-1.795^{***}	-0.048
	(0.203)	(0.163)
ρ_{los_rr}		0.078
		(0.567)
Observations	14956	14956

Standard errors are given in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table EC.8 shows the results of the model given in equations (7)–(8) with dichotomized hospital characteristics.

EC.11 Hospital Mixed Effects

Table EC.9 shows the results of the model given in equations (7)–(8) with hospital mixed effects.

EC.12 Region Characteristics

Table EC.10 shows the results of the mixed effects model given in equations (7)–(8) with region random effects and hospital fixed effects.

Table EC.7 The Estimation Results from Different Readmission Periods on Risk of Readmission.

	15-day	30-day	60-day	90-day
	Dependent Variable: Readmission Risk			
Patient Volume	-0.069^{*}	-0.039	-0.053^{*}	-0.054^{**}
	(0.036)	(0.031)	(0.029)	(0.026)
Patient Volume × HRI Patient	-0.034	-0.023	0.016	0.007
	(0.034)	(0.027)	(0.034)	(0.032)
Patient Volume × Revisiting Patient	-0.004	0.020	0.033	0.022
	(0.024)	(0.021)	(0.025)	(0.023)
Hospital Focus	0.011	-0.000	0.010	0.005
	(0.035)	(0.028)	(0.028)	(0.028)
Hospital Focus × HRI Patient	0.102^{**}	0.116^{***}	0.077	0.113^{**}
	(0.044)	(0.036)	(0.050)	(0.046)
Hospital Focus × Revisiting Patient	0.023	-0.010	-0.032	-0.035
	(0.039)	(0.031)	(0.032)	(0.030)
log(Ward LOS)	-0.425^{***}	-0.427^{***}	-0.312^{**}	-0.298^{*}
	(0.156)	(0.120)	(0.124)	(0.160)
log(Ward LOS)^2	-0.011^{**}	-0.011^{***}	-0.013^{***}	-0.013^{***}
	(0.005)	(0.004)	(0.004)	(0.005)
Constant	-1.836^{***}	-1.488^{***}	-1.458^{***}	-1.353^{***}
	(0.329)	(0.238)	(0.185)	(0.207)
	Dependent Variable: log(Ward LOS)			
Patient Volume	-0.070^{*}	-0.081^{**}	-0.083^{**}	-0.081^{**}
	(0.037)	(0.039)	(0.038)	(0.038)
Patient Volume × HRI Patient	-0.041^{**}	-0.037^{*}	-0.048^{**}	-0.046^{**}
	(0.021)	(0.022)	(0.021)	(0.023)
Patient Volume × Revisiting Patient	0.011	0.017	0.013	-0.001
	(0.033)	(0.032)	(0.031)	(0.034)
Hospital Focus	0.004	0.013	0.016	0.013
	(0.032)	(0.034)	(0.034)	(0.034)
Hospital Focus × HRI Patient	0.087^{***}	0.083^{**}	0.097^{***}	0.111^{***}
	(0.032)	(0.034)	(0.036)	(0.040)
Hospital Focus × Revisiting Patient	-0.031	-0.036	-0.029	-0.021
	(0.024)	(0.025)	(0.028)	(0.029)
log(ED LOS)	-0.227^{***}	-0.239^{***}	-0.242^{***}	-0.235^{***}
	(0.036)	(0.036)	(0.037)	(0.037)
log(ED LOS)^2	0.048^{***}	0.050^{***}	0.052^{***}	0.051^{***}
	(0.008)	(0.008)	(0.008)	(0.008)
Constant	0.248	0.222	0.221	0.216
	(0.164)	(0.163)	(0.168)	(0.172)
Observations	15693	14956	13641	12150

Standard errors are given in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table EC.8 The Effects of Dichotomized Hospital Characteristics on Risk of Readmission Through Ward LOS with Endogeneity-corrected IV.

	Dependent Variable	
	Readmission Risk	log(Ward LOS)
High Patient Volume	0.040	0.077
	(0.062)	(0.056)
High Patient Volume × HRI Patient	−0.155	−0.220***
	(0.100)	(0.069)
High Patient Volume × Revisiting Patient	−0.079	−0.039
	(0.075)	(0.059)
High Hospital Focus	−0.090*	−0.197***
	(0.050)	(0.050)
High Hospital Focus × HRI Patient	0.184**	0.249***
	(0.093)	(0.079)
High Hospital Focus × Revisiting Patient	0.107	0.007
	(0.066)	(0.052)
log(Ward LOS)	−0.420***	
	(0.120)	
log(Ward LOS)^2	−0.011***	
	(0.004)	
log(ED LOS)		−0.235***
		(0.036)
log(ED LOS)^2		0.050***
		(0.008)
Constant	−1.469***	0.264
	(0.246)	(0.163)
ρ_{los_rr}	0.623***	
	(0.201)	
Observations	14959	14959

Standard errors are given in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

EC.13 Subsample Analysis

Table EC.11 shows the results of the model given in equations (7)–(8) for different sub-samples of diagnosis classes on “F20-F29”, “F30-F39”, and “F40-F48”. For subsample “F20-F29”, patient volume and hospital focus do not affect the risk of readmission directly. They do affect the risk of readmission indirectly however by significantly impacting the ward LOS. Patient volume decreases the ward LOS for low resource-intensive and new patients; its effect however disappears for revisiting patients. Therefore, patient volume increases the risk of readmission for new patients with schizophrenia-related illnesses indirectly through ward LOS. Hospital focus increases the ward LOS of patients regardless of their type. This indirectly causes higher

Table EC.9 The Effects of Hospital Characteristics on Risk of Readmission Through Ward LOS with Endogeneity-corrected IV and Random-effects of Hospitals.

	Dependent Variable	
	Readmission Risk	log(Ward LOS)
Patient Volume	-0.031^{**}	-0.084^{*}
	(0.014)	(0.045)
Patient Volume × HRI Patient	-0.004	-0.038
	(0.028)	(0.028)
Patient Volume × Revisiting Patient	0.018	0.018
	(0.019)	(0.034)
Hospital Focus	0.014	0.017
	(0.020)	(0.032)
Hospital Focus × HRI Patient	0.077^{**}	0.082^{*}
	(0.039)	(0.046)
Hospital Focus × Revisiting Patient	0.001	-0.037
	(0.041)	(0.024)
log(Ward LOS)	0.008	
	(0.047)	
log(Ward LOS)^2	-0.014^{***}	
	(0.005)	
log(ED LOS)		-0.236^{***}
		(0.045)
log(ED LOS)^2		0.051^{***}
		(0.011)
Constant	-1.590^{***}	0.924^{***}
	(0.146)	(0.219)
Observations	14956	14956

Standard errors are given in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

hospital focus to have a lower risk of readmission. Thus, our primary results are robust in the subsample "F20-F29".

In subsample "F30-39", we observe similar results for the risk of readmission: there is no direct effect of hospital characteristics. Nonetheless, they have indirect effects on the risk of readmission through the mediation of ward LOS, similar to our original results. So our results are robust in subsample "F30-F39". Subsample "F40-F48" does not contain any significant results. We note two contributing factors to these results: the cohorts are smaller in these subsamples, and the within-group variations decrease in each subsample given the large number of fixed effects in our model (e.g., hospitals, times, and chief complaints).

Higher ward LOS reduces the risk of readmission in subsample "F20-29", while it has no effect in the other two subsamples. The difference between the average ward LOS of these groups can explain this discrepancy. The average ward LOS in subsample "F20-F29" is 24.5 days (with a 95% confidence interval

Table EC.10 Results of The Original Model with Controls for Regions Heterogeneity.

	Dependent Variable	
	Readmission Risk	log(Ward LOS)
Patient Volume	-0.039^{**} (0.019)	-0.081^{***} (0.029)
Patient Volume × HRI Patient	-0.023 (0.034)	-0.037^{*} (0.022)
Patient Volume × Revisiting Patient	0.020 (0.026)	0.017 (0.036)
Hospital Focus	-0.000 (0.026)	0.013 (0.025)
Hospital Focus × HRI Patient	0.116^{**} (0.056)	0.083^{***} (0.032)
Hospital Focus × Revisiting Patient	-0.010 (0.044)	-0.036 (0.023)
log(Ward LOS)	-0.427^{***} (0.071)	
log(Ward LOS)^2	-0.011^{***} (0.004)	
log(ED LOS)		-0.239^{***} (0.031)
log(ED LOS)^2		0.050^{***} (0.007)
Constant	-1.488^{***} (0.031)	0.222 (0.163)
ρ_{los_rr}		0.634^{***} (0.133)
Observations	14956	14956

Standard errors are given in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of [23.4,25.6]) while it is 15.4 days (with a 95% confidence interval of [14.8,16.1]) in subsample "F30-F39," and 10.7 days (with a 95% confidence interval of [9.5,11.8]) in subsample "F40-F48". We point out that our model specification captures the discrepancies between different groups of the population. However, the complexity of the model may cause over-specification when we run it on subsamples, which can explain the insignificance of some of the factors. Overall, the results from our original model are robust and reliable.

Table EC.11 The Effects of Hospital Characteristics on Risk of Readmission Through Ward LOS with Endogeneity-corrected IV for the Most Frequent Sub-samples.

Sub-samples of Diagnosis Classes:	"F20-F29"	"F30-F39"	"F40-F48"
	Dependent Variable: Readmission Risk		
Patient Volume	-0.084	0.125	0.256
	(0.102)	(0.231)	(1.000)
Patient Volume × HRI Patient	-0.023	0.023	-1.124
	(0.038)	(0.066)	(0.737)
Patient Volume × Revisiting Patient	0.052	0.071^{***}	-0.094
	(0.073)	(0.023)	(0.178)
Hospital Focus	0.138	-0.119	0.233
	(0.109)	(0.321)	(0.524)
Hospital Focus × HRI Patient	0.079	-0.007	0.771
	(0.060)	(0.129)	(0.492)
Hospital Focus × Revisiting Patient	-0.049	0.016	0.066
	(0.054)	(0.062)	(0.153)
log(Ward LOS)	-0.681^{***}	-0.002	0.543
	(0.058)	(0.373)	(0.417)
log(Ward LOS)^2	-0.003	-0.010	-0.031
	(0.004)	(0.010)	(0.025)
Constant	-0.017	-1.690^{**}	-3.189^{***}
	(0.286)	(0.779)	(1.006)
	Dependent Variable: log(Ward LOS)		
Patient Volume	-0.214^{*}	-0.021	0.328
	(0.114)	(0.218)	(0.461)
Patient Volume × HRI Patient	-0.058	-0.063^{***}	0.052
	(0.041)	(0.023)	(0.166)
Patient Volume × Revisiting Patient	0.090^{***}	-0.039^{*}	0.186
	(0.032)	(0.020)	(0.147)
Hospital Focus	0.299^{**}	-0.151	0.013
	(0.135)	(0.258)	(0.279)
Hospital Focus × HRI Patient	-0.002	0.092^{*}	-0.341
	(0.047)	(0.054)	(0.243)
Hospital Focus × Revisiting Patient	-0.061	-0.044	-0.158
	(0.044)	(0.031)	(0.145)
log(ED LOS)	-0.272^{***}	-0.319^{***}	-0.225
	(0.061)	(0.060)	(0.222)
log(ED LOS)^2	0.054^{***}	0.063^{***}	0.072
	(0.012)	(0.015)	(0.050)
Constant	1.187^{***}	0.423	0.828
	(0.317)	(0.392)	(0.509)
ρ_{rr_los}	1.087^{***}	0.108	-0.626
	(0.187)	(0.426)	(0.776)
Observations	3787	4414	1137

Standard errors are given in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$