The Effect of Community of Discharge on Length of Stay for Unplanned Hospitalizations: An Indicator of Community Care Integration?

by

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For my parents, Lee and Janet Robinson.

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ABSTRACT

Objective: Adjusted hospital length of stay (LOS), widely used to benchmark hospital efficiency, does not account for community-driven variation. We estimate the extent to which community affects LOS for unplanned hospitalizations, whether this differs by complex needs, and identify communities significantly different from the provincial average.

Methods: The outcome is LOS, adjusted for demographics and disease case-mix. Variation in LOS explained by community of residence is estimated using random intercept regression. Complex needs are defined using Elixhauser and Resource Intensity Weights. Small-area empirical Bayes estimates are calculated and mapped.

Results: Community of residence is associated with adjusted LOS, and its effect differ by complex needs. Of 77 communities, 17 had an adjusted LOS differing from the provincial average.

Conclusion: The community to which patients are discharged is associated with hospital LOS. Research is needed to understand why these communities are associated with longer or shorter adjusted LOS.

LIST OF ABBREVIATIONS USED

ALC	Alternate Level of Care
CI	Confidence Interval
CIHI	Canadian Institute for Health Information
CMG	Case Mix Groups
DAD	Discharge Abstract Database
DRGs	Diagnosis-Related Groups
EBLUPs	Empirical Best Linear Unbiased Predictors
EoL	End-of-Life
FSA	Forward Sortation Area
FY	Fiscal Year
HCP	Health Care Professionals
HDNS	Health Data Nova Scotia
HRM	Halifax Regional Municipality
ICC	Intra Class Correlation Coefficient
ICD	International Classification of Disease
LOS	Length of Stay
LTC	Long-Term Care
MSI	Medical Services Insurance
MSSU	Maritime SPOR SUPPORT Unit
PCCF	Postal Code Conversion File
RIWs	Resource Intensity Weights
SARV	Small Area Rate Variation
SES	Socioeconomic Status

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CHAPTER 1: INTRODUCTION

When patients are not able to be discharged safely to their communities, they are likely to be kept longer in hospital, increasing their length of stay (LOS). This results in individuals remaining in hospital after they are no longer in need of inpatient acute care services. Longer hospital stays are of particular concern as they increase hospital expenditures and contribute to potentially harmful outcomes for patients.[1–3] Longer than necessary LOS result from complex interrelationships between patient-level, hospital-level, and community-level factors, though the community-level factors have been the least studied in the literature.

Health care professionals (HCPs) highlight that when making discharge decisions, it is not only the medical status and care requirements of the patient that are taken into consideration. The community environment to which the patient is discharged is also an important consideration. Through a consultation process organized by the Maritime SPOR SUPPORT Unit (MSSU), HCPs involved in discharge planning shared, from their experiences, that organizing discharge to some communities are more difficult than others. They also described the large role family, a crucial component of community, plays in a safe and timely discharge; where the presence of family members able to act as supports and provide informal care greatly affects their confidence in discharging a patient home. These insights emphasize that longer than medically necessary LOS are impacted by a range of non-medical factors other than the continued need for acute care, community included.

Communities can be viewed as complex adaptive systems of care that enable patients to overcome barriers to discharge.[4] This approach is common in quality improvement frameworks.[5–7] Complex adaptive systems of care encompass formal, informal and health-related supports, resources and services, and their interactions and relationships.[8,9] They house a multitude of formal health services and resources that support patients at discharge to help the transition home.[10–12] Informal supports are also important for the patient in returning to their community. These include the presence of family and friends acting as supports or providing care, and community closeness.[13,14] Other community attributes related to health such as socio-economic distribution, social integration and housing can also impact the ability of an individual to be discharged home.[10] This system of supports, resources and services, and their interactions and relationships can influence the ability of a community to support an individual being discharged home. This system also varies by context and is therefore specific to each community.[4]

This integration, availability, comprehensiveness and quality are likely to be more important for some types of patients than others. Patients with complex needs arguably require more resources and supports, as well as greater integration between them, to be discharged home. The complexity of patients' needs is not only a function of characteristics of the patient themselves but also of the ability of the system of care in meeting the needs of the individual.[15] Co-occurring physical health conditions and the presence of mental illness can complicate someone's care needs and material and social disadvantage can pose substantial barriers to meeting them.[16–18] The interaction of supports, resources, and services in a community would therefore have to be of sufficient character and intensity to overcome barriers required to meet these needs, the complexity of which could vary by community.

Though the role of community in affecting longer than necessary LOS may seem obvious, LOS has typically been used as an institution-centric benchmark hospital efficiency.[19–23] Indicators of these longer than medically necessary LOS, such as alternate level of care (ALC) days and adjusted length of stay, are widely used in Canada to measure hospital performance and are a common target for quality improvement efforts to reduce hospital spending.[24–26] In the Canadian context, the Canadian Institute for Health Information (CIHI), routinely reports average adjusted LOS as a performance measure for hospital.[27] To appropriately target LOS and reduce longer than necessary LOS however, we need to look beyond hospitals to downstream community-level factors that facilitate patient transitions such as those that support recovery and management post discharge. This is supported by work from a team at the University of Calgary. They developed a conceptual framework to describe influences on LOS which includes community level factors.[28] Recognizing the importance of community, they have since completed work testing risk-adjustment models for LOS that include community factors as important determinants.[29] Therefore, in much the same way as measures of LOS have been used as indicators of hospital performance, they could just as appropriately be used to measure the performance of communities in their ability to facilitate or impede discharge from hospital.

There is a large body of research evaluating specific services or interventions at the community level designed to facilitate the transition from hospital to community. For example, there is a vast literature dedicated to the impact of resources that help in the transition home and the discharge planning or supports.[12,30–33] However, it is important to recognize that these resources work as part of a system of care, and therefore evidence on effectiveness of a service or intervention may depend on the context in which it is delivered. Many of these works do not take into account broader health and social systems and most fail, or are unable, to consider the impact of variation in informal support, likely because these constructs are exceedingly difficult to measure.[34] Without accounting for this contextual piece, the relevant evidence is difficult to synthesize into effective policy. Community systems are adaptive to policy or interventions which might act on a single element in this system of care, which can alter the interactions and relationships between these different supports, resources and services.[35,36] Policy or interventions may be targeted at hospital discharge or on upstream factors in the community. Therefore, while an intervention might be successful in one community, it might not in others, depending on need deficits and components targeted.

The aim of this study is to estimate the variation in case-mix adjusted episode LOS due to community of discharge for unplanned hospitalizations in Nova Scotia, and to identify communities that have higher or lower LOS as compared to the provincial average. Considering communities as complex adaptive systems of care, we estimate the variation in episode LOS, as an indicator of longer than medically necessary LOS. This will indicate how successfully individual communities, as systems of care, support discharge from hospital. We also assess if this variation is more pronounced for patients with more complex needs. This research aims to provide a more complete picture of the influence of downstream community-associated factors on longer than necessary LOS. These results provide a starting point for policy focused research to reduce longer than necessary LOS through improved and specific community-based care.

CHAPTER 2: BACKGROUND

2.1 Hospital LOS

According to 2014 data, 11.2% of Canada's gross domestic product was healthcare.[37] Hospitals accounted for 30% of these healthcare expenditures, making up the largest portion of healthcare spending.[38,39] Despite the extensive efforts to ensure that acute care facilities are used as intended, we continue to see them being used for transitional or long-term patient care. Ensuring hospital resources are used appropriately is important for both the efficient use of health care resources and management of hospital cost. Long LOS are a key factor driving hospital costs, and there has been an ongoing focus on mitigating avoidable high healthcare costs stemming from system inefficiency.

In Canada, LOS in hospitals first received major attention in the 1990s. As the result of an economic recession, the 1990s were a period with major cutbacks in spending on healthcare. This meant reductions in federal cash transfers to provinces and a resulting high burden on provinces.[40,41] As hospitals account for the largest portion of healthcare budget, as mentioned above, they were targeted for cost reductions.[40,41] Funds were conserved through reductions in hospital admissions and LOS. The reduction in LOS was attributed to the increase in outpatient treatments,[41,42] to the evolution and dramatic uptake of laparoscopic surgery (minimally invasive surgery cut down on recovery time in hospital),[43] and to the reallocation of patients to healthcare settings more appropriate to their care needs.[41] Reductions in LOS and admissions contributed to a drop of more than 40% of acute bed days between 1984 and 1994.[40] Importantly, this dramatic reduction did not result in any noticeable difference in the health of patients.[40] These findings demonstrated that patients did not need to be kept in hospital as long as they had been previously. This marks the point in both research and policy where we began to search for the optimal LOS for patients, providing them with necessary care while minimizing resource expenditure associated with keeping them in hospital; a balance which would minimize negative health outcomes and cost. This is not a simple task, as LOS is affected by a multitude of factors that interact in complex ways, resulting in variation and gaps in understanding surrounding LOS.

When patients are no longer in need of acute care, remaining in hospitals can in fact be harmful. This is associated with an increased risk of the individual developing a hospital acquired infection, experiencing a decrease in function, and mortality.[2] Beyond these negative physical outcomes, there could also be psychological or emotional consequences to patients and their families.[2,3] A qualitative study evaluating the experiences of a small sample of 20 patients whose needs were no longer acute but they remained in hospital and their families, described the impact of this experience on the emotional well-being of patients.[3] These patients were aware that they no longer needed to be in the hospital, and that the beds would be of better use to patients who need acute care. This generated feelings of guilt in the patients, who felt less deserving of hospital resources and therefore tried to minimize their burden on the staff, which lead to some basic needs of the patient being overlooked.[3] The costs associated with hospital stay to themselves and their family members also added to the burden carried by the patients.[3] The minimal social interaction, perceived loss of autonomy, and in some cases, reduced functional ability negatively impacted quality of life.[3] Another potential negative impact of remaining in hospital beyond what is deemed medically necessary is the financial burden that may be placed on patients who are given a formal designation of no longer requiring hospital care. If days in hospital are the result of a failure in the system to support patients, they are likely able to remain in hospital with their cost covered by the publicly funded health care system. However, if the inability to be discharged rests on the lack of readiness or willingness on the part of family or friends to provide informal care, the patient may in fact be billed for their hospital stay while designated as not requiring hospital care. The ability for a patient to be discharged when they no longer require acute care is important for appropriate use of resources and the well-being of patients.

Long LOS in hospital are not always unwarranted and may represent the situation of optimal use of resources and reduction of negative outcomes. Long LOS are medically necessary if the needs of the patient are best met through acute hospital care.[44] They may also be necessary for the safety of the patient if there is no other, or more appropriate, system of care to meet their needs (though this is inefficient cost-wise compared to other settings). Formally, medically necessary LOS refers to the clinical need of the patient, including comorbidities and/or mental illness, as well as disease severity, acuity, and age.

Risk adjustments models, incorporating these characteristics, are used to determine how long a person might be expected to require acute care.[45] Factors not related to acute care needs that may warrant a long LOS are related to the inability to safely discharge an individual to another setting. Reasons for this include the absence of family supports at home, unavailability of long-term care (LTC) beds, and lack or inaccessibility of healthcare resources, services, or supports in the community. If an individual cannot be safely discharged from hospital, then a longer LOS is likely to occur.

2.2 Predictors of Medically Necessary LOS

Risk adjustment techniques estimate medically necessary LOS include disease groupers, where individuals are grouped based on clinical characteristics or procedures. Comorbidity indices produce a score of disease severity based on comorbidities. These techniques, however, do not include other non-clinical factors that might affect LOS. In a systematic review done by a team from the University of Calgary, they found that risk adjustment methods were primarily disease groupers or comorbidity indices.[28] They developed a framework which highlighted the need to consider other, non-clinical variables in risk-adjustment, highlighting community variables.[28] This team has since done further work where they have run models predicting LOS where they include these non-clinical variables in their risk adjustments.[29] The focus on the inclusion of clinical variables is to help distinguish how much of the hospital stay is medically necessary, to then determine the length of time spent in hospital beyond what is medically appropriate.

A well-known disease grouper is diagnostic-related groups (DRGs). DRGs group patients based on their main diagnosis or procedure for the purpose of sorting individuals into groups that would have similar hospital stays or cost.[28,46] This grouping system has historically been based of International Classification of Disease (ICD) coding schemes which have been updated since the DRG system was developed in the late 1960s.[47] The DRG technique served as a base grouping technique which has been built upon to create other methods of grouping. One such method is the All Patient Refined Diagnosis-related Groups (APR-DRG), which uses ICD-10 codes and incorporates information on disease severity.[28,46] Other methods include Refined Diagnostic Related Groups (RDRG), which incorporates the secondary diagnosis of the patient,[46] and Diagnosis Related Groups of the Health Care Financing Administration (HCFA-DRG), which aims to estimate the cost-intensity of patients and is categorized using the Major Diagnostic Category (MDC) of the patient.[46]

The disease grouper most used in Canada is called Case Mix Groups (CMGs).[46,48] CMGs use ICD Tenth Revision with Canadian Enhancements (ICD-10-CA), and with Canadian Classification of Health Interventions (ICD-10-CCI).[48] Groups are based on Major Clinical Categories (MCC) (i.e., MDC) which is assigned based on the Most Responsible Diagnosis (MRDx) of the patient, the diagnosis for which the largest portion of LOS and resource use can be attributed.[46,48] CMGs also incorporate five factors to account for additional patient-level variation in LOS and resource use: *age category* and *comorbidity level* to estimate resource use predicted by age and multimorbidity-associated burden of disease; and *flagged intervention*, *intervention event* and *out-of-hospital intervention* to capture resource intensive interventions.[46,48] The CMGs and these factors are used to calculate important hospital measures such as resource intensity weights (RIWs) which is a measure of expected hospital resource use, cost, and LOS.[45]

Next, there are indices which specifically address disease severity or act as a comorbidity index.[28] The Charlson Index is a commonly used index that was developed for the purpose of predicting 1-year mortality rates for hospital patients.[49] This index considers the number of comorbidities as well as their severity.[28,49] Another popular index based on mortality prediction among hospital inpatients is the Elixhauser Comorbidity Index which uses ICD codes for risk stratification.[50] This index dichotomously assesses the presence or absence of each comorbidity category to predict resource use or in-hospital mortality.[50] More recently, the Johns Hopkins Adjusted Clinical Groups (ACG) system has been developed, which predicts healthcare utilization, but it broader in scope, using ambulatory and outpatient data.[51] This method uses the ICD system to collect information on medical diagnoses, as well as demographic information to express morbidity using a proprietary algorithm.[52] Sometimes comorbidity is captured as simply a count of either diagnoses or number of medications, which have been found to be strong predictors of hospital utilization and cost.[53]

2.3 Predictors of Longer than Medically Necessary LOS

The time spent in hospital that is not acutely necessary is represented by different terms in the literature, including inappropriate hospital days, stays, use, or bed utilizations, prolonged length of stay, and delayed hospital discharges.[2,54–60] There are two different approaches used to assess longer than medically necessary LOS. One approach is based on the formal designation of patients in hospital as no longer requiring acute care. In the Canadian context, the Alternate Level of Care (ALC) designation is assigned to medical/surgical inpatients who no longer require acute inpatient care.[24,61] This represents the inability of the hospital to immediately discharge the patient to another setting that is better matched for their needs, most often a LTC facility or home.[24,62] A second approach uses risk adjustment models to estimate patients' expected stay in hospital , based on medical factors, and compares this to their observed days in hospital.[26]

ALC designation is given by a HCP in hospital to a patient whose health needs are no longer appropriately matched to the acute care nature of hospitals.[24,62] This designation is reported in the patient chart and contained in the discharge abstract which is collected and amalgamated by CIHI into the Discharge Abstract Database (DAD). According to 2007/2008 data from CIHI, ALC patients accounted for 14% of hospital days, with the LOS averaging 10 days,[24] however these numbers are likely an underestimation. Though the quality of the ALC data has been shown to be very high, with 100% reliability in the coding of ALC,[24] the promptness of health care professionals in designating patients as ALC as soon as acute care is no longer required is likely variable, resulting in this suggested underestimation.[24,25] This variability in designating patients as ALC could be a result of many factors: the reporting habits of the practicing health care professional, the loosely applied criteria,[24] and the hopes of avoiding possible financial repercussions to patients who receiving this designation.

The second approach uses risk adjustment models to estimate an adjusted measure of LOS. This adjusted LOS compares the number of days that the individual is expected to require acute inpatient care with the number of days the individual actually spent in hospital.[26] For example, the CIHI employs CMGs, a risk adjustment technique described above, as well as other clinically related factors, to determine how long an individual is expected to require acute care services, and therefore how long they are expected to stay in hospital.[45] This expected LOS is calculated for typical hospital stays (no transfers, deaths or sign-outs without a pass), and compared to the actual LOS in hospital.[45] Days spent in the hospital beyond this expected LOS could therefore mark the time spent in hospital beyond what is medically necessary. In the literature, there are various risk adjusters that have been included in models estimating risk-adjusted LOS, and the use of specific risk adjusters or the number of different risk adjusters to include in the model varies.[28] There is also heterogeneity regarding the models that are best suited to estimate risk-adjusted LOS.[28,29]

2.4 Known Influences on LOS

LOS can be influenced by a combination of factors: those at the patient-level, hospital-level, and community-level. As the determinants of medically unnecessarily long LOS are multifactorial, established risk adjustment methods only partially account for variation in LOS. Clinically related factors, such as age and disease profile are those typically taken into consideration in hospital risk adjusters while other important determinants such as social isolation, socioeconomic status (SES), income, education, and housing which can also impact the LOS, are not. It is important to account for all factors that legitimately affect resource utilization and LOS. The interaction between these different factors are complex, and together they may explain more of the variation in LOS than any one factor could alone.

2.4.1 Patient-Level: Influences on Acute Care Needs

Age is known to be associated with LOS.[63] It can serve as a proxy for some biological factors that can complicate the needs of a patient, and is therefore an important factor in predicting LOS.[64] Clinically, increasing age is a proxy for factors such as burden of comorbidity and frailty, and an overall decline in functional independence - all of which may impact how long the patient is required to stay in the hospital. Comorbidities are known to impact the LOS of the patient.[63,65,66] Comorbidities can complicate the needs and the recovery of the patient, as well as extend the time to treatment and possibly length of the treatment. These scenarios could result in the prolonged need for hospital services, and therefore prolong LOS.[63] Another important age-associated factor is frailty.

Frailty has been shown to be important to LOS.[67–69] Similar to comorbidities, frailty could complicate the needs and recovery of the patient. Both in the case of comorbidities and frailty, another avenue through which they could affect LOS is by complicating discharge. To be safely discharged, an individual with comorbidities and/or who is frail may require a wider variety of health resources, professionals, or supports in their community. When considering specific disease groups, the literature highlights disease specific patient-level factors that affect acute care needs.[70–76]

Mental illness is another important factor affecting the LOS of a patient. This is true for more severe and persistent mental illnesses and for mental illnesses that are often comorbid with other conditions.[77,78] The presence of a mental illness could complicate the hospital stay of the individual through its competing demands with other comorbidities. It also can take a physical and mental toll on the body which could lead to longer LOS through the need of more care or resources. One possible mechanism for how a mental illness could have physical impacts, as hypothesized in a study assessing mental health and HIV/AIDS, is that a mental illness, depression in particular, could have a negative effect on immune function.[79] This negative effect is not specific to immune function, as it has been described for cardiac health as well.[80] These negative impacts on health could contribute to a longer LOS as the patient's needs become more complex, requiring more resources. Furthermore, mental illness is related to high rates of modifiable risk factors for disease, such as higher BMI and smoking.[81] These higher rates of modifiable risk factors would imply a greater burden of disease for individuals with mental illness. Therefore, theoretically their health needs would be further complicated, which may increase their LOS in hospital.

The need and use of resources and supports to meet the health needs of an individual becomes greater during the last year of life.[82] End-of-life (EoL) is a resource intensive time and may therefore make it difficult for an individual to be discharged home if the community cannot support their needs. Acute care has been found to make up the largest portion of the associated costs in the last year of life, indicating that individuals are spending a lot of this time in hospitals.[82] Inpatient costs increase drastically in the last few months of life, once again indicating that this time is spent in hospitals instead of other systems of care.[82] Most patients at EoL, as well as their families, would prefer to be at home during this time, and there have been palliative care programs nested in communities shown to be successful in allowing patients to do so.[83]

2.4.2 Patient-Level: Other Health-Related Influences on Need

Along with the clinical characteristics directly related to acute need, there are other health-related factors that can affect LOS and complicate the health needs of an individual. These health-related factors, such as social isolation, social determinants of health and health behaviours are not captured in typical risk adjustment methods, as described above. Such factors may therefore contribute to hospital days that are beyond what is deemed to be necessary, as they affect the needs of an individual and go unmeasured in the estimation of LOS.

Social factors can affect LOS as well complicate the care needs of an individual. Social isolation has been associated with delays in discharge.[60] One mechanism through which social isolation could delay hospital discharge is through negative impact on physical and mental health.[84] Another mechanism could be through the lack of supports when returning to the community; the success of home care programs for example are dependent on the support of informal caregivers, as they provide the bulk of care.[13]

Socioeconomic status (SES) is another variable which factors into patient complexity and impacts LOS.[85,86] SES is in part comprised of education and income. Lower levels of education and lower income, could generate disadvantages that prolong one's hospital stay.[87,88] Lower education levels are related to lower health literacy and poorer self-management of disease, [89,90] both of which, in combination with other system factors, could affect the ability of an individual to return to their community in a timely manner after they no longer require acute care. Lower income can impact LOS through the ability for the individual to access the resources required for a safe discharge.[91] Not all healthcare resources are covered financially by the province.[92,93] In fact, provinces are only required to cover the cost of medically necessary physician or hospital services; it then varies by province as to what other services they cover or subsidize for individuals, such as home care, or drug coverage. Therefore, individuals with lower income may not have sufficient funds to access resources necessary for management or recovery in their communities. In Canada, there are also private insurance plans available which help cover certain health services, such as dental care, prescription drugs and outpatient services. With the exception of the fact that most regions provide pharmacare for seniors,[94] an important population impacted by long LOS, these plans are most often provided through employment, and therefore negatively correlated with income.[95] As a result, individuals with lower income may face greater financial barriers in accessing things like prescription medicine.[96] Health behaviours such as smoking, physical inactivity, and poor diet are associated with lower SES and poor health in general,[97,98] both of which could result in the need for more services or supports, or in a longer recovery time after treatments.

Another factor that can affect hospital LOS is housing.[99,100] This is not directly a person-level factor; however, housing impacts and reflects many social determinants of health discussed above. Issues with housing, such as homelessness, poor or unstable housing, or an inappropriate layout of the residence can negatively impacts on LOS. Poor housing or homelessness is related to a high burden of morbidity,[101,102] which as described above, can result in longer LOS. Furthermore, the lack of appropriate housing may affect the safety of the discharge, resulting in a longer stay in hospital.[103] These issues are not only seen in situations of homelessness, but also with unstable or poor housing. Though someone has a home to which they can be discharged, they may have poor access to services they need in the community for this transition. This poor access relates to both the related financial difficulties in accessing services or medications they may require, and the apprehension of some health care workers in visiting these homes. Furthermore, if the layout of the home of an individual is not appropriate for their needs, it may delay discharge as accommodations are made. Location of someone's home affects access to healthcare. Access issues can lead to unmet healthcare needs, which subsequently put the individual at risk for worse health outcomes.[104,105] Where an individual lives in terms of urbanization can affect access,[105] which could then subsequently affect LOS. Rural location is associated with less use of post-acute care resources,[106] which may be due to a lack of access or availability of the resources. With worse access to necessary resources, the transition from hospital to home may not be safe, resulting in longer stay in an acute care facility. There are however positive aspects of smaller communities which could act as enablers in the safe and timely transition home from hospital. Namely, the vast social networks, strong ties, and sense of community closeness.[107]

2.4.3 Patients with Complex Needs

Patient-level factors acting alone or together, can contribute to the complexity of healthcare needs of an individual. Complex healthcare needs likely contribute to longer hospital LOS. Someone with complex needs may require more, or better resources both at the hospital and community levels for their needs to be met, effectively lengthening hospital stays. They would need a larger "circle of care",[108] requiring resources from a variety of health disciplines.[109]

There is no standard definition for patients with complex health needs because the concept of complex health needs has been operationalized in different ways in the literature. One way it has been operationalized is through the combination of clinical factors, such as mental illness or comorbidities, with other health-related factors such as social isolation or poverty.[16,18,110–114] Another interpretation is that complexity is based not only on individual factors, but also on the environment and HCPs. [15,115] If the environment or setting is not equipped to manage the needs of an individual, or if the HCP lacks the knowledge or skills to address these needs, it creates a situation where meeting the needs of the individual becomes complex.[17] Access barriers to community-based HCPs also increase the likelihood that patients with complex needs will end up being managed in hospital, contributing LOS that may have been avoided entirely.[116] Therefore, we know that complexity goes beyond disease alone, and ideally would also take into account other health and health-related factors as well as the environment in which an individual is being treated. Despite this complementary knowledge, complexity is often treated as an exclusively clinical construct in the literature, where the use of disease counts, indices (such as the Elixhauser or Charlson), and groupers have predominantly been used.[17,18,112–114,117,118] This is likely due to data limitations on social or other health-related factors, or because clinical factors most acutely explain variance in cost and health system resource requirements.[45] However, underlying these potential reasons is the challenge in measuring a highly complex construct.

2.4.4 Hospital-Level Factors

In addition to patient-level factors, there are hospital-level factors that can influence LOS. These are related to characteristics of a hospital as a facility and the characteristics of the HCPs providing care. Hospital characteristics that can impact the LOS of a patient include: bed size, teaching status, and availability of services.[28] Hospitals with a greater bed capacity may be more likely to keep patients longer than expected if they are not able to be safely discharged. It may also be true that when beds are available, there may be more willingness to keep people in hospital longer. Teaching status has been found to have mixed results on LOS, where teaching hospitals were found to be related to both longer and shorter LOS.[119,120] Availability of services and resources in hospital may also affect LOS through the length of time it takes to meet the care needs of the patient with limited or unavailable services or resources. The use of clinical guidelines as well as generally the quality of care in hospital have been identified as important in their potential influence on LOS.[121]

Physicians in hospital are responsible for designating as ALC when patients no longer require hospital care, though there is variation among HCP in ALC coding. Difference in HCP characteristics, including variation or uncertainty in medical decision making, their practice style, preferred clinical pathways, training, and inclusion in multidisciplinary teams in the hospital may influence their propensity to discharge.[28] There are other hospital-level factors to be considered, and similar to the patient-level factors affecting LOS, they vary by and are specific to, disease groups. [71–73,75,76,122] These include the availability, and use, of procedures, therapies, or treatments specific to treating an illness or its symptoms.

Hospitals have long been targeted as the avenue to reducing long LOS. However, the hospital factors described above also depend on their interaction with the patient and with other systems of care. The community to which a patient is being discharged is a system of care that plays a significant role in the ability and comfort of HCPs in discharging a patient, impacting LOS.

2.5 Community-Level Factors and LOS

LOS may be affected by the perceived quality, availability, and integration of healthcare resources and supports in the community. These include formal and informal resources and supports, as well as resources in health-related sectors.[8,9] These factors relate to longer than necessary hospital stays through their impact on the ability of a patient to be discharged back to their community. The formal aspect of a community system of care encompasses what we traditionally associate with the healthcare system, including a variety of resources, services, and professionals. Examples include but are not limited to: primary care practices and physicians, other health care professionals such as occupational therapists, mental health professionals, and nurse practitioners, as well as home care programs, transitional care facilities, rehabilitation services.[10–12] The informal aspect of a community system of care includes social supports, the presence of family and friends and their capacity to provide needed care, informal caregiving, and community closeness.[13,14,107] Finally, health-related or social service sectors are also important to community systems of care. They include income support, transportation, housing support, and education programs.[10]

2.5.1 Long-Term Care Facilities

Many patients no longer in need of acute care might not be able to be discharged home due to their high need for continuing care. This need for continuing care may be best met by a placement in an LTC facility.[24] Though these facilities are situated in communities, they are stand-alone systems of care. These facilities are limited by the number of rooms or beds, and consequently have ongoing wait lists - a feature of LTC facilities that would delay discharge from a hospital. This is apparent through the association between LTC and an ALC designation.[24,61] In theory, individuals who require admittance to a LTC facility can be considered a different population than those whose needs can be met by the community and be discharged home. However, in reality whether someone is discharged to a LTC facility versus discharged home from hospital can be influenced by community factors. Furthermore, this influence of community on whether someone is discharged to a LTC facility or home might vary by community. There is literature on LTC facilities in affecting hospital LOS due to its strong link with ALC designations.

What has been neglected is the effect of other community factors on these longer than necessary hospital stays.

2.5.2 Literature on Reducing LOS

Currently in the literature, communities are not being assessed as complex adaptive systems. The focus has been the assessment of isolated components of a community on LOS. As such, the literature on community-level interventions has generally failed to take into account the interplay of community-level factors. Furthermore, much of the literature on interventions to reduce hospital LOS is focused on hospitals themselves. As discussed above, LOS has been primarily used as a measure of hospital efficiency, implying that people staying in hospital beds too long is a shortcoming of the hospital system. Therefore, many interventions described in the literature have focused on reducing LOS by targeting aspects of the hospital system. However, there has been an increasing shift towards the recognition that LOS depends on the coordination between hospital and community supports. This shift can be seen through the recent number of interventions that focus on the discharge of the patient from hospital to community.

A rapid evidence assessment conducted by Miani et al. compiled evidence from systematic reviews and primary studies on interventions targeted at reducing hospital LOS.[33] Strategies to reduce LOS for unplanned hospital visits have fewer clear solutions than for planned visits. Approaches focused on hospital are those that tackle different aspects of the hospital visit or assess clinical pathways and their indirect effects on LOS. Other approaches focus on systems of care outside of the hospital - those that will be supporting the patient post-discharge.[33] Many interventions took place in the hospital setting. These include multidisciplinary care approaches, case management techniques, nurse-led interventions, and staffing interventions, all of which produced mixed results in their effect on LOS.[33] Other hospital-focused interventions aimed to impact LOS through changes in clinical pathways.[33] Such interventions are specific to disease groups, and their impact on LOS varied; some studies demonstrated increases in LOS, others a decrease or no significant change.[33] As demonstrated in this evidence assessment, interventions at the level of the hospital do not produce consistent positive findings with respect to their effect on LOS.

Though it is important to assess hospitals when looking to reduce hospital LOS, there is an increasing focus on community supports. Miani et al. also reviewed interventions focused on discharge planning, though they did not consistently impact hospital LOS.[33] Other interventions targeted early supported discharge and post-discharge, though these interventions also did not consistently prove effective in reducing LOS for specific disease groups or levels of severity.[33] These inconsistencies may support the need to first consider communities systems of care instead of targeting specific programs or resources in the community out of context.

Home care programs are a widely studied example of a specific program in the community that is targeted for its relationship with hospitals in transitioning patients from hospital to home. Home care is a broad term, encompassing a wide range of services that may target medical needs or assist with activities of daily living. CIHI describes home care programs as delivering a range of services, both short and long-term, to help people recover from an acute event or remain at home with a chronic need.[123] Home care can also encompass palliative care or rehabilitation programs,[123] as well as hospital-at-home programs.[12,124] A variety of home care programs use shortening hospital LOS as a measure of effectiveness.[12,30,125,126] Individual studies that assessed home care programs for patients with multi-morbidity, patients at end-of-life, and elderly patients, found the program to be associated with a decrease in hospital LOS.[30,125,126] However, these results should be interpreted with caution; the use of uncontrolled pre-post study designs to reach these conclusions lends the possibility that they are due to a natural trend towards decreased LOS. A systematic review of randomized control trials (RCTs) of hospital-at-home programs for individuals recovering from stroke, older individuals with a range of conditions, and individuals who had elective surgery also demonstrated reductions in LOS, though the authors noted that these finding should be interpreted with caution due to substantial heterogeneity.[12]

The between-study heterogeneity in the effectiveness of interventions to reduce LOS, and in their impact on LOS, makes it difficult to systematically translate the literature into generalizable and actionable policy or guidelines. This body of evidence highlights both the narrow focus of the current interventions in reducing LOS, and the overwhelming number of interventions in place with this aim. As demonstrated, assessing only hospitals or only individual components of communities do not appear to be sufficient in attaining significant results of reduced LOS, which might be due to the variation added by all the unmeasured factors surrounding these community interventions. These interventions happen within a context and system, and different communities will have different strengths and weaknesses. Therefore, results cannot easily be used by policy makers to translate an intervention to different community contexts [35]. It is thus important for policy makers and researchers to take a systems approach to first understand which communities are doing well or poorly in terms of reducing LOS, and then delve further to identify why, providing important information to consider when implementing programs in other communities. We can then begin to understand which programs are contextually appropriate and likely to render the greatest benefit in reducing LOS in each community.

2.5.3 Communities as Complex Adaptive Systems of Care

To address the gaps in the literature discussed above, communities should be evaluated in their effect on LOS as complex adaptive systems of care. This characterization of communities as complex adaptive systems of care arises from the fact that resources, supports and services in a community interact with one another and are integrated within that specific context – creating a system of care that is unique to each community.[127] Not only is it important to view communities as a complex adaptive system of care to fully understand the effect of community on hospital LOS, but it is also important when developing programs or interventions for those communities deemed to be performing poorly on that measure. This is because the implementation of programs or interventions into a community system likely leads to adaptive behaviours which change the dynamic of the community system of care.[35,36]

2.6 Rationale

In all, there are complex interactions between patient, hospital and clinician, and community-level factors in affecting longer than medically necessary LOS. Looking at any one factor independent of the others cannot give the whole picture. LOS has most often been used as a performance measure in evaluating hospital efficiency.[19–23]

However, when assessing only hospital factors we neglect the impact of community of discharge on hospital LOS. [128–131] Hospital systems interact with other systems of care, and all systems of care interact with the characteristics and health needs of an individual.

Communities as systems of care are especially important in the discharge of a patient. They can support discharge through their integrated supports, resources and services. To understand how communities can impact longer than necessary hospital stays, it is therefore important to assess them as complex adaptive systems of care. Considering communities as complex adaptive systems of care, we aim to estimate the extent that the Nova Scotia community to which a patient is discharged affects LOS for unplanned hospitalizations and determine whether effect of community on variation in LOS is modified by patients' medical complexity.

CHAPTER 3: OBJECTIVES

For Nova Scotian residents, aged 30 years and older, with at least one unplanned inpatient hospitalization during fiscal years (FY) 2010-2014, our objectives are to:

1. Estimate the extent of community variation in case-mix adjusted episode LOS across Nova Scotia.
2. Estimate if community variation in case-mix adjusted episode LOS is different for patients with higher medical complexity, as compared to patients with lower medical complexity.

CHAPTER 4: METHODS

4.1 Overview

This cross-sectional, descriptive study employed secondary data analyses of hospital discharge data. The study population was Nova Scotian residents, aged 30 years and older, who have had at least one unplanned inpatient hospitalization resulting in a discharge to a community setting, between fiscal years (FY) 2010-2014. The unit of analysis was each patient's most recent discharge from an unplanned inpatient hospitalization. For both objectives, the dependent variable was hospital episode LOS, and community geography was delineated by the first three digits of the postal code, called the forward sortation area (FSA).

To measure community variation, we used general linear mixed effect regression models predicting episode LOS. The models included community as a random intercept and case-mix adjustments for age-sex groups, proximity to end-of-life, resource intensity weight (RIW), Elixhauser index score, count of major health conditions, and indicator variables for individual health conditions as fixed-effects. For objective one, we used the variation in the random intercept to determine whether community is significantly associated with episode LOS, after adjustment for case-mix variables. Empirical Best Linear Unbiased Predictors (EBLUP) estimators were then used to obtain small area estimates and confidence intervals (CIs) of the case-mix adjusted average episode LOS for each community. For objective two, we operationalized patient medical complexity using both the Elixhauser index and the RIW, then compared results. The model for this objective was similar to one used for objective one, except that separate random intercepts were estimated for low and high complex needs groups. We assessed whether there were significant differences in community variation by complexity of health needs. As well, we estimated and compared small area estimates for low and high complexity groups to assess differences in spatial patterns.

4.2 Study Population

The population included in this study were Nova Scotian residents with at least 365 days of Medical Services Insurance (MSI) eligibility, aged 30 years or older who have at least one included unplanned inpatient hospitalization resulting in discharge to a community setting during the study period of FY 2010-2014. Hospitalizations for which the most responsible diagnosis was obstetric or psychiatric, or where the patient left hospital against medical advice, were not included. The time period of April 1, 2010 to March 31, 2014 was chosen for purposes of geotemporal comparability with a companion study on community variation in unplanned repeat hospitalizations. An age cutoff of 30 years was chosen because chronic conditions and multi-morbidities in younger adults and children are largely different than those that are prevalent in individuals aged 30 and older. As well, developmental and childhood conditions are associated with different supports and services, and thus community effects below age 30 may be different.

Our analyses focused on the last unplanned, inpatient hospitalization with discharge to a community setting for each individual in our study period. Unplanned hospitalizations were those labeled urgent or emergent in the *admit to* field in the Canadian Institute for Health Information (CIHI) Discharge Abstract Database (DAD). Discharge to a community setting was based on the DAD *discharge disposition* field: either "discharged to home or a home setting with support services" or "discharged home with no support service from an external agency required".

We focus on unplanned hospitalizations because organizing community and family supports are likely most challenging for unplanned hospitalizations. For planned hospitalizations, the patient has the opportunity to make advanced arrangements for their discharge from hospital. This includes creating a discharge plan prior to admission, reaching out to family or friends to help in their care upon discharge, and prearrange necessary services, such as home care. It also has the advantage of some flexibility in scheduling the hospitalization to accommodate the availability of such supports and resources. When the hospitalization is unplanned, these advanced arrangements are less feasible. Therefore, unplanned hospitalizations may better reflect the integration of such services and supports in a community.

The exclusion of individuals with less than 365 days of MSI eligibility was applied in the source dataset where we pulled our data, and therefore applies to our project. We excluded hospitalizations related to obstetrics and those where the most responsible diagnosis was a psychiatric disorder, as well those hospitalizations where people left hospital "inappropriately". We excluded hospitalizations related to obstetrics as they are systematically different from hospitalizations related to physical morbidity, mental illness, or other procedures. The exclusion related to obstetrics were based on codes related to pregnancy or birth in the DAD *main patient service* field. Hospitalizations with a most responsible diagnosis of a psychiatric disorder were excluded because this population has unique community-based care and discharge planning issues that warrant separate study, and because they have a very long average LOS which should not be included with conditions with shorter average LOS. However, hospitalizations where a mental illness was coded as a secondary diagnosis were included. Finally, we did not include hospitalizations where the *discharge disposition* variable is "sign out" or "did not return from pass", as these indicate patients who either left against medical advice, left without informing anyone, or did not return to the hospital after leaving on a pass.

We also decided to exclude hospitalizations with a very long LOS, due to the skewed distribution of the LOS distribution, and the recognition that the circumstances of long lengths of stay are likely to be unique in many respects, and not well assessed by our approach to case-mix adjustment. The cut-off for very long LOS was defined empirically, post data exploration, as it is not defined consistently in the literature. We tested different points for very long LOS found in the literature: greater than or equal to 21 days, greater than 30 days, greater than 90 days, greater than the median and greater or equal to the 75th percentile.[29,132–137] We then assessed for each cut-off point, how much of our data was excluded and whether the residuals became more normally distributed. Based on this assessment, we defined very long LOS as an episode LOS of greater than 30 days.

4.3 Data Sources

We employed data from Reid's work on small area variations in unplanned repeat hospitalizations,[138] which drew data from the Nova Scotia Insured Patient Registry and the Discharge Abstract Database (DAD) from the Canadian Institute for Health Information (CIHI). Both were accessed and linked through Health Data Nova Scotia (HDNS). **The Insured Patient Registry** provided information on age, sex, periods of eligibility for provincial health coverage, and date of death, used to identify the eligible study population. The information from the CIHI **DAD** includes hospital LOS data, RIW, as well as clinical information (diagnostic codes), and postal code (where FSA is the first 3 digits of the postal code), which was linked with the Insured Patients Registry to identify unplanned inpatient hospitalization for our eligible population. These databases were linked through unique encrypted and anonymized Health Card numbers and only presented to researchers as unique study identifiers. We received data access approval from HDNS. Ethics approval was granted by the Nova Scotia Health Authority Research Ethics Board.

4.4 Measures

4.4.1 Outcome Variable

For both objectives, the outcome was episode LOS. Episode LOS is the time spent in hospital from admission to discharge back to the community, in days, which was obtained from the DAD for each hospitalization[138] An episode includes a single hospitalization or sequential hospitalizations. Sequential hospitalizations encompass transfers between hospitals and admissions within 48 hours of a discharge (all hospitalizations must be inpatient as described above). Hospital admissions within 48 hours of a discharge were included because they are associated with premature discharge from hospital, not community factors.[138,139] Therefore, an episode of care begins at admission, encompasses all transfers and admissions within 48 hours of a discharge, and ends with a discharge to a community setting.

4.4.2 Measure of Community

The measure of community of residence for both objectives is FSA, the first three digits of a postal code. Currently, FSA is the most reliable geographic variable available to distinguish communities. Though it is not ideal, as it was not created for the purpose of encompassing systems of care, it is advantageous compared to other available levels of geography because postal code conversion to other geographies has large errors, especially for rural areas.[140] Statistics Canada created a Postal Code Conversion File (PCCF) with the aim of allocating postal codes to censual units, such as dissemination block, census subdivisions, and dissemination areas. Postal codes may border different areas, and the PCCF uses probability and estimated population weights to allocate it to one area. Researchers in Nova Scotia recently evaluated this methodology against latitude and longitude information, and found large misclassification, especially in rural areas [140]. FSA however, has set geographic boundaries that are not subject to misclassification.

4.4.3 Covariates for Case-Mix Adjustment

Case-mix adjustment enables comparison of an outcome where there is a differing mix of patients included,[141] and accounts for factors causing patients' LOS to be legitimately different, so that residual differences reflect non-need factors. The factors presented below are included in our case-mix adjustment as fixed effects in our model.

Demographics: Age and sex, obtained from the Insured Patient Registry were available for every observation. Age was the age at hospitalization and was categorized into five-year age groups starting at age 30, with the last age category for ages 85 and older. Age-sex groups were created for the analysis to encompass the interaction between these demographic variables.

End-of-Life (EoL): EoL was obtained by information on eligibility for Nova Scotia health insurance and death from the Insured Patient Registry and was available for every observation. Health needs at the EoL are high,[82] therefore it is likely that LOS in the last year of life would be systematically higher than those not in last year of life. This variable was coded to indicate whether the discharge from hospital was within the last year of life or not.

Conditions and Multimorbidity: Information on conditions and multimorbidity was obtained from the DAD and was available for every observation. Our analysis includes indicator variables for 25 conditions (see Appendix A). Furthermore, our analysis includes a count of conditions, categorized into whether there were 0, 1, 2, or 3+ conditions identified for the hospitalization, and the Elixhauser index for measuring comorbidity to predict resource use or in-hospital mortality [50].

Resource Intensity Weights (RIW): RIW was obtained from the DAD and was available for every observation; where there is an episode with sequential discharges, RIW was included from the last hospital in the sequence. It is a measure of hospital resource use and associated cost. It takes into consideration case-mix groups (CMG), age and comorbidity level factors, intervention events, flagged and out-of-hospital interventions, admitting facility, fiscal year, and any interactions between these factors.[45]

Hospital: Hospital factors play a role in LOS. We therefore explored the inclusion of an indicator variable for hospital in our case-mix adjustment. Due to the anticipated high collinearity between hospital and community, we explored this relationship prior to including hospital as a variable in our model.

4.5 Engagement

This project is part of a larger program of research that has obtained insights and guidance from front-line providers who work directly with patients and their families on discharge planning (e.g. social workers and nursing staff), and thus have a rich understanding of discharge experiences. The initial work was conducted by Dr. Kephart and staff in the MSSU. The purpose was to draw on the expertise of front-line health professionals to both provide study direction and to help us contextualize findings. From these consultations, the team gained insights on the difficulties in discharging individuals to their homes and learned from health care providers involved in discharge planning that difficulties varied depending on the community to which the patient was being discharged. It was partly from this consultation process that my research topic emerged, and it helped to guide the review of the literature.

4.6 General Modeling Approach

Our analyses employed generalized linear mixed models of the following form:

$$\log y_{ij} = X\beta_{ij} + Z\gamma_i + \varepsilon_{ij}\,,\ \ \gamma_i \sim N(0, \Sigma_\gamma)\ and\ \varepsilon_{ij} \sim N(0, \sigma^2)$$

Where $\log y_{ij}$ is the log transformed mean outcome (episode LOS) and ε_{ij} is the associated error term. For person (j) in area (i), $X\beta_{ij}$ is a vector of covariates and fixed effects (case-mix adjustments), and in area (i), $Z\gamma_i$ is a vector community random effects (to estimate difference in episode LOS across FSAs). For our analysis, $X\beta_{ij}$ includes age-sex groups, EoL, RIW, indicators for individual conditions, a count of those conditions, and an Elixhauser index score. For objective one, $Z\gamma_i$ includes only a random intercept for the random effect portion. For objective two, it includes two random intercepts, corresponding to low and high complexity groups by FSA. The random intercept part of the model describes the extent of community variation in episode LOS. It is important to note that this model assumes the distribution of random effects is normal, and examination of residuals confirmed that that this assumption was not violated. Small area estimates of the case-mix adjusted average episode LOS for each FSA was obtained using Empirical Best Linear Unbiased Predictors (EBLUPs), and then mapped.

EBLUPs are an empirical Bayesian estimator where the predictions are based on estimated model parameters.[142] EBLUPs combine the estimated normal distribution of the random intercepts of each area (the prior distribution) with information about each area (the case-mix adjustment) to produce a posterior distribution of the random intercepts of each area as compared to the provincial mean.[142] The mean of the posterior distribution (the empirical Bayes prediction) is between the mean of the prior distribution and the mean distribution with just case-mix adjustment considered.[142] This shrinkage of the estimate is beneficial for areas with few observations, as it will reduce the impact of outliers.[142] This could result in type II errors, where we incorrectly identify a community as not significantly different than the provincial mean in its effect on case-mix adjusted episode LOS, when in fact it is, though we do not have the power to detect that effect.

4.7 Descriptive Analyses

We summarized the characteristics of individuals in the study population, and characteristics of the communities, as defined by FSA.

4.8 Modeling Approach for Objective 1

The purpose of objective one is to estimate the overall magnitude of small area variation in case-mix adjusted episode LOS across communities, as well to identify communities which stand out as having higher or lower case-mix adjusted average episode LOS than the provincial mean. Objective one applied the generalized linear mixed model of the form above.

The effect of hospital on adjusted LOS is well documented, and we know that patients in different communities use different hospitals. Therefore, when assessing the effect of community on LOS, it would be desirable to adjust for these hospital effects. However, it is possible that hospital effects differ by community of residence and vice versa, complicating the ability to adjust for the effect of one for the other. To assess this relationship, and therefore whether we would be able to adjust for hospital, we estimated a model with crossed random effects for hospital and FSA and compared it to a model with crossed random effects for hospital and FSA that also included random interaction between hospital and FSA. We used a likelihood ratio (LR) test to compare the two models. We then collapsed hospital and FSA to a single variable that consisted of one hospital-FSA combination per level. In order to keep the number of levels at a meaningful size, we collapsed the small hospitals into one. We started with 77 FSAs and 32 hospitals and produced 158 hospital-FSA levels. We then created a model with a random effect for the hospital-FSA variable. By calculating and plotting small area effects for each hospital-FSA combination we see how different FSAs interact with different hospitals and vice versa. For example, for each FSA we saw how the effect of different hospitals varied.

Given the large size of our dataset, it is important to assess the practical significance of estimated community variation as well as the statistical significance. We assessed the contribution of the random effect first by evaluating its statistical significance using the LR test, second by the tightness of its 95% confidence interval (CI) around its standard deviation (SD), and third by the significance of the intraclass correlation coefficient (ICC). The LR test and the tightness of the 95% CI surrounding the estimated SD of our random intercept allows us to determine whether the effect of community in our model is statistically significant. The LR test compares the model with case-mix adjustment and the random intercept for FSA, against a model without a random intercept for FSA. The size of the estimated SD of the random intercept itself allowed us to determine the impact of being an FSA one SD away from the mean on episode LOS. Finally, the ICC estimates the percent of total variance in case-mix adjusted episode LOS explained by community:

$$ICC = \frac{\sigma^2_{\text{random intercept}}}{\sigma^2_{\text{random intercept}} + \sigma^2_{\text{error term}}}$$

After assessing the overall significance of community variation on case-mix adjusted episode LOS, we estimated the random effect by FSA using EBLUPs to identify specific communities that stand out as having higher or lower case-mix adjusted episode LOS than the provincial mean.

4.9 Modeling Approach for Objective 2

The purpose of objective two is to estimate whether community variation in LOS is different for patients with more complex health needs. Objective two also applied the generalized linear mixed model of the form above, where the random part of the model included two random intercepts (for low and high medically complex needs) by FSA.

We initially defined patients with complex health needs using the Elixhauser index comorbidity score. The score ranges from zero to ten, increases with increasing level of comorbidity, and is a validated index against health outcomes.[50] We defined patients with low and high complex needs using two cut-offs of the Elixhauser index: (1) a score of 0-1 for patients with low complex needs and greater than 1 for high complex needs, and (2) a score of 0-2 for patients with low complex needs and greater than 2 for high complex needs. We tested these two different cut-offs for distinguishing between low and high complex needs groups since there is no consensus in the literature for operationalizing low and high complex needs using the Elixhauser index. We tested cut-off (1) to lend more power to detect specific communities that have significantly higher or lower episode LOS for the high complex needs group, however we are less confident in the exclusive capture cases with high complex needs. Therefore, we tested cut-off (2) to be more confident that our high complex needs group in fact captured individuals with high complex needs; however, this resulted in less power for the small area estimates in this high complex needs group. A concern with the Elixhauser is that 33.5% of subjects had a score of zero, suggesting that this index misses a lot of complexity because of the limited number of diagnostic categories considered.

Due to the lack of a "correct" way to define patients with complex needs in the literature, and the high percent of persons identified as low complexity by the Elixhauser, we also conducted an analysis defining groups that have low and high complex needs using a different measure, the resource intensity weight (RIW). RIW is a measure of the cost of a hospital stay based on resource use in hospital, it was not developed to predict health outcomes.[45] While it is validated for cost, this measure may reasonably capture the complexity of health needs influencing LOS, as it captures a wide range of diagnosis and interventions.[45] A RIW score of one indicates that the resource use in hospital expected for the hospitalization is no different than average, a score greater than one indicates greater resource use than average, and a score less than one indicates less resource use than average. In our sample, the median RIW score was 1.11, the low complex needs group includes those with a RIW of the median score or less, and the high complex needs group includes those with a RIW of greater than the median score.

To address the second objective, the model was extended to include two random intercepts, one for patients with less medically complex needs and one for patients with greater medically complex needs by FSA (for all the ways we defined and classified complex needs); fixed effects were constrained to be equal across the two groups. We assessed whether they significantly differed based on two criteria: the statistical significance of the LR test (against a model with a single, pooled intercept) and the extent of overlap (based on the 95% CI) between the SD estimates for each random intercept. Statistical significance would indicate that the model with random intercepts for low and high complexity groups by FSA is a better fit to the data. Comparing the 95% CIs of the SD random intercept estimates allows us to determine the magnitude of difference between the estimated SD of the intercepts for the groups on the case-mix adjusted episode LOS. If at least one of our criteria held true, we produced small area estimates (with 95%CI) of the case-mix adjusted average episode LOS for both the low and high medically complex needs groups using EBLUPs for each FSA then mapped and compared the area estimates that were significant different than the provincial mean.

CHAPTER 5: RESULTS

5.1 Descriptive

There were 147,969 unplanned hospitalizations in our four-year study period. Our analyses focused on the last unplanned hospitalization for each individual in our study population (n = 81,493). Our sample was further restricted to episodes that had a LOS 30 or fewer days long (excluding 7.84% of hospitalizations). Our analyses employed 75,113 observations. The average episode LOS in our final study sample was 6.5 days with a SD of 6.2, and the median episode LOS was 4 days, demonstrating that out outcome variable was right-skewed. When we log transformed the outcome, the exponentiated average episode LOS was 4.3 days with a SD of 2.6, and the median episode LOS was 4 days, producing a more normal distribution. As shown in Table 1, the population was evenly split between males and females (51.2% males), and the most common age group was 65-69 years of age (12.1% of total observations). The majority of discharges from hospital did not occur within the last year of life (95.8%). The median RIW was 1.11, which represents about the average in-hospital resource use. Hospitalization episodes that included transfers or re-admittance within 48 hours of a discharge represented 6.5% of hospitalizations in our dataset. The five most prevalent conditions were: hypertension (24.0%), cardiovascular disease (21.1%), diabetes (17.1%), injury (16.1%), and cancer (16.1%). Most often there was just one condition reported (29.2%) and similarly, the most frequent Elixhauser index score was zero (33.5%).

Our study population was discharged to 77 different communities, as defined by FSAs, across Nova Scotia. Fourteen of these communities were rural (second digit was zero) and 63 were urban (second digit was greater than zero). There was a wide range in the number of observations (8 to 3,503) across these communities. A slightly higher portion of episodes consisting of a transfer or readmission within 48 hours of a discharge were discharged to rural versus urban communities (54.0% versus 46.0%). We observed that 9.6% of all episodes discharged to a rural community involved a transfer or a readmission within 48 hours of a discharge compared to 4.7% of all episodes discharged to an urban community. Other characteristics of these communities (defined as FSA) are based on Statistics Canada and Maritime Health Atlas data are presented in Table 2. The number of individuals living in each of these communities varied from 41 to 40,417 in 2016.

Approximately 30% of the population experienced low income (defined as household income below $20,000/year), with a variation of about 9% between communities in the 25th percentile and 75th percentile. The percentage of the population who had less than a grade 12 education was on average 23%, however again this varied between communities in the 25th and 75th percentile by about 10%. There was also variation of about 7% for communities in the 25th and 75th percentile for the percent of the population who lived alone or had single mother families.

5.2 Objective 1

Our final model for objective one included fixed effects for age-sex groups, EoL, RIW, Elixhauser index score, count of conditions categorized, and indicator variables for each condition (see Appendix A), and the random effect portion include a random intercept for community (FSA). A log transformation of our outcome was applied to create a more normal distribution of the residuals (see Figure 1).

Because of the recognized variation in adjusted LOS between hospitals, we explored the adjustment of community effects for hospital effects in our models. In the absence of such adjustment, apparent community effects might reflect the effects of hospitals that community members are discharged from. However, we found that hospital and community effects on LOS interact in ways that preclude simple adjustment by a single linear product term. A crossed random effect model with interaction between random effects for hospital and community provided a significantly better fit to the data than a model with independent random effects for hospital and community ($p < 0.001$). Hospital and FSA thus interact in affecting case-mix adjusted episode LOS. Plotting the effects of each FSA-hospital interaction we can see the effects of community were not consistent across hospitals and vice-versa; hospital effects vary within communities, and community effects vary within hospitals (see Appendix B). Due to the significant and complex interaction, the effects of community and hospital on case-mix adjusted episode LOS cannot be differentiated and thus we decided not to adjust for hospital in our reported results.

We found that community is significantly associated with episode LOS (Table 3). Statistical significance was confirmed by a LR test comparing our model against a model with no random effects ($p < 0.001$), a reasonably tight 95% CI around our estimated SD of the random intercept (0.046 [95% CI: 0.036, 0.058]), and an ICC significantly different than zero (0.003 [95% CI:0.002, 0.005]). The significant LR test demonstrates that our model with a random intercept for community is a significantly better fit than a model with only fixed effects. Given the large size of the dataset, we also investigated the effect size of this variation. The ICC estimates that community explains 0.3% of the total variance in case-mix adjusted episode LOS. While small, the implied aggregate effects are substantial. The logged nature of the output allows us to interpret effects as proportionate changes in LOS. A one SD difference in a community's case-mix adjusted episode LOS translates into a 4.6% difference in episode LOS, compared to the mean of communities. By multiplying this proportionate change by the mean episode LOS, we can crudely determine that a communities one SD above the mean would have an excess of 30 days per 100 admissions than the provincial mean, and those one SD below the mean would have 30 fewer days than the provincial mean per 100 admissions.

Small area estimates of the case-mix adjusted average episode LOS revealed that being discharged to certain communities is associated with a significantly higher or lower adjusted episode LOS (based on their 95% CIs) than the provincial mean (Table 4). Of the 77 communities, 17 were significantly different than the provincial mean: 11 had significantly longer, and 6 had significantly shorter case-mix adjusted average episode LOS than the provincial mean (Figure 2). These communities ranged from having significantly longer or shorter case-mix adjusted average episode LOS of between 3% and 14%. The community with the longest LOS was Digby Neck (0.088 95%CI [0.031, 0.145]); meaning that individuals discharged from their last unplanned hospitalization to Digby Neck had on average, a 9% (95%CI [3%, 15%]) longer hospital stay than the provincial average (greater than two SDs away from the mean).

The small area estimates are mapped in Figure 3. Areas with significantly longer and those with significantly shorter average episode LOS tended to be spatially clustered.

This becomes even more apparent when all point estimates (regardless of significance) are mapped (Figure 4).

5.3 Objective 2

The model for objective one was extended to include two random intercepts, one for patient with less complex needs and one for patients with more complex needs, by FSA, to produce our model for objective two. We defined complex health needs two ways based on the Elixhauser index: the first scenario classified high complex health needs using an Elixhauser score of 0 or 1 (38% of observations), the second scenario classified high complex health needs using an Elixhauser score of 0, 1 or 2 (18% of observations). We also used the median RIW score to classify low and high complex health needs (see Table 5). Small area estimates were produced for all definitions of complex needs, based on the fact that at least one of our criteria (significant LR test and extent of overlap of estimates SDs of the random intercepts) was met in each case. For each community, an estimate of the case-mix adjusted average episode LOS and its 95% CI were produced for both the low and high complex needs groups.

Across all three definitions of complex health needs, we found that community variation in case-mix adjusted LOS varies significantly between persons with lower and higher medically complex needs. All methods of defining complex needs (the two Elixhauser index cutoffs and the RIW median split) resulted in a significant improvement in model fit as assessed by LR tests against constrained models with a single intercept. However, the LR test for the model in Elixhauser scenario one ($p = 0.0217$) was less significant than the model in Elixhauser scenario two ($p = 0.0008$), and both were less significant than the LR test using RIW to define complex needs ($p < 0.0001$) (Table 5). The proportionate differences associated with a 1 SD difference are similar across all complexity groups except for the low complexity RIW group (Table 6). Interpreting the absolute magnitude of effects between groups is difficult because the SD represents proportionate change. The mean episode LOS differed between the low and high complexity groups as defined by RIW (4.15 days and 8.83 days, respectively). To crudely understand the absolute magnitude of a one SD difference, this proportionate change can be multiplied by the mean episode LOS for each group (Table 6). We can see that the low complexity group as defined by RIW has a large proportionate and absolute effect on community variation as compared to the high complexity group.

We estimated small area effects using EBLUPs (Table 5) and mapped the effects by complexity groups defined using RIW (Figure 5ab). These effects are compared to the provincial mean across both complexity groups. Not surprisingly, compared to the provincial mean, all of the communities identified among the low complexity group have lower case-mix adjusted average episode LOS than this provincial mean. However, as compared to this overall provincial mean, there were also five communities identified among the high complexity group as having significantly shorter case-mix adjusted average episode LOS than this provincial mean.

TABLES

Table 1. *Distribution of characteristics of Nova Scotian residents included in our final model, aged 30 years and older, for their last unplanned inpatient hospitalization to a community setting during FY 2010-2014 (n=75,113).*

Variable	Frequency n	Percentage of Population (%)
Age Categories (years)		
30-34	1,765	2.35
35-39	2,557	3.40
40-44	3,528	4.70
45-49	4,880	6.50
50-54	6,389	8.51
55-59	7,343	9.78
60-64	8,609	11.46
65-69	9,118	12.14
70-74	8,321	11.08
75-79	7,612	10.13
80-74	6,806	9.06
85+	8,185	10.90
Sex		
Male	38,456	51.20
Female	36,657	48.80
Resource Intensity Weight (median)	1.1148	
Number of Conditions		
0	17,452	23.23
1	21,896	29.15
2	16,350	21.77
3+	19,415	25.85
Most Prevalent Conditions		
Hypertension	18,047	24.03
Cardiovascular Disease	16,102	21.44
Diabetes	13,442	17.90
Injury	12,121	16.40
Cancer	12,094	16.10
Elixhauser Index		
0	25,174	33.51
1	21,269	28.32
2	15,456	20.58
3	7,848	10.54
4	3,389	4.51
5	1,337	1.78
6	465	0.62
7	124	0.17
8	36	0.05
9	10	0.01
10	5	0.01
End-of-Life		
0 (not at all in last year of life)	71,928	95.76
1 (completely in last year of life)	3,185	4.24
Hospitalization with a transfer or admission within 48 hours of a discharge	4,855	6.46

Variable	Frequency n	Percentage of Population (%)
No	70,258	93.54
Yes	4,855	6.46

Table 2. *Descriptive information on FSAs in Nova Scotia (n=77) from Statistics Canada and the Maritime Health Atlas.*

Characteristic of FSA	Mean	SD	Percentile			Min	Max
			25th	50th (median)	75th		
Population in 2016	11994.78	9863.12	4492.00	9953.00	16997.00	41.00	40417.00
# of private dwellings, 2016	5955.43	5181.07	1951.00	4485.00	7929.00	116.00	23591.00
Population with low income (%) [a]	30.36	5.98	26.00	31.00	35.00	14.00	47.00
Population with < Grade 12 Education (%)	23.15	9.24	17.08	21.63	27.87	4.34	61.91
Population with Single-Mother Families (%)	14.80	6.34	10.42	13.29	17.54	6.45	42.95
Population Living Alone (%)	11.68	5.20	7.60	11.535	13.99	3.47	31.45

[a] Defined as household income below $20,000/year

Table 3. *Output of fixed and random effect parameters from model for objective one.*

Parameter *	Estimate	Std. Err.	95% CI	
			Lower	Upper
FIXED EFFECT				
Constant	0.739	0.030	0.681	0.798
RANDOM EFFECT				
FSA: SD (constant)	0.046	0.006	0.036	0.058
SD (residual)	0.856	0.002	0.852	0.860
LR test of model vs fixed effect only model: $chi^2(1) = 112.16$; $p < 0.000$				

FSA = Forward Sortation Area
SD = Standard Deviation
LR = Likelihood Ratio
* Model also adjusted for age-sex groups, EoL, comorbidity count, Elixhauser Index, RIW, individual conditions.

Table 4. *EBLUP estimates of random effects of average case-mix adjusted episode LOS for each community from model for objective one.*

FSA	Effect Estimate	95% CI Lower	95% CI Upper
B0V*	0.088	0.031	0.145
B6L*	0.073	0.023	0.123
B0P*	0.069	0.040	0.098
B4N*	0.063	0.024	0.103
B2N*	0.062	0.026	0.097
B0W*	0.061	0.033	0.090
B1H*	0.050	0.004	0.097
B0E*	0.042	0.011	0.072
B5A*	0.040	0.001	0.079
B0N*	0.035	0.008	0.062
B0K*	0.035	0.009	0.060
B1R	0.033	-0.031	0.097
B3A	0.033	-0.004	0.070
B9A	0.033	-0.032	0.097
B1A	0.031	-0.006	0.068
B0S	0.031	-0.006	0.068
B3G	0.029	-0.024	0.082
B1P	0.028	-0.011	0.068
B1S	0.022	-0.029	0.073
B2S	0.020	-0.040	0.081
B4R	0.019	-0.053	0.092
B1N	0.016	-0.041	0.072
B2J	0.013	-0.074	0.100
B1G	0.013	-0.058	0.083
B1W	0.009	-0.061	0.080
B2E	0.009	-0.080	0.097
B3V	0.008	-0.053	0.069
B1X	0.007	-0.074	0.089
B4P	0.002	-0.053	0.057
B1V	0.002	-0.051	0.055
B0L	0.002	-0.069	0.072
B1M	0.002	-0.078	0.081
B3J	0.002	-0.068	0.071
B2C	0.001	-0.084	0.086
B3E	0.001	-0.058	0.060
B1L	0.001	-0.062	0.064
B1C	0.001	-0.072	0.074
B1E	0.000	-0.074	0.074
B0M	-0.001	-0.041	0.038
B2H	-0.001	-0.040	0.037

FSA	Effect Estimate	95% CI Lower	95% CI Upper
B1T	-0.002	-0.086	0.083
B1J	-0.002	-0.081	0.077
B0R	-0.003	-0.060	0.054
B2G	-0.003	-0.046	0.041
B0H	-0.005	-0.048	0.037
B2Z	-0.005	-0.060	0.050
B2Y	-0.007	-0.049	0.035
B2R	-0.007	-0.081	0.066
B3B	-0.008	-0.090	0.074
B2W	-0.009	-0.039	0.022
B2V	-0.009	-0.060	0.042
B4H	-0.010	-0.055	0.035
B1K	-0.012	-0.079	0.054
B3N	-0.013	-0.058	0.032
B4V	-0.013	-0.051	0.024
B2A	-0.014	-0.063	0.035
B1Y	-0.015	-0.072	0.042
B1B	-0.016	-0.091	0.058
B3P	-0.017	-0.069	0.036
B3R	-0.018	-0.069	0.033
B0J	-0.021	-0.048	0.006
B3L	-0.022	-0.066	0.022
B3M	-0.026	-0.061	0.009
B2X	-0.028	-0.077	0.020
B3K	-0.030	-0.069	0.010
B3H	-0.033	-0.080	0.014
B4A	-0.034	-0.079	0.011
B4B	-0.036	-0.094	0.021
B4G	-0.039	-0.105	0.026
B0T*	-0.042	-0.080	-0.004
B3S	-0.045	-0.093	0.003
B2T	-0.046	-0.095	0.002
B4E*	-0.053	-0.099	-0.008
B3T*	-0.061	-0.106	-0.015
B4C*	-0.066	-0.106	-0.027
B3Z*	-0.077	-0.123	-0.031
B0C*	-0.137	-0.199	-0.075

* statistically significantly different than the provincial mean at $\alpha = 0.05$

Table 5. *Summary of the significance and magnitude of effect of different operationalizations of complex health needs on community variation in case-mix adjusted average episode LOS.*

System used to classify complexity	Low Complex Needs score; n (%)	High Complex Needs score; n (%)	LR Test [a] p value	Statistical significance of magnitude of difference of SD for low versus high complex needs [b] no/yes	# of communities with significantly longer case-mix adjusted average episode LOS than the provincial mean [c]		# of communities with significantly shorter case-mix adjusted average episode LOS than the provincial mean [c]	
					Low Complex Needs	High Complex Needs	Low Complex Needs	High Complex Needs
Elixhauser Index [d]	Score ≤ 1 46,443 (62%)	Score > 1 28,670 (38%)	$p = 0.0217$	No	11	4	5	1
Elixhauser Index [d]	Score ≤ 2 61,899 (82%)	Score > 2 13,214 (18%)	$p = 0.0008$	No	11	1	7	0
Resource Intensity Weight	Score < median [e] 37,556	Score ≥ median [e] 37,557	$p < 0.0001$	Yes	0	8	75	5

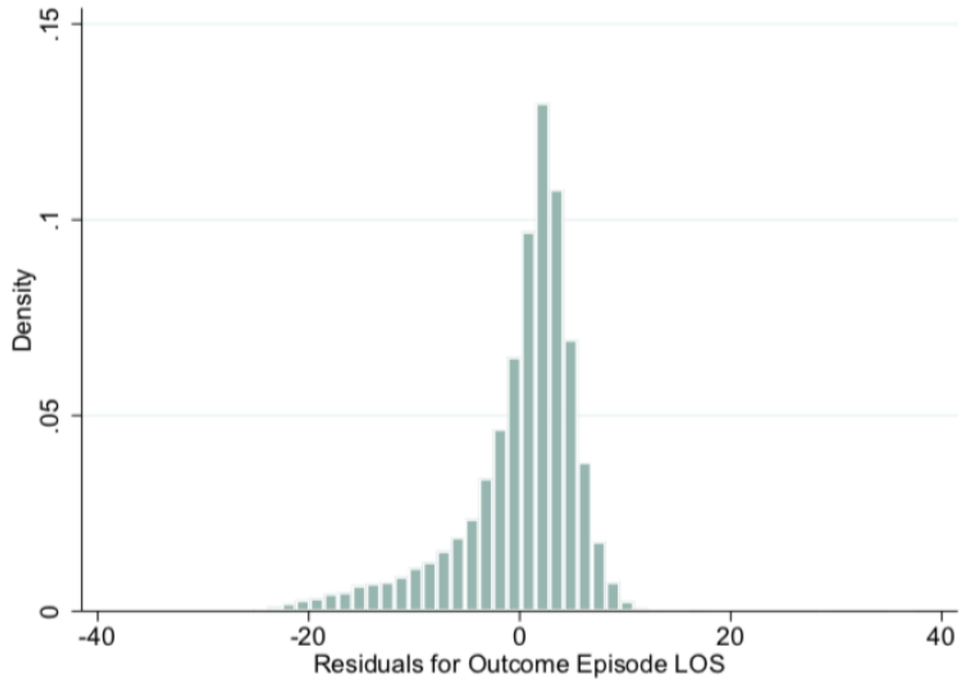
[a] LR test comparing the model where the random effect portion was two random intercepts (one the low and one for the high complex needs group) by FSA against the model where the random effect portion was just one random intercept for FSA.
[b] statistical significance = no overlap between 95% CIs surrounding the SD for the low and high complex needs groups
[c] out of 77 communities (FSAs)
[d] Elixhauser index ranges from 0 to 10
[e] median score = 1.1148

Table 6. *Proportionate (standard deviation (SD)) and absolute effects (excess days) on community variation of low and high complex needs groups based on the definition of complex needs.*

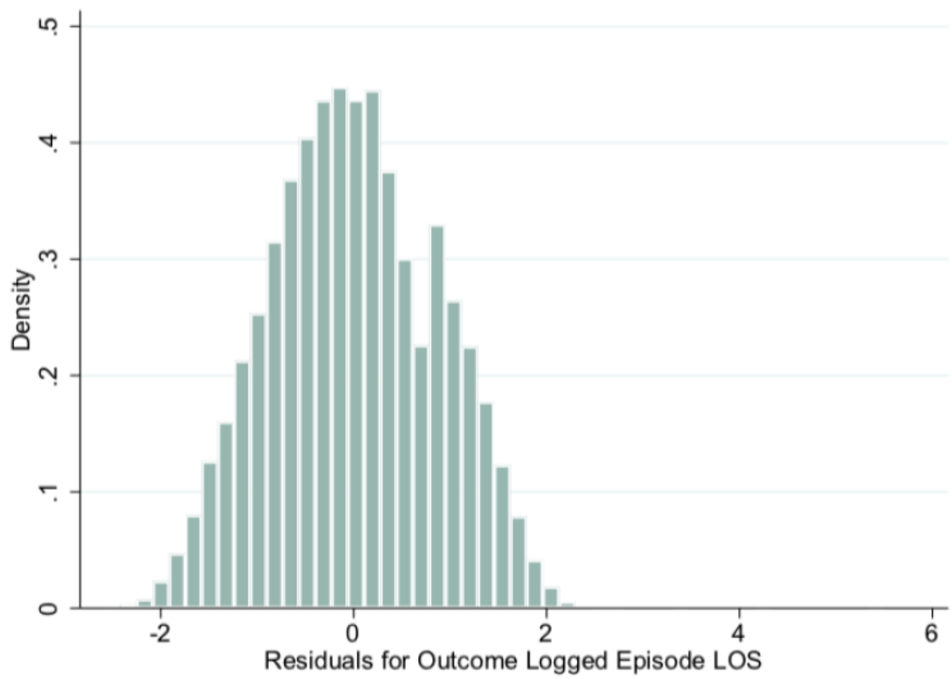
System used to classify complexity	Low Complex Needs			High Complex Needs		
	SD (95%CI)	Mean LOS (days)	Excess Days	SD (95%CI)	Mean LOS (days)	Excess Days
Elixhauser Index [a]	0.053 (0.041, 0.068)	5.24	0.278	0.045 (0.032, 0.065)	8.52	0.383
Elixhauser Index [b]	0.051 (0.040, 0.065)	5.85	0.298	0.048 (0.028, 0.081)	9.51	0.456
Resource Intensity Weight (RIW) [c]	0.593 (0.504, 0.698)	4.15	2.461	0.047 (0.035, 0.062)	8.83	0.415

[a] low complex needs = Elixhauser index score ≤ 1; high complex needs = Elixhauser index score >1
[b] low complex needs = Elixhauser index score ≤ 2; high complex needs = Elixhauser index score >2
[c] low complex needs = RIW score < median; high complex needs = Elixhauser index score ≥median

FIGURES



(a)



(b)

Figure 1. *Distribution of residuals when outcome variable is (a) episode LOS, and (b) log transformed episode LOS.*

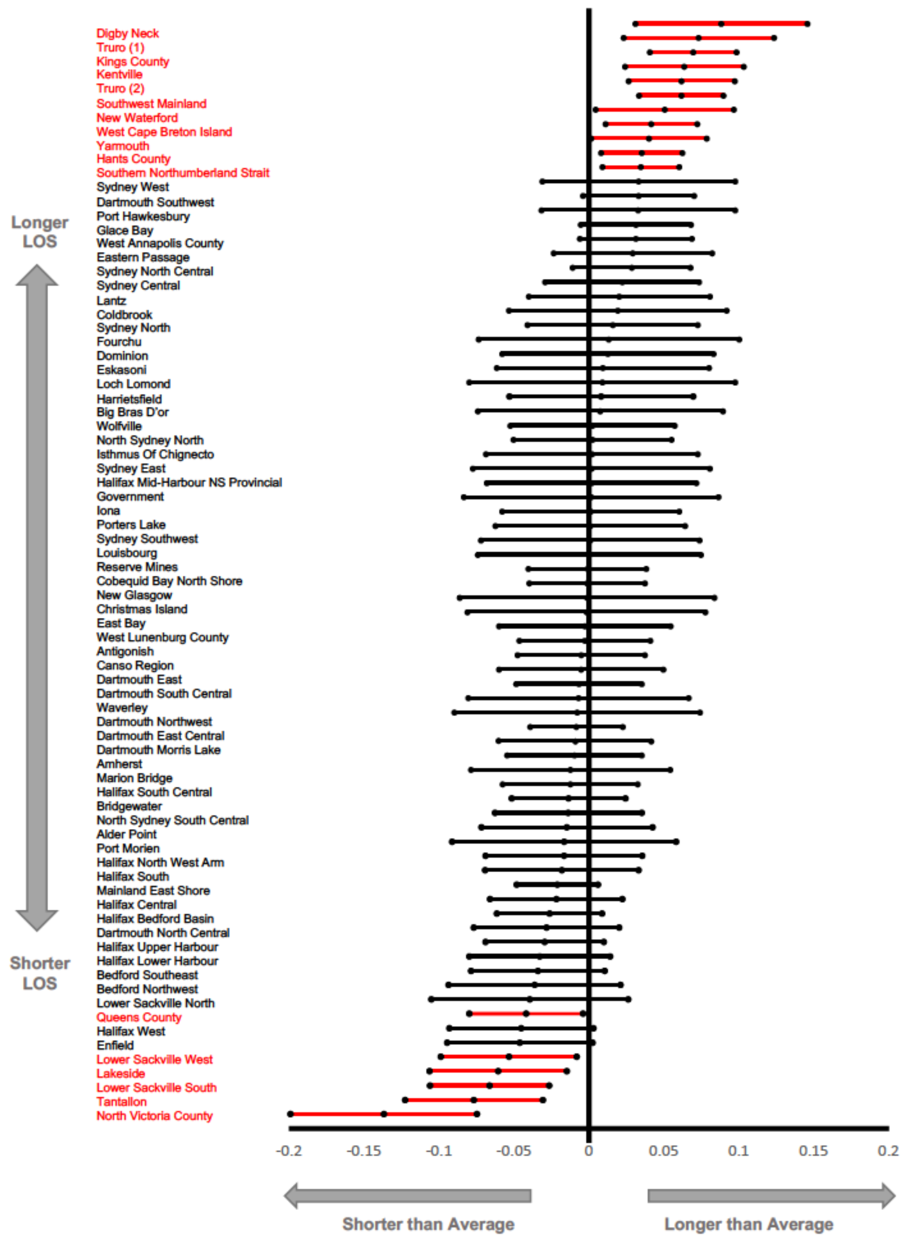


Figure 2. *Caterpillar plot of random effects of average case-mix adjusted episode LOS for each community from model for objective one.*

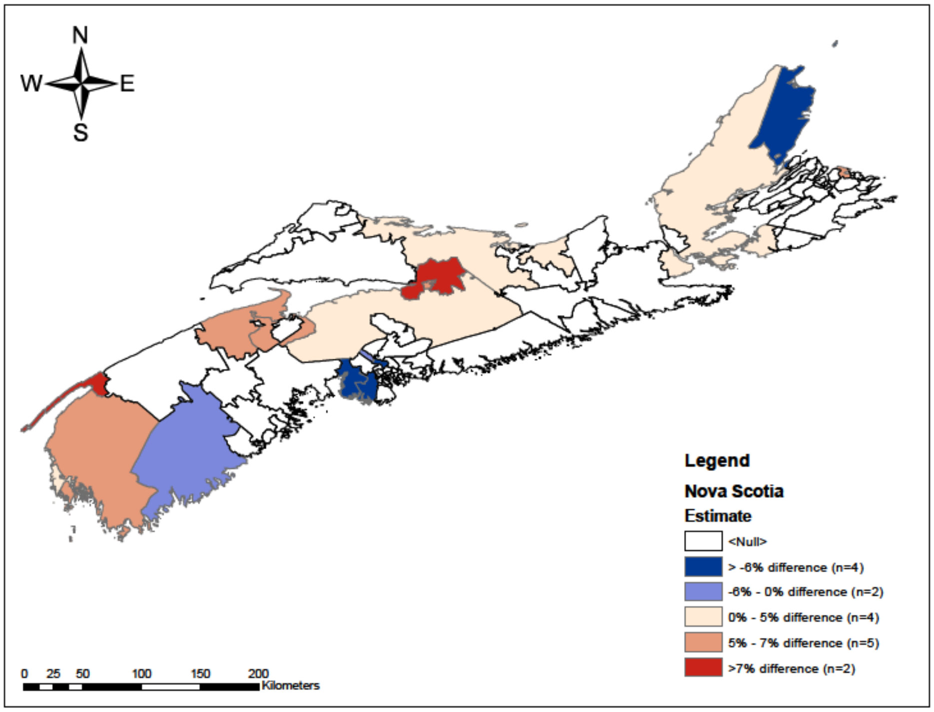


Figure 3. *Map of random effects of communities that are statistically significantly different than the Nova Scotia mean.*

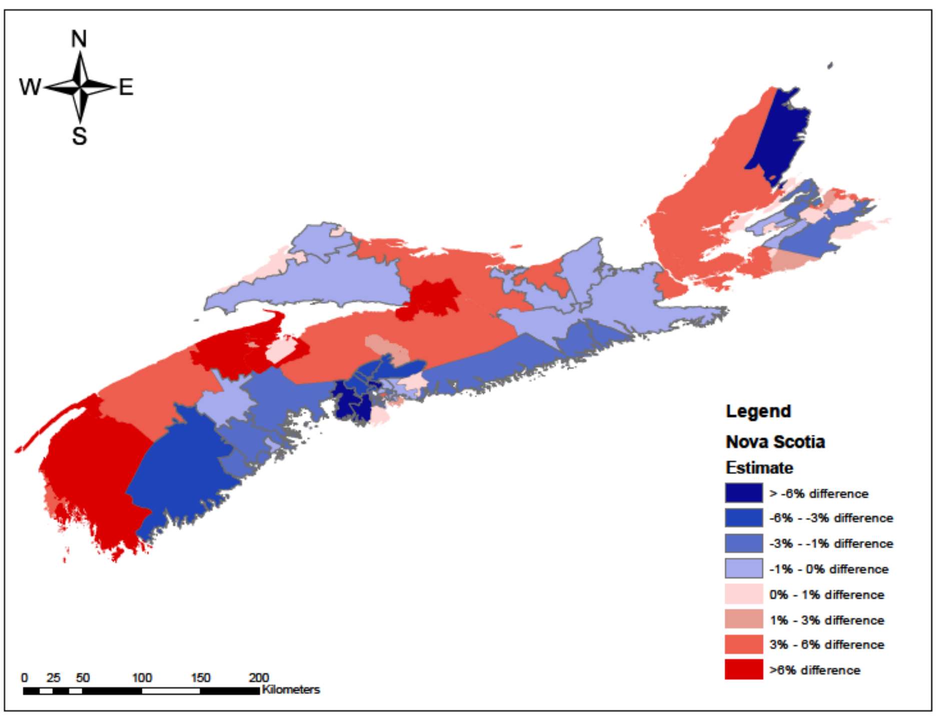
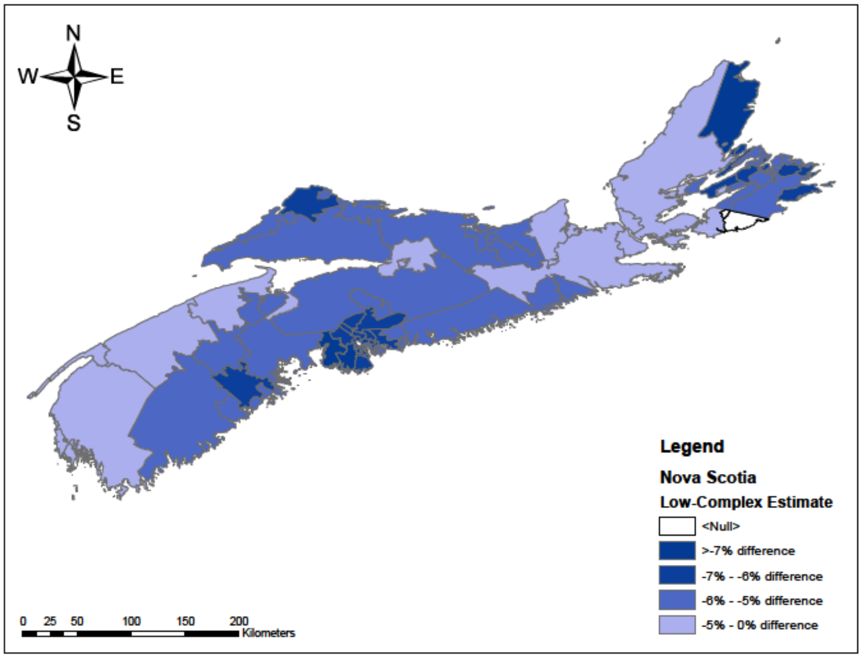
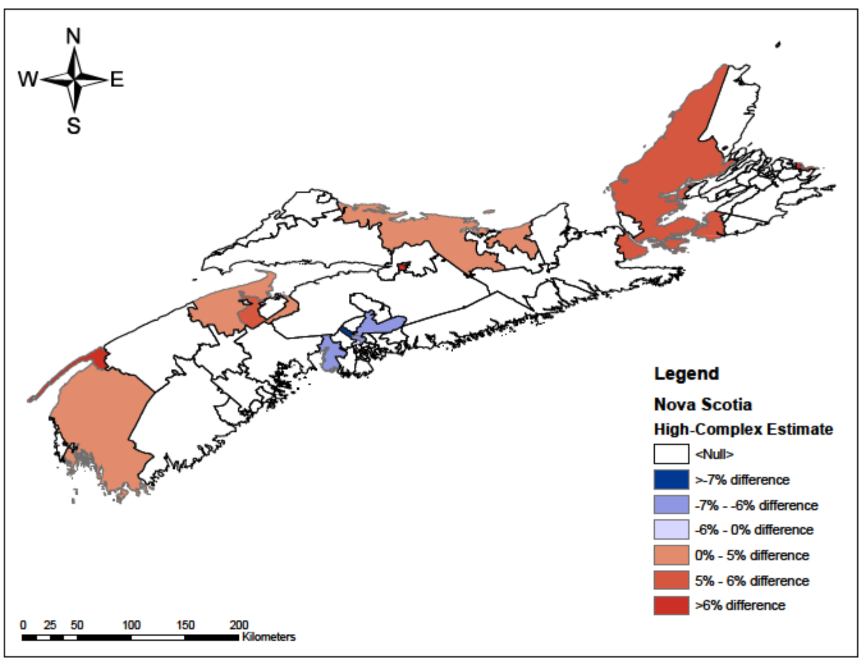


Figure 4. *Map of random effects of all communities in Nova Scotia.*



(a)



(b)

Figure 5. *Map of random effects of communities that are significantly different than the Nova Scotian mean when complexity is defined by an RIW median score cut-off (1.1148) for (a) the group with low complex needs, and (b) the group with high complex needs.*

CHAPTER 6: DISCUSSION

6.1 Objective 1 and Next Steps

We found that community of residence is significantly associated with episode LOS. This association is both statistically significant, as demonstrated in the results, and practically significant. From a practical standpoint, compared to the average episode LOS in NS, there is a difference of 30 days per 100 admissions for communities that are one SD away from this average. Thus, this excess case-mix adjusted LOS is likely to have large cost implications. This finding is strengthened by its similarities with other works on small area rate variation (SARV) in healthcare outcomes.[138,143]

We also identified 17 communities where people are discharged to that are associated with a significantly longer or shorter episode LOS. These might represent communities where communities have good or poorly integrated systems of care, but this is not definitive, nor does it tell us why. There are important points to consider in the interpretation of our findings and the information our findings provide.

Our project was purely descriptive. With our data, we do not have the means to say whether a community associated with significantly longer or shorter LOS is a good or bad thing. The strongest means of inferring whether these identified communities are in fact performing poorly or not is to compare them with other SARV works. Notably, there were three communities identified as having significantly longer case-mix adjusted average episode LOS than the provincial mean that were also highlighted in both other SARV works (see Figure 6).[138,143] This overlap of communities across these works is interesting for a few reasons.

The first is the credibility it lends to the SARV program of research. Our larger program of research is assessing community variation in health system outcomes (high-cost healthcare use,[143] unplanned repeat hospitalization,[138] and long adjusted LOS) as indicators of community performance as a system of care, and then exploring the reasons for this variation. The tendency for communities with high cost healthcare use to have both high rates of unplanned repeat hospitalizations and long adjusted LOS shows that both of these factors are contributing to community variation in healthcare costs.

The second is in the comparison with the unplanned repeat hospitalization work. One might assume that when people are staying longer in hospital, they would have lower rates of unplanned repeat hospitalization. However, it is also plausible that if it is difficult to discharge someone home, it is also difficult to support someone in their home setting while recovering or managing your health needs. There were four communities that overlapped with the unplanned repeat hospitalization work alone (see Figure 6), which represent communities where people are not only staying long in hospital but are also returning to hospital at a quicker rate. These four challenged this first assumption and may support the second that if a community as a system of care cannot support your discharge home, it also likely has challenges in continuing to support your health needs. This lends credibility to targeting communities when assessing these health system outcomes. These identified communities, especially the three which are significantly associated with both high unplanned repeat hospitalizations and high-cost healthcare use have more evidence implying they have a poorly integrated system of care or may be lacking downstream supports that would result in high hospital use. Though it still does not allow us to conclude anything definitively, these are communities worth targeting for future research and policy work.

Next, there is no benchmark for what the optimal hospital LOS should be. We discussed our findings in relation to the provincial average, however there is no evidence demonstrating that the provincial average is the appropriate benchmark to strive for regarding hospital LOS. In the literature, there are many different cut-off points for defining unnecessary LOS,[29,132–137] and therefore, the benchmark of an "optimal" LOS differs. Ideally, we would want to understand what would be achievable in terms of reducing LOS while still optimizing health outcomes.

Minimizing hospital LOS to a benchmark that is too low could result in people being discharged prematurely and are experiencing negative health (e.g. morbidity) and system (e.g. unplanned repeat hospitalizations) outcomes. This would likely result in excess costs to the healthcare system without improvement in patient outcomes. Therefore, though our results imply that a reduction of LOS to the mean is the goal, we must consider LOS in the context of other factors, including patients' needs, and hospital and community factors. However, the comparability with Reid's work does indicate that our goal might not be completely inappropriate in and of itself. None of the communities identified as having significantly lower case-mix adjusted average episode LOS than the provincial mean were identified in Reid's work as having significantly higher rates of unplanned repeat hospitalizations (Figure 6).

More in depth work is required to understand why the communities identified as having significantly different case-mix adjusted episode LOS than the mean do differ, and whether they represent systems of care that are, or are not, well integrated. The methods used to address this question should reflect the complex interactions between different formal and informal services that are embedded in the community system.[9] Currently, most of the work done to understand the community effect on LOS uses methods that do not allow them to consider these complex interactions. They instead focus on individual programs that are meant to improve the transition home from hospital, which takes these programs out of the context of their system of care.[12,30,33,123–126] Complex interactions in a community system of care can affect whether a program is effective in different settings, resulting in mixed results on effectiveness, making it difficult for policy makers to synthesize and use that knowledge.[35]

Next steps in research into these communities can be done qualitatively and quantitatively. Qualitative work will likely better account for the complex interactions in a system of care, however there is more quantitative work which can be done first to help narrow the focus of this qualitative work. This project could be repeated with the inclusion of non-clinical variables that affect hospital LOS; the adjustment of only clinically related variables in our model is a limitation of our project as we have unmeasured patient characteristics. Social isolation, SES, income, education, housing and location of your home are all factors that can affect hospital LOS, however they were not captured in our risk-adjustment measures due to data and time constraints.[60,85,105,86–91,99,100] Therefore, in future work these variables should be added to the case-mix adjustment in our model to determine how much they might contribute to the effect of community on episode LOS. Furthermore, it would be important to gain a better understanding of the individuals residing in these communities that have significantly different case-mix adjusted average episode LOS than the provincial mean. Further descriptive work using administrative or other data could allow us to differentiate individuals who are or are not experiencing long hospital stays within these communities, and also compare these individuals between communities. Our project made assessments at the community level, therefore precluding us from making inferences about needs of specific case-mixes.

This quantitative work can help inform the subsequent qualitative work. To better understand the community as a system of care, it would be important for researchers and policy makers to physically go into communities and speak to people. The quantitative work can help guide where to look first, whether it's looking into health resources, sectors outside the health system, or community supports, as well as describe characteristics of individuals who might be more acutely experiencing the lack of integration within their communities. It would be important to speak with a range of individuals including community leaders, patients, and discharge planners, to get an understanding of how community-specific integration or care deficits might be affecting timely discharge.

6.2 Objective 2

Given the three ways we defined patients with medically complex needs, we found that community variation in episode LOS does differ between groups with low and high complex health needs. However, the extent to which it differs, as well as which communities are highlighted as being significantly different than the overall provincial mean depend on how complex health needs are defined.

Defining complexity in patients' needs is an area of inconsistency in the literature.[15,110,111] This is likely due to the lack of a universal definition of what complex needs are, and the resource and data constraints placed upon different methods of research.[17,45] Ideally in defining patients with complex needs, we would consider more than just disease; we would want to also consider demographic information, information on social and material deprivation, and information from HCPs interacting with these patients.[15,16,18,110–115] Our definition of complex needs based on a measure of morbidity neglects these important factors that complicate the health needs of a patient. Due to data and time constraints, we were unable to consider social and material factors or interactions with HCPs and were limited to clinical variables from hospital administrative data. As there is no clear definition for complexity and it was likely that our results would be different based on different definitions of complex needs; we defined patients with complex needs based two different cut-offs of the Elixhauser index score (a score of one and a score of two) and the median score for RIW.

When low complex health needs were defined using the RIW score, all the communities identified as being significantly different than the overall provincial mean (combined mean of low and high complex needs group) had a lower case-mix adjusted average episode LOS. This intuitively makes sense, as individuals with less complex needs may not need their community to have as many, or as well integrated, resources to support them going home. Interestingly, among the high complex health needs group (defined using RIW), there were five communities also identified as being associated with a significantly shorter case-mix adjusted average episode LOS than the overall provincial mean. Another interesting finding was the large difference in the magnitude of communities being one SD away from the overall provincial mean between the low and high complex needs groups (defined using RIW). The proportionate effect on community variation for the low complex needs group was much larger than for the high complex needs group (SD = 0.593 and SD = 0.047, respectively). The absolute effect on community variation was also much larger among the low complex needs group, resulting in approximately a two-day difference in the excess days resulting from being one SD away from the overall mean as compared to the high complex needs group.

Further research on the communities that were identified as having shorter case-mix adjusted average episode LOS in both the low and high complex needs groups (defined using RIW) is needed. This finding may be a reflection of very strongly integrated community systems of care, or it is possible that it is capturing an effect of discharging hospital. In depth research would also be required to understand this dramatic effect and regional variation among the group with low complex needs, as it is interesting that community of residence would play such a large role for this group, especially as compared to the group with high complex needs. It may be a reflection of the fact that communities in general are well-integrated enough to support patients with low complex needs returning home with differing strengths.

Though we cannot determine which of our measures of complexity was the most "correct", there are important differences in what each of these measures captures. The Elixhauser index is validated for health outcomes; it weights the burden of certain conditions, which may indicate needs that are more complex, but only does so for a subset of conditions.[50] The RIW on the other hand is validated for cost.[45] A large contributor to cost is number of days in hospital, therefore RIW would inadvertently be incorporating the number of days an individual is expected to stay in hospital. However, it also includes all conditions, as well as information in interventions (how many and indicators for interventions for patients who have more complex needs). The RIW likely gives us more granular detail and more complete data capture, which is likely the reason it was able to identify more communities as being significantly different than the provincial mean.

6.3 Community-Hospital Interaction

Finally, an important consideration across our results is that we were unable to adjust for hospital in our analyses. We found that community effects differ by hospital and hospital effects differ by community. This suggests that these two systems of care interact in complex ways, where some hospitals might be more or less sensitive to community factors in discharging a patient home. It also suggests that hospitals are acting in a transitional care capacity for patients living in certain communities – likely the community where they reside and some surrounding areas.

The inability to adjust for hospital in our analyses has some important implications in our work and other work assessing factors that affect hospital LOS. For our work, it means that our outcome of episode LOS does not solely reflect community effects, but also incorporates the effect of hospital. The implications to other studies relates to the emerging recognition that we should be adjusting for community when assessing case-mix adjusted LOS as a measure of hospital efficiency. Our study confirms that community of residence is associated with LOS, and thus could be included in case-mix adjustment when assessing hospital efficiency. This is consistent with work done by the team from the University of Calgary, who developed a conceptual framework highlighting the importance of adjustment beyond just clinical factors, to things like community level factors [28]. They have since tested models that adjust for community level factors when assessing LOS [29]. However, the complex relationship between community and hospital demonstrated in our study also raises concerns about adjusting for community, and points to the need for more nuanced study of how community factors influence discharge decisions. Regardless, community of residence is still important to consider when evaluating hospitals on LOS, as how they interact may provide important insights.

6.4 Limitations

There are important study limitations to consider that have not been discussed above. First, using FSA as our measure of community is an important limitation in our study because the geographical boundaries set by FSA do not necessarily correspond to systems of care. FSA could span multiple "communities", as well as only represent part of other "communities", as would be defined by a system of care. This issue of FSA not representing systems of care is an example of the contextual fallacy.[144] The contextual fallacy relates to the Modifiable Areal Unit Problem (MAUP), which considers issues related to zoning (or dividing the province into same number of communities in different sizes and shapes) and scale (changing the number of communities in the province).[144] Due to the different methods of zoning and scaling to define communities in Nova Scotia, it would not be appropriate to draw any definitive conclusions about systems of care based on one method alone.[144] This means our results would likely change based on how community is operationalized. However, as discussed above, FSA was the most reliable measure of geography available to us at present, and still provides an important starting point for future work. Without further contextual information, we cannot inform improved geographical community units in how we might combine or divide FSAs.

Our results may be sensitive to how we operationalized our outcome. For this study, longer than necessary LOS was operationalized as an episode LOS significantly longer than the provincial average. We chose this over other typical predictors of longer than necessary LOS for a few reasons. First, based on the literature, ALC would likely result in an underestimation of the burden of longer than necessary LOS.[24,25] ALC would also likely represent a more extreme population of patients who remain in hospital for a long period of time, as this is a formal designation given by a HCP.[24,62] This measure is therefore not sensitive to cases where individuals are in hospital a day or two longer, which is more common and adds up to a significant portion of days contributing to LOS. The second measure considered, adjusted LOS as defined by CIHI, compares the time in hospital that a patient is expected to stay versus how long they actually stay.[26] The methodology for computing the expected LOS used by CIHI was developed after excluding cases with transfers, deaths, or sign-outs that did not return from a pass.[45] The exclusion of these cases in this methodology is especially problematic when assessing LOS in Nova Scotia, as Nova Scotia has a central tertiary care center which services the province, and therefore transfers between facilities are common.

Our case-mix adjustment encompassed a very comprehensive list of conditions (see Appendix A). This was to provide an overview of how community affected case-mix adjusted episode LOS in general for unplanned hospitalizations. However, if this project were repeated for how community affected case-mix adjusted episode LOS for a specific condition, it is possible that the communities which show up as being significantly different than the provincial average would be different than those identified in our work. This is because individuals with different specific conditions likely require different services or supports to meet their health needs in their community. There may be communities which are great at supporting the needs individuals with certain conditions, but not as good at supporting the needs of individuals with other conditions. For example, some communities might have disease-specific programs or supports that are not present in all communities. In our work, the use of average community effects may mask differences by specific conditions.

Regarding the selection of our study population, a limitation is that we focused on those individuals who are being discharged to their communities, excluding those discharged to a LTC facility. Though theoretically individuals who get discharged to a LTC facility are different than those who can be discharged home, this is not always clear-cut, and again we could imagine this might vary by community. For example, an individual may be discharged home if they live in a community with a strong system of care to support them, yet the if this same individual lived in a community with a weaker system of care, their needs may be better met in a LTC facility. Another factor at the community level would be LTC beds. If there are no available beds in any LTC facility in the community, a patient may be discharged home instead of keeping them in hospital indefinitely, where in another community with available beds in a LTC facility the same patient would be discharged to an LTC facility and not home. Therefore, in reality, whether someone is discharged home or to a LTC facility are affected by community. As a result, individuals discharged to a LTC facility instead of home to their community due to their community having a poorly integrated system of care would not be captured in our dataset, and the related communities might falsely appear to have no, or a weaker effect on episode LOS. Future work should assess why individuals are discharged to either a LTC facility or home, in order to capture cases where community factors are dictating that decision. Understanding how many cases there are, as well as where they are, would help to target communities for in depth research on how they function as a system of care.

Finally, our study period was between FY 2010-14. These years were selected for the comparability with Reid's study.[138] Although this is a strength in the comparability of the results for policy makers, it is also a limitation in its relevance to policy makers since it does not provide the most recent picture of community effects on these outcomes. However, since we used 4 years of data, we were able to identify communities with consistently different LOS than the provincial average, instead of communities which may show up as significantly different for an outlying year. This increases the likelihood that the identified communities would still show up as significant if the research was conducted for the now most recent four-year time window, though it does not guarantee this and should be repeated if results are to be most relevant to policy makers today. However, our work demonstrates that where you live does affect how long you stay in hospital and the usability of the model we created to come to this conclusion. Therefore, it does still provide important and usable information to policy makers.

6.5 Policy Relevance

The present study sought to shift the focus to communities as a system of care. It moves away from the dominant focus of LOS as a measure of hospital performance, while also filling a gap in the literature that currently focuses on individual components of a system. By assessing the effect of communities as complex adaptive systems on episode LOS, we produced information that policy makers can use in identifying systems of care that may not be functioning well. Our work demonstrates that where you live does impact how long you stay in hospital, and therefore affirms the idea that factors outside of the hospital system can affect hospital use.

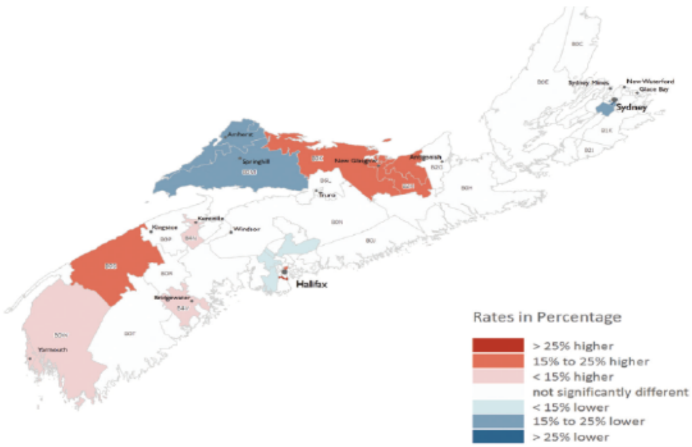
My project contributes to an already large and growing program of research in small area variation in health service use in Nova Scotia. Results from this program of research are being utilized by policy makers in the province, and they have expressed support for furthering this program of research. The ability to directly compare this work with that of Reid's on unplanned repeat hospitalizations allows policy makers a more complete picture of how community may impact hospital usage. These works support the design and implementation of community-based programs. These programs would be specific to communities in supporting their health and health-related needs, minimizing the impact on the hospital system.

Results from this project will contribute information to the Maritime Health Atlas, which is an interactive tool which includes differences in things like health service use across geographic areas in Nova Scotia and New Brunswick.[145] We will map case-mix adjusted average episode LOS in communities across Nova Scotia. This map is useful to policy makers and researchers as it facilitates the identification of communities where episode LOS is longer or shorter than the provincial to be targeted for more detailed research on their systems of care. It also facilitates the identification of communities whose effect on episode LOS differed based on the medical complexity of patients' needs. Though our project cannot explain why those communities differ, it allows us to identify them for further research into why.

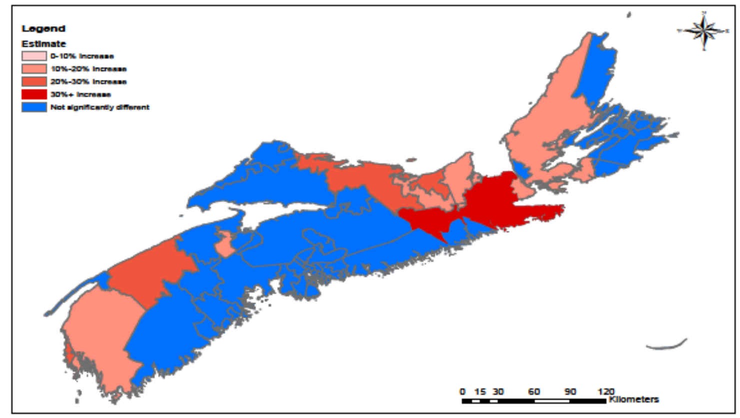
The ability to identify these communities was a necessary first step because the complex interactions between different formal and informal resources in communities precluded us from studying one of these aspects out of context in how it affects LOS. With these communities identified, research that is better tailored to teasing apart those complex relationships, such as identifying different health-related resources in the community or qualitative work where those with lived experience can help identify avenues through which solutions might be most impactful, can be done.

FIGURES

(a)



(b)



(c)

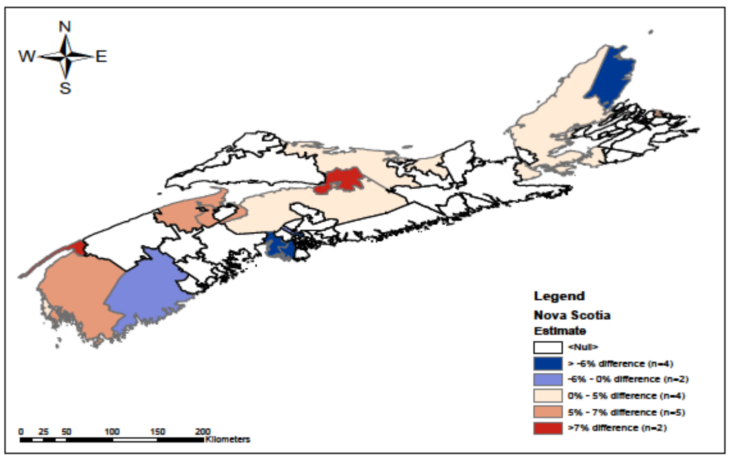


Figure 6. *Comparison of communities identified as being statistically significantly different from the provincial mean in other small area rate variation works (a) high-cost healthcare use* [143]*, (b) unplanned repeat hospitalizations* [138]*, (c) case-mix adjusted episode LOS. All adjusted for demographic and clinical variables (though exact variables used varied).*

CHAPTER 7: CONCLUSION

Our work demonstrates that where you live is important to how long you remain in hospital, and that where you live may impact the length of your hospital stay differently based on the complexity of your health needs. It also allowed us to pinpoint communities that are significantly different than the mean in how long their residents stay in hospital, however, it does not allow us to determine why this may be. It supports the idea of looking more broadly outside of the traditional healthcare system in supporting the health needs of individuals to reduce the need for, or burden on, the hospital system.

As noted above, the descriptive nature of our study does not allow us to provide any more specific insights into the community systems. However, by highlighting communities that significantly differed from the mean, we've provided a starting point for researchers and policy makers to target communities for more in-depth work into the relationship between community of residence and hospital LOS. By looking outside of the hospital system at community systems, we may better identify reasons for variation in LOS in areas across Nova Scotia. This deeper understanding can lead to the prevention of greater health or health management issues and decreases in hospital related costs.

REFERENCES

1. Canadian Institute for Health Information. *Cost of a Standard Hospital Stay*.; 2017. https://yourhealthsystem.cihi.ca/hsp/inbrief?lang=en#!/indicators/015/cost-of-a-standard-hospital-stay/;mapC1;mapLevel2;overview;trend(C2000,C1);/.

2. Rosman M, Rachminov O, Segal O, Segal G. Prolonged patients' In-Hospital Waiting Period after discharge eligibility is associated with increased risk of infection, morbidity and mortality: a retrospective cohort analysis. *BMC Health Serv Res*. 2015;15:246. doi:10.1186/s12913-015-0929-6.

3. McCloskey R, Jarrett P, Stewart C. The Untold Story of Being Designated an Alternate Level of Care Patient. *Healthc Policy*. 2015;11(1):76-89.

4. Siroux V, Agier L, Slama R. The exposome concept: a challenge and a potential driver for environmental health research. *Eur Respir Rev*. 2016;25(140):124-129. doi:10.1183/16000617.0034-2016.

5. Luft HS. From small area variations to accountable care organizations: how health services research can inform policy. *Annu Rev Public Health*. 2012;33:377-392. doi:10.1146/annurev-publhealth-031811-124701.

6. Sampalli T, Edwards L, Christian E, et al. A Patient-Centred Redesign Framework to Support System-Level Process Changes for Multimorbidities and Chronic Conditions. *Healthc Q*. 2015;18(3):34-42.

7. Sampalli T, Christian E, Edwards L, Ryer A. A Chronic Disease Prevention and Management Corridor(c) to Supporting System-Level Transformations for Chronic Conditions. *Healthc Q*. 2015;18(3):43-48.

8. Lebel A, Pampalon R, Villeneuve PY. A multi-perspective approach for defining neighbourhood units in the context of a study on health inequalities in the Quebec City region. *Int J Health Geogr*. 2007;6:27. doi:10.1186/1476-072X-6-27.

9. Tsasis P, Evans JM, Owen S. Reframing the challenges to integrated care: a complex-adaptive systems perspective. *Int J Integr Care*. 2012;12:e190.

10. World Health Organization. Declaration of Alma-Ata: International Conference on Primary Health Care, Alma-Ata, USSR, 6-12 September 1978. http://www.who.int/publications/almaata_declaration_en.pdf?ua=1.

11. Coleman EA. MODELS AND SYSTEMS OF GERIATRIC CARE Falling Through the Cracks: Challenges and Opportunities for Improving Transitional Care for Persons with Continuous Complex Care Needs. *JAGS*. 2003;51:549-555.

12. Goncalves-Bradley DC, Iliffe S, Doll HA, et al. Early discharge hospital at home. *Cochrane database Syst Rev*. 2017;6:CD000356. doi:10.1002/14651858.CD000356.pub4.

13. Health Council of Canada. *Seniors in Need, Caregivers in Distress: What Are the Home Care Priorities for Seniors in Canada?*; 2012.

14. Epstein-Lubow G, Baier RR, Butterfield K, et al. Caregiver presence and patient completion of a transitional care intervention. *Am J Manag Care*. 2014;20(10):e349-444.

15. Peek CJ. Integrating care for persons, not only diseases. *J Clin Psychol Med Settings*. 2009;16(1):13-20. doi:10.1007/s10880-009-9154-y.

16. Loeb DF, Binswanger IA, Candrian C, Bayliss EA. Primary care physician insights into a typology of the complex patient in primary care. *Ann Fam Med*. 2015;13(5):451-455. doi:10.1370/afm.1840.

17. Grant RW, Ashburner JM, Hong CS, Chang Y, Barry MJ, Atlas SJ. Defining patient complexity from the primary care physician's perspective: a cohort study. *Ann Intern Med*. 2011;155(12):797-804. doi:10.7326/0003-4819-155-12-201112200-00001.

18. Valderas JM, Starfield B, Sibbald B, Salisbury C, Roland M. Defining comorbidity: implications for understanding health and health services. *Ann Fam Med*. 2009;7(4):357-363. doi:10.1370/afm.983.

19. Organisation for Economic Co-operation and Development. Length of hospital stay. https://data.oecd.org/healthcare/length-of-hospital-stay.htm. Published 2015.

20. van de Vijsel AR, Heijink R, Schipper M. Has variation in length of stay in acute hospitals decreased? Analysing trends in the variation in LOS between and within Dutch hospitals. *BMC Health Serv Res*. 2015;15:438. doi:10.1186/s12913-015-1087-6.

21. Gyrd-Hansen D, Olsen KR, Sorensen TH. Socio-demographic patient profiles and hospital efficiency: does patient mix affect a hospital's ability to perform? *Health Policy*. 2012;104(2):136-145. doi:10.1016/j.healthpol.2011.07.010.

22. Siciliani L, Sivey P, Street A. Differences in length of stay for hip replacement between public hospitals, specialised treatment centres and private providers: selection or efficiency? *Health Econ*. 2013;22(2):234-242. doi:10.1002/hec.1826.

23. OECD. *Health at a Glance: Europe 2012*. OECD Publishing; 2012. doi:10.1787/9789264183896-en.

24. CIHI. *Alternate Level of Care in Canada*.; 2009. https://secure.cihi.ca/free_products/ALC_AIB_FINAL.pdf.

25. Sutherland JM, Crump RT. *Exploring Alternative Level of Care (ALC) and the Role of Funding Policies: An Evolving Evidence Base for Canada*.; 2011.

26. Alberta Health Services. *Acute Length of Stay (ALOS) Compared to Expected Length of Stay (ELOS)*.; 2017.

27. Canadian Institute for Health Information. *Inpatient Hospitalizations and Average Length of Stay; Trends in Canada , 2003 – 2004 and 2004 – 2005*.; 2005. https://secure.cihi.ca/free_products/hmdb_analysis_in_brief_e.pdf.

28. Lu M, Sajobi T, Lucyk K, Lorenzetti D, Quan H. Systematic review of risk adjustment models of hospital length of stay (LOS). *Med Care*. 2015;53(4):355-365. doi:10.1097/MLR.0000000000000317.

29. Sajobi T, Lu M, Jiang J, Lucyk K, Quan H. A Comparison of Risk Adjustment Models for Hospital Length of Stay. *CAHSPR Conf.*

30. Vila A, Villegas E, Cruanyes J, et al. Cost-effectiveness of a Barcelona home care program for individuals with multimorbidity. *J Am Geriatr Soc*. 2015;63(5):1017-1024. doi:10.1111/jgs.13396.

31. Robertson FC, Logsdon JL, Dasenbrock HH, et al. Transitional care services: a quality and safety process improvement program in neurosurgery. *J Neurosurg*. July 2017:1-8. doi:10.3171/2017.2.JNS161770.

32. Mary Naylor, PhDFAAN and Stacen A. Keating, PhD R. Transitional Care: Moving patients fro one care setting to another. *Am J Nurs*. 2008;108:58-63. doi:10.1097/01.NAJ.0000336420.34946.3a.Transitional.

33. Miani C, Ball S, Pitchforth E, et al. *Organisational Interventions to Reduce Length of Stay in Hospital: A Rapid Evidence Assessment.* Southampton (UK); 2014. doi:10.3310/hsdr02520.

34. Best A, Greenhalgh T, Lewis S, Saul JE, Carroll S, Bitz J. Large-system transformation in health care: a realist review. *Milbank Q*. 2012;90(3):421-456. doi:10.1111/j.1468-0009.2012.00670.x.

35. Lanham HJ, Leykum LK, Taylor BS, McCannon CJ, Lindberg C, Lester RT. How complexity science can inform scale-up and spread in health care: understanding the role of self-organization in variation across local contexts. *Soc Sci Med*. 2013;93:194-202. doi:10.1016/j.socscimed.2012.05.040.

36. Peters DH. The application of systems thinking in health: why use systems thinking? *Heal Res policy Syst*. 2014;12:51. doi:10.1186/1478-4505-12-51.

37. CIHR-IHSPR. *Pan-Canadian Vision and Strategy for Health Services and Policy*.; 2015.

38. Canadian Institute for Health Information. *National Health Expenditure Trends , 1975 to 2016*. Vol 36.; 2016. doi:10.1007/s10916-010-9605-x.

39. Canadian Institute for Health Information. *Understanding Variability in the Cost of a Standard Hospital Stay*.; 2017.

40. Naylor CD. Health care in Canada: incrementalism under fiscal duress. *Health Aff (Millwood)*. 1999;18(3):9-26.

41. Roos NP, Brownell M, Shapiro E, Roos LL. Good news about difficult decisions: the Canadian approach to hospital cost control. *Health Aff (Millwood)*. 1998;17(5):239-246.

42. Canadian Institute for Health Information. *Health Care in Canada: A First Annual Report 2000*.; 2002. doi:10.2165/00128415-200711570-00010.

43. Kelley WEJ. The evolution of laparoscopy and the revolution in surgery in the decade of the 1990s. *JSLS J Soc Laparoendosc Surg*. 2008;12(4):351-357.

44. DeCoster C, Kozyrskyj A. Long-Stay Patients in Winnipeg Acute Care Hospitals. 2000;(September):1-67.

45. Canadian Institute for Health Information. DAD Resource Intensity Weights and Expected Length of Stay for CMG+ 2017. 2012.

46. Fischer W. The DRG Family. 2011;2011(January 2008):1-33.

47. Gilardi F. Learning from what ? The diffusion of labor market reforms in OECD countries. 2008:1-21.

48. CIHI. CMG + Methodology Overview. 2015;(December 2015).

49. Charlson ME, Pompei P, Ales KL, MacKenzie CR. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. *J Chronic Dis*. 1987;40(5):373-383.

50. Elixhauser A, Steiner C, Harris DR, Coffey RM. Comorbidity measures for use with administrative data. *Med Care*. 1998;36(1):8-27.

51. Johns Hopkins. The Johns Hopkins ACG System. https://www.hopkinsacg.org/. Published 2018.

52. University of Manitoba. Concept: Adjusted Clinical Groups® (ACG®) - Overview. http://mchp-appserv.cpe.umanitoba.ca/viewConcept.php?printer=Y&conceptID=1304. Published 2015.

53. Quail JM, Lix LM, Osman BA, Teare GF. Comparing comorbidity measures for predicting mortality and hospitalization in three population-based cohorts. *BMC Health Serv Res*. 2011;11:146. doi:10.1186/1472-6963-11-146.

54. Bianco A, Pileggi C, Rizza P, Greco MA, Angelillo IF. An assessment of inappropriate hospital bed utilization by elderly patients in southern Italy. *Aging Clin Exp Res*. 2006;18(3):249-256.

55. Ghods AA, Khabiri R, Raeisdana N, et al. Predictors of inappropriate hospital stay: experience from Iran. *Glob J Health Sci*. 2014;7(3):82-89. doi:10.5539/gjhs.v7n3p82.

56. Fellin G, Apolone G, Tampieri A, et al. Appropriateness of hospital use: an overview of Italian studies. *Int J Qual Heal care J Int Soc Qual Heal Care*. 1995;7(3):219-225.

57. Barisonzo R, Wiedermann W, Unterhuber M, Wiedermann CJ. Length of stay as risk factor for inappropriate hospital days: interaction with patient age and co-morbidity. *J Eval Clin Pract*. 2013;19(1):80-85. doi:10.1111/j.1365-2753.2011.01775.x.

58. Caminiti C, Meschi T, Braglia L, et al. Reducing unnecessary hospital days to improve quality of care through physician accountability: a cluster randomised trial. *BMC Health Serv Res*. 2013;13:14. doi:10.1186/1472-6963-13-14.

59. Majeed MU, Williams DT, Pollock R, et al. Delay in discharge and its impact on unnecessary hospital bed occupancy. *BMC Health Serv Res*. 2012;12:410. doi:10.1186/1472-6963-12-410.

60. Landeiro F, Leal J, Gray AM. The impact of social isolation on delayed hospital discharges of older hip fracture patients and associated costs. *Osteoporos Int*. 2016;27(2):737-745. doi:10.1007/s00198-015-3293-9.

61. CIHI. *Alternate Level of Care in Atlantic Canada , 2009 – 2010 Introduction How Old Were ALC Patients ?*; 2011. https://secure.cihi.ca/free_products/alc_aib_january2011_e.pdf.

62. Canadian Institute for Health Information. *Definitions and Guidelines to Support ALC Designation in Acute Inpatient Care.*; 2016. https://www.cihi.ca/sites/default/files/document/acuteinpatientalc-definitionsandguidelines_en.pdf.

63. Canadian Institute for Health Information. *The Cost of Hospital Stays: Why Costs Vary.*; 2008. http://publications.gc.ca/collections/collection_2008/cihi-icis/H118-47-2008E.pdf.

64. McDonagh MS, Smith DH, Goddard M. Measuring appropriate use of acute beds. A systematic review of methods and results. *Health Policy*. 2000;53(3):157-184.

65. Bergeron E, Lavoie A, Moore L, Clas D, Rossignol M. Comorbidity and age are both independent predictors of length of hospitalization in trauma patients. *Can J Surg*. 2005;48(5):361-366.

66. Kuwabara K, Imanaka Y, Matsuda S, et al. The association of the number of comorbidities and complications with length of stay, hospital mortality and LOS high outlier, based on administrative data. *Environ Health Prev Med*. 2008;13(3):130-137. doi:10.1007/s12199-007-0022-9.

67. Rose M, Pan H, Levinson MR, Staples M. Can frailty predict complicated care needs and length of stay? *Intern Med J*. 2014;44(8):800-805. doi:10.1111/imj.12502.

68. Hilmer SN, Perera V, Mitchell S, et al. The assessment of frailty in older people in acute care. *Australas J Ageing*. 2009;28(4):182-188. doi:10.1111/j.1741-6612.2009.00367.x.

69. Bo M, Fonte G, Pivaro F, et al. Prevalence of and factors associated with prolonged length of stay in older hospitalized medical patients. *Geriatr Gerontol Int*. 2016;16(3):314-321. doi:10.1111/ggi.12471.

70. Jackson KL, Glasgow RE, Mone MC, Sheng X, Mulvihill SJ, Scaife CL. Does travel distance influence length of stay in elective pancreatic surgery? *HPB (Oxford)*. 2014;16(6):543-549. doi:10.1111/hpb.12180.

71. Wright SP, Verouhis D, Gamble G, Swedberg K, Sharpe N, Doughty RN. Factors influencing the length of hospital stay of patients with heart failure. *Eur J Heart Fail*. 2003;5(2):201-209.

72. Quintana JM, Unzurrunzaga A, Garcia-Gutierrez S, et al. Predictors of Hospital Length of Stay in Patients with Exacerbations of COPD: A Cohort Study. *J Gen Intern Med*. 2015;30(6):824-831. doi:10.1007/s11606-014-3129-x.

73. Mancuso CA, Duculan R, Craig CM, Girardi FP. Psychosocial Variables Contribute to Length of Stay and Discharge Destination after Lumbar Surgery Independent of Demographic and Clinical Variables. *Spine (Phila Pa 1976)*. July 2017. doi:10.1097/BRS.0000000000002312.

74. Arnold PM, Rice LR, Anderson KK, McMahon JK, Connelly LM, Norvell DC. Factors affecting hospital length of stay following anterior cervical discectomy and fusion. *Evid Based Spine Care J*. 2011;2(3):11-18. doi:10.1055/s-0030-1267108.

75. Vavalle JP, Lopes RD, Chen AY, et al. Hospital length of stay in patients with non-ST-segment elevation myocardial infarction. *Am J Med*. 2012;125(11):1085-1094. doi:10.1016/j.amjmed.2012.04.038.

76. Menendez R, Cremades MJ, Martinez-Moragon E, Soler JJ, Reyes S, Perpina M. Duration of length of stay in pneumonia: influence of clinical factors and hospital type. *Eur Respir J*. 2003;22(4):643-648.

77. Johansen H, Finè s P. *Acute Care Hospital Days and Mental Diagnoses*.; 2015. http://www.statcan.gc.ca/pub/82-003-x/2012004/article/11761-eng.htm.

78. Canadian Institute for Health Information. Hospital Mental Health Services in Canada , 2009-2010. *Can Inst Heal Inf*. 2010:1-29.

79. Hoover DR, Sambamoorthi U, Walkup JT, Crystal S. Mental illness and length of inpatient stay for medicaid recipients with AIDS. *Health Serv Res*. 2004;39(5):1319-1339. doi:10.1111/j.1475-6773.2004.00292.x.

80. Correll CU, Solmi M, Veronese N, et al. Prevalence, incidence and mortality from cardiovascular disease in patients with pooled and specific severe mental illness: a large-scale meta-analysis of 3,211,768 patients and 113,383,368 controls. *World Psychiatry*. 2017;16(2):163-180. doi:10.1002/wps.20420.

81. DE Hert M, Correll CU, Bobes J, et al. Physical illness in patients with severe mental disorders. I. Prevalence, impact of medications and disparities in health care. *World Psychiatry*. 2011;10(1):52-77.

82. Tanuseputro P, Wodchis WP, Fowler R, et al. The health care cost of dying: a population-based retrospective cohort study of the last year of life in Ontario, Canada. *PLoS One*. 2015;10(3):e0121759. doi:10.1371/journal.pone.0121759.

83. Ontario Hospital Association. *Ideas and Opportunities for Bending the Health Care Cost Curve: Advice for the Government of Ontario*.; 2010.

84. Leigh-Hunt N, Bagguley D, Bash K, et al. An overview of systematic reviews on the public health consequences of social isolation and loneliness. *Public Health*. 2017;152:157-171. doi:10.1016/j.puhe.2017.07.035.

85. Moore L, Cisse B, Batomen Kuimi BL, et al. Impact of socio-economic status on hospital length of stay following injury: a multicenter cohort study. *BMC Health Serv Res*. 2015;15:285. doi:10.1186/s12913-015-0949-2.

86. Perelman J, Closon M-C. Impact of socioeconomic factors on in-patient length of stay and their consequences in per case hospital payment systems. *J Health Serv Res Policy*. 2011;16(4):197-202. doi:10.1258/jhsrp.2011.010047.

87. Mikkonen J, Raphael D. *Social Determinants of Health: The Canadian Facts*.; 2010. doi:10.1016/B978-012288145-9/50048-6.

88. Baker EH. Socioeconomic Status, Definition. In: *They Wiley Blackwell Encyclopedia of Health, Illness, Behavior and Society*. ; 2014:4.

89. Mantwill S, Monestel-Umana S, Schulz PJ. The Relationship between Health Literacy and Health Disparities: A Systematic Review. *PLoS One*. 2015;10(12):e0145455. doi:10.1371/journal.pone.0145455.

90. Maitra S. Can patient self-management explain the health gradient? Goldman and Smith's "Can patient self-management help explain the SES health gradient?" (2002) revisited. *Soc Sci Med*. 2010;70(6):802-805. doi:10.1016/j.socscimed.2009.08.043.

91. Lazar M, Davenport L. Barriers to Health Care Access for Low Income Families: A Review of Literature. *J Community Health Nurs*. 2018;35(1):28-37. doi:10.1080/07370016.2018.1404832.

92. Nova Scotia Department of Health and Wellness. Continuing Care. https://novascotia.ca/dhw/ccs/.

93. Health Canada. Health Care System. http://www.hc-sc.gc.ca/hcs-sss/medi-assur/faq-eng.php.

94. Government of Canada. Provincial and Territorial Public Drug Benefit Programs. https://www.canada.ca/en/health-canada/services/health-care-system/pharmaceuticals/access-insurance-coverage-prescription-medicines/provincial-territorial-public-drug-benefit-programs.html.

95. Allin S, Hurley J. Inequity in publicly funded physician care: what is the role of private prescription drug insurance? *Health Econ*. 2009;18(10):1218-1232. doi:10.1002/hec.1428.

96. Angus Reid Insitute. *Prescription Drug Access and Affordability an Issue for Nearly a Quarter of All Canadian Households*.; 2015.

97. Adler NE, Newman K. Socioeconomic disparities in health: pathways and policies. *Health Aff (Millwood)*. 2002;21(2):60-76.

98. Pampel FC, Krueger P, Denney J. Socioeconomic disparities in health behaviors. *Annu Rev Sociol*. 2010;36:349-370. doi:10.1146/annurev.soc.012809.102529.Socioeconomic.

99. NHS England. *Quick Guide : Health and Housing*.

100. American Hospital Association. *Housing and the Role of Hospitals*.; 2017.

101. Jaworsky D, Gadermann A, Duhoux A, et al. Residential Stability Reduces Unmet Health Care Needs and Emergency Department Utilization among a Cohort of Homeless and Vulnerably Housed Persons in Canada. *J Urban Health*. 2016;93(4):666-681. doi:10.1007/s11524-016-0065-6.

102. Argintaru N, Chambers C, Gogosis E, et al. A cross-sectional observational study of unmet health needs among homeless and vulnerably housed adults in three Canadian cities. *BMC Public Health*. 2013;13:577. doi:10.1186/1471-2458-13-577.

103. Care & Repair England. If Only I Had Known. 2014.

104. Yamada T, Chen C-C, Murata C, et al. Access disparity and health inequality of the elderly: unmet needs and delayed healthcare. *Int J Environ Res Public Health*. 2015;12(2):1745-1772. doi:10.3390/ijerph120201745.

105. Zhang X, Dupre ME, Qiu L, Zhou W, Zhao Y, Gu D. Urban-rural differences in the association between access to healthcare and health outcomes among older adults in China. *BMC Geriatr*. 2017;17(1):151. doi:10.1186/s12877-017-0538-9.

106. Burke RE, Jones CD, Coleman EA, Falvey JR, Stevens-Lapsley JE, Ginde AA. Use of post-acute care after hospital discharge in urban and rural hospitals. *Am J accountable care*. 2017;5(1):16-22.

107. Phillips CD, McLeroy KR. Health in rural America: remembering the importance of place. *Am J Public Health*. 2004;94(10):1661-1663.

108. Toscan J, Mairs K, Hinton S, Stolee P. Integrated transitional care: patient, informal caregiver and health care provider perspectives on care transitions for older persons with hip fracture. *Int J Integr Care*. 2012;12:e13.

109. Toscan J, Santi SM, Stolee P. " Just another fish in the pond " : the transitional care experience of a hip fracture patient. *Int J Integr Care*. 2013;13:10-11.

110. McCarthy D, Ryan J, Klein S. Models of Care for High-Need, High-Cost Patients: An Evidence Synthesis. *Issue Brief (Commonw Fund)*. 2015;31:1-19.

111. Mount JK, Massanari RM, Teachman J. Patient care complexity as perceived by primary care physicians. *Fam Syst Health*. 2015;33(2):137-145. doi:10.1037/fsh0000122.

112. Zulman DM, Asch SM, Martins SB, Kerr EA, Hoffman BB, Goldstein MK. Quality of care for patients with multiple chronic conditions: the role of comorbidity interrelatedness. *J Gen Intern Med*. 2014;29(3):529-537. doi:10.1007/s11606-013-2616-9.

113. Nardi R, Scanelli G, Corrao S, Iori I, Mathieu G, Cataldi Amatrian R. Co-morbidity does not reflect complexity in internal medicine patients. *Eur J Intern Med*. 2007;18(5):359-368. doi:10.1016/j.ejim.2007.05.002.

114. Safford MM, Allison JJ, Kiefe CI. Patient complexity: more than comorbidity. the vector model of complexity. *J Gen Intern Med*. 2007;22 Suppl 3:382-390. doi:10.1007/s11606-007-0307-0.

115. Peek CJ, Baird MA, Coleman E. Primary care for patient complexity, not only disease. *Fam Syst Health*. 2009;27(4):287-302. doi:10.1037/a0018048.

116. Shippee ND, Shah ND, May CR, Mair FS, Montori VM. Cumulative complexity: a functional, patient-centered model of patient complexity can improve research and practice. *J Clin Epidemiol*. 2012;65(10):1041-1051. doi:10.1016/j.jclinepi.2012.05.005.

117. Huntley AL, Johnson R, Purdy S, Valderas JM, Salisbury C. Measures of multimorbidity and morbidity burden for use in primary care and community settings: a systematic review and guide. *Ann Fam Med*. 2012;10(2):134-141. doi:10.1370/afm.1363.

118. de Groot V, Beckerman H, Lankhorst GJ, Bouter LM. How to measure comorbidity. a critical review of available methods. *J Clin Epidemiol*. 2003;56(3):221-229.

119. Hyder O, Sachs T, Ejaz A, Spolverato G, Pawlik TM. Impact of hospital teaching status on length of stay and mortality among patients undergoing complex hepatopancreaticobiliary surgery in the USA. *J Gastrointest Surg*. 2013;17(12):2114-2122. doi:10.1007/s11605-013-2349-4.

120. Dolmatova E V, Moazzami K, Klapholz M, Kothari N, Feurdean M, Waller AH. Impact of Hospital Teaching Status on Mortality, Length of Stay and Cost Among Patients With Cardiac Arrest in the United States. *Am J Cardiol*. 2016;118(5):668-672. doi:10.1016/j.amjcard.2016.05.062.

121. Busby J, Purdy S, Hollingworth W. A systematic review of the magnitude and cause of geographic variation in unplanned hospital admission rates and length of stay for ambulatory care sensitive conditions. *BMC Health Serv Res*. 2015;15:324. doi:10.1186/s12913-015-0964-3.

122. Jacobs R, Gutacker N, Mason A, et al. Determinants of hospital length of stay for people with serious mental illness in England and implications for payment systems: a regression analysis. *BMC Health Serv Res*. 2015;15:439. doi:10.1186/s12913-015-1107-6.

123. Canadian Institute for Health Information. Home Care.

124. Shepperd S, Iliffe S. Hospital-at-home versus in-patient hospital care. *Cochrane database Syst Rev*. 2000;(2):CD000356. doi:10.1002/14651858.CD000356.

125. Landi F, Onder G, Russo A, et al. A new model of integrated home care for the elderly: impact on hospital use. *J Clin Epidemiol*. 2001;54(9):968-970.

126. Canadian Home Care Association. *High Impact Practices: Enhanced Palliative Care Program.*; 2006.

127. Reynolds K, Lewis B, Nolen JDL, Kinney GL, Sathya B, He J. Alcohol consumption and risk of stroke: a meta-analysis. *JAMA*. 2003;289(5):579-588.

128. Jones CE, Hollis RH, Wahl TS, et al. Transitional care interventions and hospital readmissions in surgical populations: a systematic review. *Am J Surg*. 2016. doi:10.1016/j.amjsurg.2016.04.004.

129. Rennke S, Ranji SR. Transitional Care Strategies From Hospital to Home: A Review for the Neurohospitalist. doi:10.1177/1941874414540683.

130. Kansagara D, Chiovaro JC, Kagen D, et al. So many options, where do we start? An overview of the care transitions literature. *J Hosp Med*. 2016. doi:10.1002/jhm.2502.

131. Voss R, Gardner R, Baier R, Butterfield K, Lehrman S, Gravenstein S. HEALTH CARE REFORM The Care Transitions Intervention Translating From Efficacy to Effectiveness.

132. NHS England, NHS Improvement. *Long-Stay Patients Methodology*.; 2018.

133. Crawford TC, Magruder JT, Grimm JC, et al. A Comprehensive Risk Score to Predict Prolonged Hospital Length of Stay After Heart Transplantation. *Ann Thorac Surg*. 2018;105(1):83-90. doi:10.1016/j.athoracsur.2017.07.012.

134. Barba R, Marco J, Canora J, et al. Prolonged length of stay in hospitalized internal medicine patients. *Eur J Intern Med*. 2015;26(10):772-775. doi:10.1016/j.ejim.2015.10.011.

135. Lee SY, Lee S-H, Tan JHH, et al. Factors associated with prolonged length of stay for elective hepatobiliary and neurosurgery patients: a retrospective medical record review. *BMC Health Serv Res*. 2018;18(1):5. doi:10.1186/s12913-017-2817-8.

136. Collins TC, Daley J, Henderson WH, Khuri SF. Risk factors for prolonged length of stay after major elective surgery. *Ann Surg*. 1999;230(2):251-259.

137. Toh HJ, Lim ZY, Yap P, Tang T. Factors associated with prolonged length of stay in older patients. *Singapore Med J*. 2017;58(3):134-138. doi:10.11622/smedj.2016158.

138. Reid PM. Small Area Variations in Unplanned Repeat Hospitalization in Nova Scotia. 2018.

139. Araujo TG de, Rieder M de M, Kutchak FM, Franco Filho JW. Readmissions and deaths following ICU discharge: a challenge for intensive care. *Rev Bras Ter intensiva*. 2013;25(1):32-38.

140. Terashima M, Kephart G. Misclassification errors from postal code-based

geocoding to assign census geography in Nova Scotia, Canada. *Can J Public Health*. 2016;107(4-5):e424-e430.

141. acorn. *Case Mix Adjustment*. https://www.psychoutcomes.org/OutcomesMeasurement/CaseMixAdjustment.

142. Rabe-Hesketh S, Skrondal A. *Multilevel and Longitudinal Modeling Using Stata, Volume 1: Continuous Responses, Third Edition*.; 2012.

143. Kephart G, Asada Y, Atherton F, Burge F, Campbell LA, Campbell M, Dowling L, Dyer J, Lawson B L, L, Levy A TM. Small area variation in rates of high-cost healthcare use across Nova Scotia. 2016.

144. Fowler CS, Frey N, Folch DC, Nagle N, Spielman S. Who are the People in my Neighborhood?: The "Contextual Fallacy" of Measuring Individual Context with Census Geographies. *Geogr Anal*. 2018.

145. Maritime SPOR SUPPORT Unit. Maritime Health Atlas. http://healthatlas.ca/Home/Index.

APPENDIX A: Conditions included as case-mix adjustments and their associated ICD-10 codes.

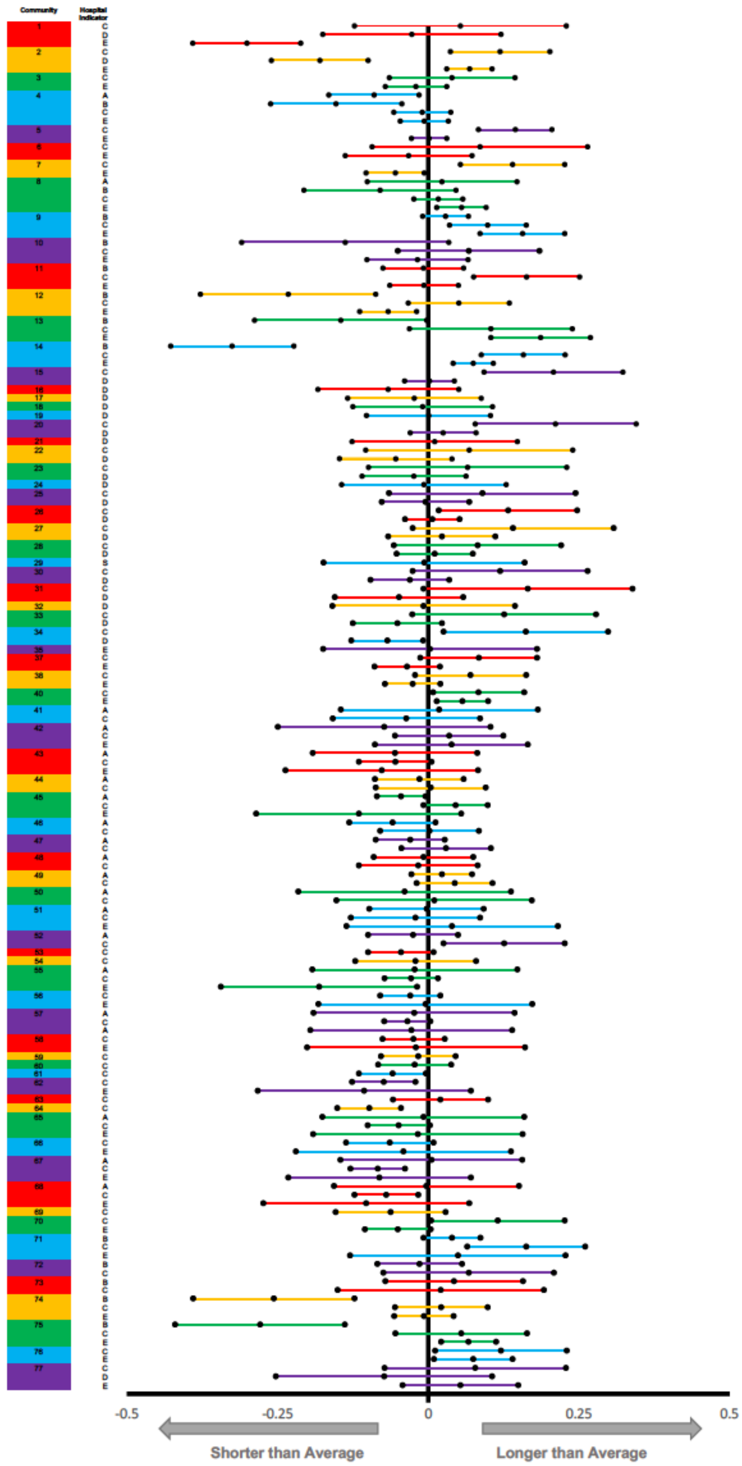
* Includes all sub-codes unless sub-codes are already specified

Condition	ICD-10 Codes *
1. Hypertension	I10, I15.0, I15.8
2. Obesity	E66
3. Diabetes (types 1 and 2)	E10, E11
4. Chronic Obstructive Pulmonary Disease or Pneumoconiosis	J43, J44, J47, J60 – J64
5. Asthma & Chronic Bronchitis	J40-J42, J45
6. Hyperlipidemia	E78.0, E78.1, E78.2, E78.3, E78.4, E78.5
7. Cancer	C00 – C96
8. Cardiovascular Disease	I20, I21, I22, I23, I24, I25, I48
9. Heart Failure	I110, I130, I09.81, I50
10. Osteoarthritis or Rheumatoid Arthritis	M05.00, M05.30, M05.60, M06.1, M06.9, M15, M16, M17, M18, M19
11. Cerebrovascular	G45, I60 - I69
12. Thyroid Problem	E00-E07
13. Kidney Disease or Failure	N17, N18, N18.1, N18.2, N18.3, N18.4, N18.5, N18.6, N18.9, N19
14. Osteoporosis	M80, M81.0, M81.6, M81.8
15. Dementia	F01, F02, F03, F03.90, F05
16. Musculoskeletal Problem	M25.70, M25.729, M35.3, M54.10, M54.14, M54.15, M54.16, M54.17, M54.2, M54.30, M54.5, M54.6, M54.89, M54.9, M60.9, M65.30, M65.4, M65.80, M65.849, M65.879, M65.9, M70.039, M70.10, M70.20, M70.30, M70.40, M70.50, M70.60, M70.70, M71.50, M72.9, M74.40, M75, M75.00, M75.30, M75.80, M76.10, M76.20, M76.40, M76.50, M76.60, M76.829, M76.899, M77.00, M77.10, M77.20, M77.30, M77.40, M77.50, M77.9, M79.0, M79.1, M79.2, M79.609, M79.7, S72.08, S72.01, S82, S06, M17
17. Stomach Problem	K21.9, K25.4, K25.5, K25.6, K25.7, K25.9, K56.60,
18. Colon Problem	K50.10, K50.80, K50.90, K51.00, K51.40, K51.50, K51.80, K51.90, K58
19. Liver Disease	K70.0, K70.10, K70.30, K70.9, K73.0, K73.2, K73.8, K73.9, K74.0, K74.1, K74.3, K74.4, K74.5, K74.60, K74.69, K75.4, K76.0, K76.89, K76.9
20. Urinary Problem	N13.4, N13.5, N13.70, N13.71, N13.721, N13.722, N13.729, N13.8, N28.82, N28.89, N28.9, N30.10, N30.11, N30.20, N30.21, N30.90, N30.91, N34.1, N34.2, N34.3, N39 (and all sub-codes), N40, N41.1, N41.3, N41.4, N41.8, N41.9, N42.0, N42.1, N42.3, N42.89, N42.9
21. Diseases of the Nervous System	G000, G001, G002, G003, G008, G009, G01, G02, G030, G031, G032, G038, G039, G0400, G0401, G0402, G041, G042, G0430, G0431, G0432, G0439, G0481, G0489, G0490, G0491, G053, G054, G060, G061, G062, G07, G08, G09, G10, G110, G111, G112, G113, G114, G118, G119, G120, G121, G1220, G1221, G1222, G1229, G128, G129, G130, G131, G132, G138, G14, G20, G210, G2111, G2119, G212, G213, G214, G218, G219, G230, G231, G232, G238, G239, G2401, G2402, G2409, G241, G242, G243, G244, G245, G248, G249, G250, G251, G252, G253, G254, G255, G2561, G2569, G2570, G2571, G2579, G2581, G2582, G2583, G2589, G259, G26, G300, G301, G308, G309, G3101, G3109, G311, G312, G3181, G3182, G3183, G3184,

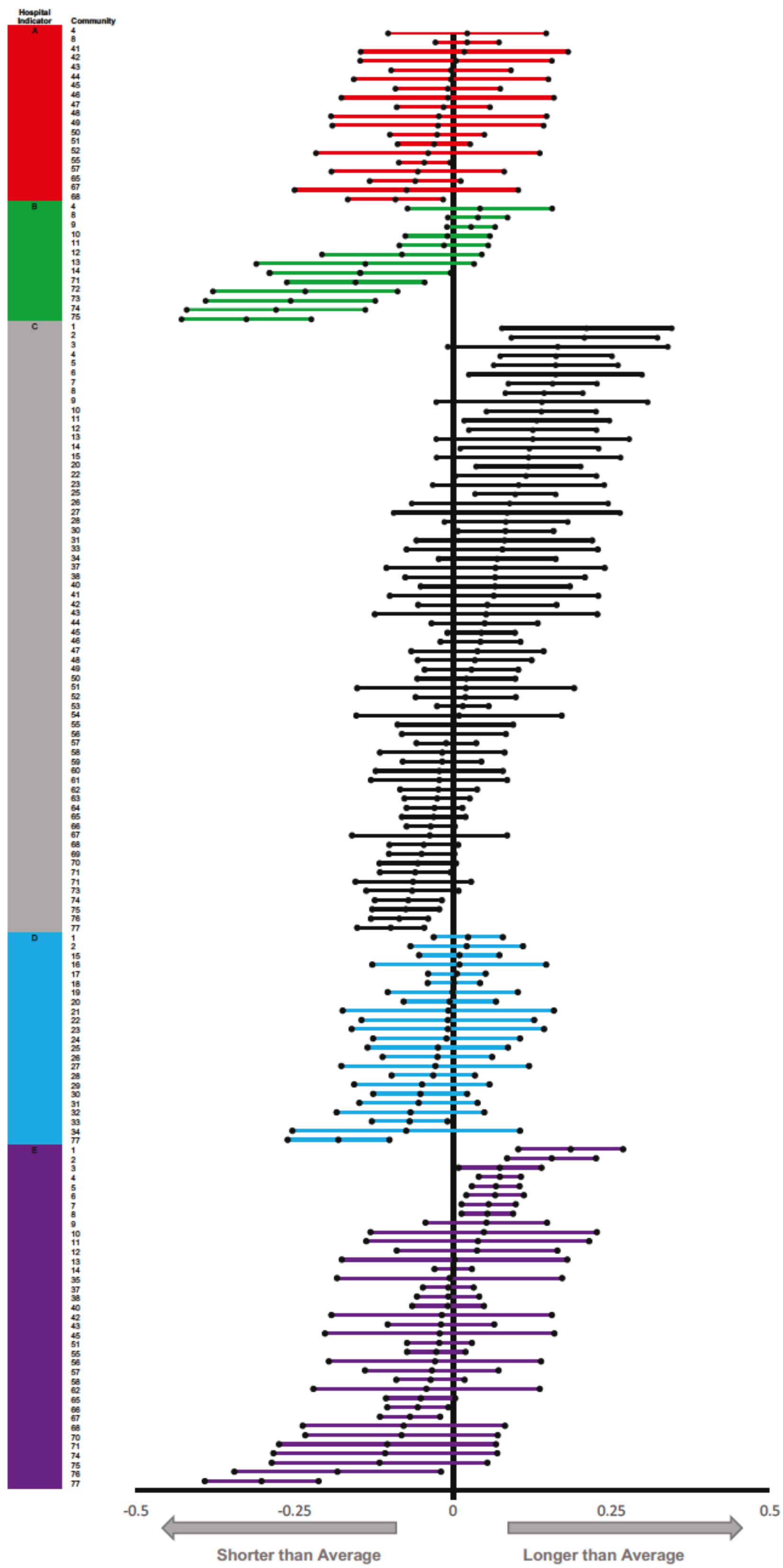
Condition	ICD-10 Codes *
	G3185, G3189, G319, G320, G3281, G3289, G35, G360, G361, G368, G369, G370, G371, G372, G373, G374, G375, G378, G379, G40001, G40009, G40011, G40019, G40101, G40109, G40111, G40119, G40201, G40209, G40211, G40219, G40301, G40309, G40311, G40319, G40401, G40409, G40411, G40419, G40501, G40509, G40801, G40802, G40803, G40804, G40811, G40812, G40813, G40814, G40821, G40822, G40823, G40824, G4089, G40901, G40909, G40911, G40919, G40A01, G40A09, G40A11, G40A19, G40B01, G40B09, G40B11, G40B19, G43001, G43009, G43011, G43019, G43101, G43109, G43111, G43119, G43401, G43409, G43411, G43419, G43501, G43509, G43511, G43519, G43601, G43609, G43611, G43619, G43701, G43709, G43711, G43719, G43801, G43809, G43811, G43819, G43821, G43829, G43831, G43839, G43901, G43909, G43911, G43919, G43A0, G43A1, G43B0, G43B1, G43C0, G43C1, G43D0, G43D1, G44001, G44009, G44011, G44019, G44021, G44029, G44031, G44039, G44041, G44049, G44051, G44059, G44091, G44099, G441, G44201, G44209, G44211, G44219, G44221, G44229, G44301, G44309, G44311, G44319, G44321, G44329, G4440, G4441, G4451, G4452, G4453, G4459, G4481, G4482, G4483, G4484, G4485, G4489, G450, G451, G452, G453, G454, G458, G459, G460, G461, G462, G463, G464, G465, G466, G467, G468, G4700, G4701, G4709, G4710, G4711, G4712, G4713, G4714, G4719, G4720, G4721, G4722, G4723, G4724, G4725, G4726, G4727, G4729, G4730, G4731, G4732, G4733, G4734, G4735, G4736, G4737, G4739, G47411, G47419, G47421, G47429, G4750, G4751, G4752, G4753, G4754, G4759, G4761, G4762, G4763, G4769, G478, G479, G500, G501, G508, G509, G510, G511, G512, G513, G514, G518, G519, G520, G521, G522, G523, G527, G528, G529, G53, G540, G541, G542, G543, G544, G545, G546, G547, G548, G549, G55, G5600, G5601, G5602, G5610, G5611, G5612, G5620, G5621, G5622, G5630, G5631, G5632, G5640, G5641, G5642, G5680, G5681, G5682, G5690, G5691, G5692, G5700, G5701, G5702, G5710, G5711, G5712, G5720, G5721, G5722, G5730, G5731, G5732, G5740, G5741, G5742, G5750, G5751, G5752, G5760, G5761, G5762, G5770, G5771, G5772, G5780, G5781, G5782, G5790, G5791, G5792, G580, G587, G588, G589, G59, G600, G601, G602, G603, G608, G609, G610, G611, G6181, G6189, G619, G620, G621, G622, G6281, G6282, G6289, G629, G63, G64, G650, G651, G652, G7000, G7001, G701, G702, G7080, G7081, G7089, G709, G710, G7111, G7112, G7113, G7114, G7119, G712, G713, G718, G719, G720, G721, G722, G723, G7241, G7249, G7281, G7289, G729, G731, G733, G737, G800, G801, G802, G803, G804, G808, G809, G8100, G8101, G8102, G8103, G8104, G8110, G8111, G8112, G8113, G8114, G8190, G8191, G8192, G8193, G8194, G8220, G8221, G8222, G8250, G8251, G8252, G8253, G8254, G830, G8310, G8311, G8312, G8313, G8314, G8320, G8321, G8322, G8323, G8324, G8330, G8331, G8332, G8333, G8334, G834, G835, G8381, G8382, G8383, G8384, G8389, G839, G890, G8911, G8912, G8918, G8921, G8922,

Condition	ICD-10 Codes *
	G8928, G8929, G893, G894, G9001, G9009, G901, G902, G903, G904, G9050, G90511, G90512, G90513, G90519, G90521, G90522, G90523, G90529, G9059, G908, G909, G910, G911, G912, G913, G914, G918, G919, G92, G930, G931, G932, G933, G9340, G9341, G9349, G935, G936, G937, G9381, G9382, G9389, G939, G94, G950, G9511, G9519, G9520, G9529, G9581, G9589, G959, G960, G9611, G9612, G9619, G968, G969, G970, G971, G972, G9731, G9732, G9741, G9748, G9749, G9751, G9752, G9781, G9782, G980, G988, G990, G992, G998
22. Pneumonia and influenza & other acute lower respiratory infections	J09-J18, J20 – J22
23. Injury	E920, W25-W29, W45-W46, E830, E832, E910, V90, V92, W65-W74, E880-E886, E888, W00-W19, E890-E899, X10-X19, E922, W32-W34, E919, W24, W30-W31, E810-E819 (.0-.1), V30-V79(.4-.9),V83-V86(.0-.3), E810-E819 (.2-.3), V20-V28(.3-.9), V29(.4-.9), E810-E819 (.6), V12-V14(.3-.9), V19(.4-.6), E810-E819 (.7), V02-V04(.1), V02-V04(.9), V09.2, E810-E819 (.4-.5, .8-.9), V80(.3-.5), V81-V82(.1), V87(.0-.8), V89.2, E800-E807(.3), E820-E825(.6), E826.1, E826.9, V10.0-V11.9, V12-V14(.0-.2), V15.0-V18.9, V19(.0-.3), V19.8, V19.9, E800-E807(.2), E820-E825(.7), E826-E829(.0), V01(.0-.9), V02-V04(.0), V05.0-V06.9, V09.0, V09.1, V09.3, V09.9, E800-E807(.0-.1), E800-E807(.8-.9), E820-E825(.0-.5), E820-E825(.8-.9), E826(.2-.8), E827-E829(.2-.9), E831, E833-E838, E840.0-E845.9, E846, E847-E848, V20-V28(.0-.2), V29-V79(.0-.3), V80(.0-.2), V80(.6-.9), V81-V82(.0), V81-V82(.2-.9), V83-V86(.4-.9), V87.9, V88(.0-.9),V89(.0-.1), V89.3, V89.9, V91, V93-V99, E850-E869, E924.1, X40-X49, E916-E917, W20-W22, W50-W52, E911-E913, W75-W84, E914-E915, W44, E970-E978, E990-E999, Y35-Y36, Y89(.0-.1), E950-E959, E87
24. Severe and Persistent Mental Illness	F20-F29, F30, F31, F32.3, F33.3
25. Other Mental Illness	F32.0, F32.1-2, F32.4-9, F33.0, F33.1-2, F33.4-9, F34 F38-F39, F40-41, F05, F42, F44-F50, F54, F60-F69, F430, F4320-25, F4329, F4312, F438, F4310, F4390, F43948, X60-X84, F985, F959, F950-52, F984, F509, F502, F983, F9821, F508, F9829, F980, F981, F633, F51-F53, F55-F59, F99

APPENDIX B: Caterpillar plots of interactions between hospitals and communities of residence of patients; (a) hospitals sorted within communities, and (b) communities sorted within hospitals.



(a) Hospital E encompasses 28 hospitals that do not discharge to many FSAs.



(b) Hospital E encompasses 28 hospitals that do not discharge to many FSAs.