SMALL AREA VARIATIONS IN UNPLANNED REPEAT HOSPITALIZATION IN NOVA SCOTIA

by

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Dedication

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Abstract

Objective: Unplanned readmission to hospital is widely used as an indicator of hospital performance. Community-based primary health care systems likely also play a role in unexpected returns to hospital. Our objective was to estimate the effect of community on the time to an unplanned, repeat hospitalization (URH) after an index discharge.

Approach: Using methods for small area rate estimation, we used an accelerated failure time model with a random effect for community to estimate the adjusted relative risk of experiencing an unplanned repeat hospitalization as a function of community of residence.

Results: Community of residence had a large and significant effect on the time to experiencing an URH. The risk of URH associated with living in particular communities can be larger than the adjusted risk of conditions like cardiovascular disease and diabetes.

Conclusion: Community of residence can play a substantial role in the time until someone returns to hospital unexpectedly.

List of abbreviations used

AFT – Accelerated Failure Time

CDM – Chronic Disease Management

CIHI – Canadian Institute for Health Information

CIHR – Canadian Institute of Health Research

DAD – Discharge Abstract Database

FSA – Forward Sortation Area

HDNS – Health Data Nova Scotia

OPD – Out Patient Department

PCIPM – Patient-Centered Innovations for Persons with Multimorbidity Group

URH – Unplanned Repeat Hospitalizations

Acknowledgements

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Chapter 1

Introduction

Chronic diseases are common and costly (1,2). In 2015, chronic conditions were responsible for approximately 39.5 million deaths -- 70% of all deaths worldwide (3), and they are projected to cost the world $47 trillion USD during the years 2010-2030 (4). Chronic diseases are also largely preventable. Solutions currently exist that could enable governments, patients and other stakeholders to reduce risk factors that lead to chronic disease, slow their progression, and prevent complications (5). Despite these potential solutions, the number of people with multiple chronic conditions is increasing (6). There is an ongoing need to monitor and improve long-term chronic disease management (CDM).

Current studies of chronic disease management interventions have shown mixed results. There is evidence to suggest that, when studied in the context of specific diseases or procedures, chronic disease management strategies can effectively improve health outcomes (7–12). When looked at in the context of people with multiple and diverse chronic conditions however, the evidence of the effectiveness of chronic disease management programs is less clear (13–18). There are many potential reasons for this disparity, but one of the most compelling may be that multimorbidity requires more complex and less targeted care than interventions focused on particular conditions.

Addressing multiple and more complex chronic conditions involves systems of formal and informal care, and much of the work in chronic disease management happens outside the traditional scope of primary care practitioners. Complex chronic disease management strategies are time and resource intensive, making it difficult for traditional primary care providers to implement them consistently and effectively. In these more complex cases, team-based care with wider community-based primary health care system supports is important for long-term, effective chronic disease management (19–21).

For the purposes of this project we have defined “primary care” and “primary health care” using the definitions provided by the government of Canada:

> Primary health care refers to an approach to health and a spectrum of services beyond the traditional health care system. It includes all services that play a part in health, such as income, housing, education, and environment. Primary care is the element within primary health care that focusses on health care services, including health promotion, illness and injury prevention, and the diagnosis and treatment of illness and injury (22).

Primary health care is a system whose characteristics will vary from community to community. Disparities between the diversity, comprehensiveness and accessibility of services available in different areas will affect where and how primary caregivers offer treatment. Similarly, how well existing services are integrated at the community level will influence medical practice and care patterns. Since levels of service, comprehensiveness, accessibility and integration are not uniform throughout the

province, it is likely that the same chronic disease management intervention undertaken in different communities could result in different outcomes.

One outcome that is of particular interest as it relates to chronic disease management is unplanned repeat hospitalizations (URH). Unplanned repeat hospitalizations have a major effect on both patients and health care systems (23). This study views rates of unplanned repeat hospitalization as an indicator of a community's ability to support long-term chronic disease management. To assess the viability of this perspective, we assessed whether community of residence is associated with time to an unplanned return to hospital after an index discharge.

Study objective

To estimate the variation between the age, sex and multimorbidity adjusted time to an unplanned repeat hospitalization after an index discharge between Nova Scotia communities amongst adults aged 30 years and older between 2010-2015.

Chapter 2

Background

Chronic disease is the dominant driver of health care utilization and cost around the world. It is estimated that the global economic burden of chronic disease will be approximately $47 trillion USD during the years 2010-2030 (24). That loss represents 75% of the global GDP in 2010, or enough money to eliminate two dollar-a-day poverty among the 2.5 billion people in that state for more than half a century (4). In contrast to acute medical problems, chronic diseases are often long-term and develop slowly. This results in an expanded set of challenges for patients, caregivers and medical staff. Dealing with symptoms, disability, emotional impacts, complex medication regimens, difficult lifestyle adjustments and obtaining helpful medical care are all key issues that need to be addressed within the context of long-term CDM (25). In cases of chronic disease, neither the disease nor its consequences are static; they interact to create symptoms requiring continuous and complex management (26).

The burden of chronic disease in Canada and Nova Scotia

Chronic diseases are the leading cause of disability in Canada (27), and rates of chronic diseases are increasing across the country through all socioeconomic classes (28). Almost 40% of Canadians over the age of twenty have at least one of the top ten most common chronic diseases (29). Conditions like cancer, arthritis, diabetes, mental illness, cardiovascular and chronic respiratory diseases are major contributors to reduced quality of life, loss of productivity, increased hospitalization, health care costs and

premature death in this country (30). In many cases, patients are afflicted with multiple chronic conditions. According to the Centre for Chronic Disease Prevention, 14.8% of Canadians had two or more chronic diseases in 2016 (29). These patients present a disproportionately large challenge to health care infrastructure, which has principally been designed to treat one acute condition at a time (31).

Compared to other Canadians, Nova Scotians have particularly high rates of chronic illness (32). In 2009/10, Nova Scotians had an age-standardized prevalence of the use of health care services for mental illness of 16.8%. This is the highest rate in Canada, and 3.2% greater than the national average (33). In 2014 Nova Scotians had the highest age-standardized percentage of people in its population with two or more chronic diseases (17.7% compared to a national average of 12.8%)(34), the highest percentage of people with COPD (5.9%)(35) and the fourth highest percentage of people with diabetes (8.2%) (36). In 2016, Nova Scotia also had the fourth highest number of new cancer cases per 100,000 people in the country with 521.6 new cancer cases per 100,000 people. The national average for new cancer cases in 2016 was 506.56 per 100,000 people (37).

The number of people with multiple, co-occurring chronic conditions is growing (6). This is cause for concern, as the Canadian health care system has evolved to respond primarily to acute illness or injury rather than chronic disease (38). Increases in the prevalence of chronic conditions conditions will amplify pressure on already stressed health care systems (39). The long-term nature of chronic conditions means that

patients need to rely on themselves, as well as both formal and informal care systems within their communities (40,41). Effective CDM in general, and the management of multiple morbidities in particular, may require a much more systems-based approach to health care than is common in current practice.

Current research on CDM policy and interventions

It is becoming clear that many aspects of CDM involve components that are not strictly medical in nature. As far back as 1996 Wagner et al highlighted the importance of community resources and policies in developing effective chronic care models (42). In recent decades there have been efforts by a variety of stakeholders to develop and implement effective long-term CDM strategies. For example, since 2002 the Government of Ontario has implemented a variety of new and innovative primary care models to increase access and improve the quality and delivery of primary care services (43). The Nova Scotia Health Authority (NSHA) has also implemented a number of initiatives within the primary care system. Programs like the community health teams, the Chronic Disease Innovation Fund, and the implementation of LEAN practices like value stream mapping into primary care planning all seek to improve CDM in different ways. Through these initiatives, the NSHA has sought to embrace a wellness model with more effective chronic disease management as one of its primary goals (41,44). A need to shift the focus of the health care system away from acute care and towards effective, long-term CDM is beginning to be more widely recognized amongst decision-makers and government officials (45,46).

There is considerable evidence to suggest that CDM strategies and interventions, when directed to specific diseases or conditions, can improve outcomes and reduce unplanned repeat hospitalizations (7). In 2005, Holland et al. conducted a review that concluded that multidisciplinary interventions for heart failure reduce both hospital admission and all-cause mortality and that the most effective interventions were delivered at least partly in the home (8). This research was supplemented in 2015 when a review and meta-analysis by Vedel and Khanassov found that providing transitional care interventions to congestive heart failure patients reduced readmission and emergency department visits (9). A 2012 systematic review by Manderson et al. on the efficacy of patient navigation strategies found that even though the heterogeneity of the various models precluded direct comparison, patient navigators may be effective in assisting older patients as they transition between health care settings and in diverting older patients with serious and persistent medical conditions, from higher levels of care (10).

In 2014, Joo et al. undertook a review which concluded that community-based case management significantly improved hospital outcomes. In particular, community based case management strategies reduced readmissions, increased cost effectiveness and improved patient clinical outcomes and patient satisfaction (11). In a 2016 review of transitional care interventions in surgical populations, Jones et al. found that improving the coordination, individualization, and communication of postoperative care with transitional care interventions may reduce hospital readmissions; however further study

was warranted (47). It is clear that there is evidence to support the assertion that, in the context of specific populations after particular procedures, intensive outpatient CDM measures can improve health care outcomes and minimize repeat hospitalizations.

For people with multiple chronic conditions and complex needs, as opposed to specific diseases however, the evidence for the effectiveness of CDM interventions is less clear (13). A 2015 evidence synthesis of models of care for high-cost, high-need patients found that, overall, the impact of CDM management initiatives is modest, and few programs have been adopted because of a variety of barriers to their implementation (14). In 2017, a randomized control trial conducted by Zulman et al. concluded that, while an intensive outpatient care program was well received by veterans, it did not actually result in any significant cost savings or a reduction in repeat hospitalizations (15). Zulman et al.'s study supports earlier work, which concluded that even though case management may reduce psychosocial problems, it does not make a statistically significant impact on cost of care or frequency of hospitalization (16–18). While intensive outpatient CDM strategies may work within specific populations, in the broader context of complex health care users in general, they appear to be less effective.

Community-based primary health care as a complex, adaptive system

There are many potential reasons for the disparity in results between different studies, but one of the most compelling is that patients with multi-morbidity require more

diverse, integrated and less targeted care than is found in interventions addressed to a particular condition. Physical ailments often exist in conjunction with other complex conditions such as mental health, addictions and poverty, all of which require specialized supports (25,48–50). At the community level, the health system must be able to meet the needs of many different types of patients, with primary care practitioners as the cornerstone. At the clinical level, it can difficult for primary care practitioners to dedicate the time and energy required to provide all of the supports described in the targeted interventions mentioned above. Addressing multiple and more complex needs involves multiple services and systems of care, which in turn places a higher demand on existing resources. In these complex cases, the quality of community-based primary health care systems is a key component in the delivery of effective, long-term CDM.

In order to better understand the role of community-based primary health care systems in CDM, they need to be regarded as complex, adaptive entities with many interconnected and interrelated parts -- not as a series of discrete interventions or care models (51). The interaction of patient, area services and supports creates a community-based primary health care system that is unique to each area (52). We hypothesize that these community-based primary health care systems have a considerable impact on a given community's ability to support people managing chronic conditions and avoid adverse health outcomes within its population.

Despite an expansive literature on community determinants of health (53–55), existing studies have paid scant attention to community determinants of chronic disease management. Because each community-based health care system is a dynamic, complex and unique entity, it follows that the same intervention applied to different community systems can yield different outcomes. Differences in local resources, accessibility to primary care practitioners and networks of formal and informal care will all affect how well a community can support long-term CDM. Accordingly, community variation in health outcomes may be indicative of the ability of the community-based primary health care system to support people with long-term, complex chronic conditions.

Unplanned repeat hospitalizations as an outcome of suboptimal chronic disease management

One potential outcome of suboptimal chronic disease management that is particularly interesting is sequential, unplanned repeat hospitalizations (11,56–58). A 2016 study by Dantas et al. found that the risk of an avoidable hospitalization increases by a factor of 1.35 (95 % CI [1.34;1.35]) for each additional chronic condition, and 1.55 (95 % CI [1.55;1.56]) for each additional body system affected (59). Unplanned repeat hospitalizations cause additional financial and emotional burdens for both patients and caregivers and are a major driver of health care costs. Unplanned repeat hospitalizations in Canada resulted in approximately $1.8 billion in direct hospital costs in 2012 (60). They have been shown to raise the probability of mortality (61), and repeated exacerbations of chronic disease can lead to a higher incidence of psychiatric disorders, most commonly depression or anxiety (62). In a study of general medical hospital

admissions, affective disorder was diagnosed in 13% of men and 17% of women (63). In patients with chronic conditions such as diabetes or rheumatoid arthritis the rate increases to between 20% and 25% (64). It clear that repeat hospitalizations, as they relate to chronic disease, impact both individuals and society.

In the current literature, unplanned repeat hospitalizations are primarily studied in the context of hospital performance. Studies generally focus on specific medical conditions, and examine the variation between unplanned repeat hospitalization rates through the lens of hospital characteristics: bed size, volume and staffing level (65,66). This focus on hospital performance is also reflected in the emphasis on repeat hospitalization within a 30-day window, so as to include readmissions likely to result from the hospital care and the discharge process. Recent research casts doubt on the efficacy of using risk-adjusted 30-day readmission rates as a metric of hospital quality (67–73). The 30-day time-period provides a reasonable approximation of transitional care; however, transitional care is just the first step in preventing an unplanned return to hospital. After undertaking a synthesis which included 30 qualitative systematic reviews (including 515 unique studies), 102 quantitative systematic reviews (including 969 RCTs), and 61 studies in implementation, Taylor et al. concluded that supporting long-term self-management is inseparable from the high-quality care for chronic conditions (74). Hospital and transitional care initiatives are one small piece of CDM. It falls to community-based primary health care systems to facilitate the coordination and provision of integrated care, which can support chronic disease management over the long-term and reduce the risk of unplanned, repeat hospitalizations (75).

The ability of community-based primary health care systems to provide effective chronic disease management may not be uniform across Nova Scotia. Different communities have access to different types and levels of service. Similarly, different community systems will have different levels of service integration. The availability, diversity and integration of health care services in a given community affects long-term chronic disease management strategies. Beyond formal health care services, variation in community demographics, informal services (e.g. volunteer organizations) and community support networks may also play an important role in determining whether or not someone is successful in long-term chronic disease management.

This study considers unplanned repeat hospitalization as an indicator of how well a community is able to support long-term chronic disease management. Because of the variation in demographics, formal and informal services at the community level, it is likely that the same chronic disease management intervention undertaken in different areas could result in different outcomes. To test the viability of this assertion, we estimated whether community of residence is associated with the amount of time it takes for a patient to return to hospital unexpectedly after an index discharge.

Our work sought to answer two questions:

1. Overall, does community of residence have an effect on the case-mix adjusted time to an unplanned repeat hospitalization?
2. If so, which communities stand out as having the largest variation from the provincial mean?

Chapter 3

Study design and methods

Overview

This is a descriptive study which estimates community variation in the average case-mix adjusted time to experiencing an unplanned repeat hospitalization, following discharge from an index hospitalization. The study population includes all persons registered for Medicare between 2010-2014 in Nova Scotia, Canada aged 30 and older. Communities were defined as postal code forward sortation areas (FSA). Accessed through Health Data Nova Scotia (HDNS), our data was drawn from provincial health registry eligibility files and the Canadian Institute of Health Information (CIHI) Discharge Abstract Database (DAD). Our outcome of interest was an unplanned repeat hospitalization after an index discharge from hospital, and our primary exposure was community of residence. We used statistical methods for small area variation, based in mixed-effect accelerated failure time regression models, with a random effect intercept for community, to estimate variation in the case-mix adjusted time to an unplanned repeat hospitalization across Nova Scotian communities. Acceleration factors were case-mix adjusted for age-sex group, proximity to end of life, types of health conditions, and multimorbidity. To determine which communities stood out as having an accelerated or decelerated time to unplanned repeat hospitalization, our models were also used to estimate acceleration factors for each FSA relative to the provincial average, including 95% confidence intervals.

Data sources

We accessed Health Data Nova Scotia (HDNS) data from April 1st, 2010 to March 31st 2015. Analyses focused on the four-year period from April 1st, 2010 – March 31st, 2014, while the final year of data was used to observe deaths for purposes of identifying persons in the last year of life.

Eligibility periods for provincial health care coverage, date of death, and demographic information, were drawn from the provincial health registry eligibility file. Information on hospitalizations (e.g. length and timing of hospitalization episodes), and patients' diagnostic and multimorbidity information was obtained from from the CIHI Discharge Abstract Database. It includes records for all discharges from inpatient stays in hospitals, along with detailed information on length of stay, community of residence, procedures, and diagnostic information.

Study population

The study population was all persons registered for Medicare between April 1st, 2010 and March 31st, 2014 in Nova Scotia, Canada who were age 30 or over, and had a valid index hospitalization within the study period. Persons with invalid or out-of-province postal codes were excluded. The final study population consisted of of 65,839 people.

Defining an index hospitalization

Where sequential inpatient (i.e. not an emergency department, outpatient or day surgery record) hospital discharges were due to transfers between hospitals, or a re-hospitalization within 48 hours of a discharge, they were combined into single episodes of hospitalization. We defined a valid index hospitalization as any hospitalization episode that met the following criteria:

1. At least one of the separations was emergent/urgent.
2. Admit to variable was not in an emergency department, outpatient department (OPD), or day surgery.
3. None of the separations were related to pregnancy or birth.
4. The final discharge in an episode was to a community setting (i.e. not to a long-term care institution, OPD, other non-acute care institution or a psychiatric hospital).
5. The most responsible discharge diagnosis for any of the separations in the episode was not a psychiatric condition (main patient service=64, or most responsible diagnosis of a psychiatric condition: ICD-10 codes of F00-F99).
6. The *discharge disposition* variable was not 06 (sign out) or 12 (did not return from pass).

Hospitalizations involving patients who died were considered invalid index hospitalizations because their death would make repeat admission impossible. Hospitalizations involving persons who left hospital against medical advice were considered invalid index hospitalizations because re-admission rates in this situation have been shown to be systematically higher than normal (76,77). Hospitalizations involving patients entering a hospital for obstetric reasons were not considered valid index hospitalizations because obstetric patients have a fundamentally different set of medical issues which should be considered separately from the general population.

Hospitalizations involving patients admitted from/discharged to a nursing home, long term care facility or palliative care facility were considered invalid index hospitalizations because this study was focused on the effect of community of residence on unplanned repeat hospitalizations. Patients living in long-term care facilities are subject to different norms than the wider community and should be considered separately. Hospitalizations involving patients admitted to the hospital with a psychiatric condition as their most responsible diagnosis were considered an invalid index hospitalization since major psychiatric conditions requiring hospitalization are at high risk for extended and frequent admissions to hospital, and represent a unique population requiring separate study. However, hospitalizations with mental health conditions coded as secondary diagnoses were included.

Measures

Primary outcome - unplanned repeat hospitalizations

The primary outcome of interest for this study was an unplanned repeat hospitalization after discharge from a valid index hospitalization. We defined unplanned repeat hospitalization as any hospitalization occurring after a valid index hospitalization that was coded as "urgent" or "emergent" in the "Admit Type" field of the data. This excludes planned hospitalizations, such as hip or knee replacements that result from joint deterioration. While patients could have more than one series of index and unplanned repeat hospitalizations over the course of our study period, we elected to focus on the first sequence for each individual in our study. While inclusion of multiple

events per person would increase the statistical power for the study, it does so at the expense of increasing model complexity by adding an additional level of clustering to the data.

Primary exposure – community of residence

We defined community of residence as the geographic boundaries of the postal code forward sortation area (the first three digits of the postal code) to which patients were discharged. Currently there are 77 forward sortation areas (FSAs) in Nova Scotia (see Appendix 1). Due to small populations and privacy concerns, certain adjacent FSAs with very small populations were combined in order to produce an area with enough data for analysis. This resulted in a total of 73 FSAs that were modeled in our study.

The decision to use FSAs was based on practical considerations regarding available data, rather than on public or policy perceptions of community. We used FSAs because they were the only valid geographic boundaries available to us at the time of this research. Use of other geographic boundaries requires geocoding of 6-digit postal codes. While widely used, we have shown it has unacceptable error rates in Nova Scotia(78). Using FSAs also allowed us to make comparisons with earlier work done on small area rate variation in high-cost healthcare use in Nova Scotia. It is possible that alternative community definitions would affect results. One potential alternative to FSAs is the Hospital Service Area (HSAs) developed for the Dartmouth Health Atlas. An HSA is a collection of ZIP codes whose residents receive most of their hospitalizations from the hospitals in that area. HSAs were defined by assigning ZIP codes to the hospital area

where the greatest proportion of their Medicare residents were hospitalized (79). Unfortunately constructing HSAs for Nova Scotia fell outside of the scope of this study. In the interest of facilitating future research, however, our methods were developed in such a way that alternate geographies can be incorporated, as they become available, with relative ease.

Exposure time

Exposure time was defined as the interval between a patient's discharge from their index hospitalization and either an unplanned repeat admission to hospital, or the end of a person's observation time (i.e. death, end of program eligibility, or end of the study period). These intervals represent the amount of time that each patient is exposed to the risk of an unplanned hospitalization. A measurement limitation is that if a patient had a subsequent hospitalization that did not meet our criteria for an unplanned repeat hospitalization, then that the time in hospital was included as exposure time for an unplanned hospitalization (see Figure 1). For example, if a patient returned to hospital for a planned knee surgery following discharge from an index hospitalization, and then subsequently returned to hospital because of an emergency exacerbation of COPD, the knee surgery hospitalization was not accounted for in the analysis, nor was the exposure time adjusted. However, the number of records which fell into this category were relatively low (approximately 1.9% of all intervals studied), so the effect on the results should be minimal. See Figure 2 for an outline of how hospitalizations and intervals were measured.

Covariates used for case-mix adjustment

Patient demographics

We obtained age and sex for all persons in the study population from provincial registration files. Age was coded into 5-year age groups, with a single category for people 30-54 and another for ages 85 years and over. Analysis included indicator variables for all age/sex groups to capture interactions.

End of life

Persons in their last year of life are at increased risk of unplanned hospitalizations, and thus proximity to death should be accounted for the case-mix adjustment. To do so, we calculated the percentage of each person's exposure interval which fell within 365 days of their date of death, and included that number in the regression model. Death was ascertained from the provincial registry file, which includes all deaths captured on a Nova Scotia death certificate. Persons who did not die in the study period or within a year beyond the study interval are coded as zero on this variable.

Chronic disease patterns and multimorbidity

We used indicator variables for the presence of different types of health conditions, and a variable for the number of conditions to measure multimorbidity. Chronic disease categories used were from the Patient-Centered Innovations for Persons with Multimorbidity (PCIPM) group, a Canadian Institutes of Health Research (CIHR) funded research group based out of The University of Western Ontario and The Université de

Sherbrooke Quebec (80)(See Appendix 4). We added several condition categories which are not covered by the PCIPM list: diseases of the nervous system, schizophrenia/psychosis, neurotic somatoform disorders, personality disorders and adjustment disorders/attempted self-harm/other mental disorders. Our final list included 26 different condition categories that were used in our adjustment. For further discussion on the development of chronic disease measurement in this study, as well as the complete list of conditions and associated ICD-10 codes see Appendix 4.

Hospital

Some hospitals may have a greater propensity to admit patients than others, and we sought to adjust for this by including indicator variables for each hospital. However, a number of communities have little or no variation in the hospital of readmission, resulting in high co-linearity. Accordingly, this adjustment was not possible. Thus, our models are not able to separate community effects from the effects of hospitals in which patients are hospitalized.

Analytic methods

A survival analysis approach is appropriate since we have right-censored time-to-event data. Because community sample sizes are often not large enough for direct estimates of community rates with adequate precision (81), we also used modeling approaches appropriate for small area rate estimation. Specifically, we employed an accelerated failure time frailty model (AFT), also known as a mixed effects model with a random intercept for community. Our model is a 'shared frailty' model because the same

random intercept is shared by all subjects within the same FSA (82). The AFT considers the log of survival time as the dependent variable and includes a random intercept (frailty) term that is assumed to follow a particular distribution. In our case the normal distribution was used. We confirmed our results by re-running the model with a gamma distributed frailty distribution, and estimates remained consistent.

The following equation shows the log-linear representation of the AFT model for the i^{th} individual, where log T_{ij} is the log-transformed survival time, β is the vector of unkown regression coefficients corresponding to the to the covariate vector for fixed effect x_{ij} and Υ_j is the random effects vector associated with a second set of covariate values denoted by z_j.

$$logT_{ij} = x_{ij}\beta + z_j\Upsilon_j + \sigma\varepsilon_{ij} \quad (83)$$

Because the AFT is a parametric model we needed to determine the distribution of the survival curve. A Weibull distribution was chosen, as a graph of the log(cumulative hazard) against the log(exposure) was approximately linear (84).

Once exponentiated, the estimated "fixed" effects of covariates are termed "acceleration factors" (85). Similar to an incidence rate ratio, the acceleration factor expresses the proportionate change in the expected time to an event based on a given exposure. In our study however, the acceleration factor is interpreted differently than an incidence rate ratio. If the acceleration factor is > 1 then the exposure increases the

time to event, and is beneficial as compared to a reference condition. If the acceleration factor is < 1 then the exposure decreases the expected time to an event, and is harmful compared to a reference condition. For our case-mix adjustment, our reference was a female between the ages of 50-54 with no chronic conditions.

The random component of the model estimates the between-community variance in the log of the expected time to an unplanned repeat hospitalization. To facilitate interpretation, and describe the size of community effects, the estimated between-community variance was re-expressed as the standard deviation of the acceleration factors of communities in our study, relative to the average of communities. This number describes the acceleration factor that would be associated with moving from the "average" community to a community with a one standard deviation lower risk. Given the sample size, we have high power to estimate this parameter.

To identify specific communities that had a mean time to unplanned repeat hospitalization that was higher or lower than expected, we also generated case-mix adjusted small area estimates of the acceleration factors, and associated confidence intervals, for each community relative to the average intercept of all communities in the population. We employed an estimator known as the "empirical best linear unbiased predictor (EBLUP)". It is equivalent to an empirical Bayes estimate combining the model estimated normal distribution of the random intercept (as a prior distribution), with the data from each area, to produce a posterior distribution of the estimated intercept for

each community (expressed as deviations from the provincial average intercept) (81). This estimator has the smallest possible variance, and unbiased prediction error. As well, estimates are "shrunk" towards the provincial mean, based on the amount of data from each community, thus avoiding outliers. While our analysis was highly powered to estimate the variance in the overall acceleration factor between communities, it has less power to estimate the acceleration factors for specific communities. As a result, the confidence intervals for community estimates are quite large. Only communities with dramatic differences in acceleration factors and larger sample sizes were significantly different than the provincial mean. To provide community effect size comparisons, we compared the adjusted acceleration factors of communities which were significantly different from the provincial average to the adjusted acceleration factors of three major chronic conditions: cardiovascular disease, diabetes, and heart failure.

In order to address potential limitations in our study, we performed two sensitivity analyses. One challenge facing this study is that community effects may differ by type of chronic condition. In order to assess this, we ran a regression that excluded anyone who had one of the four conditions with the highest influence on time to URH in the primary analytical model: cancer, stroke, injury, or diabetes. The reduced power of this analysis meant a reduction in our ability to determine the effect of individual FSAs (only four FSAs showed significant variation from the expected rate), however it was still well powered to determine the overall influence of community on time to an URH. A second consideration is that we used five years of data, and community effects could change

over time. It is also possible that differences in follow up time could influence the nature of our results. In order to test for the effect of our study period we ran another regression using just the last three years of data. Once again, this reduction in power affected our ability to determine the effect of individual FSAs (no FSA was significantly different than the expected rate), however we were still well powered to estimate the overall influence of community.

Figures

Figure 1 - Illustration of how intervening planned hospitalizations (1.9% of records) were treated in estimation of exposure time

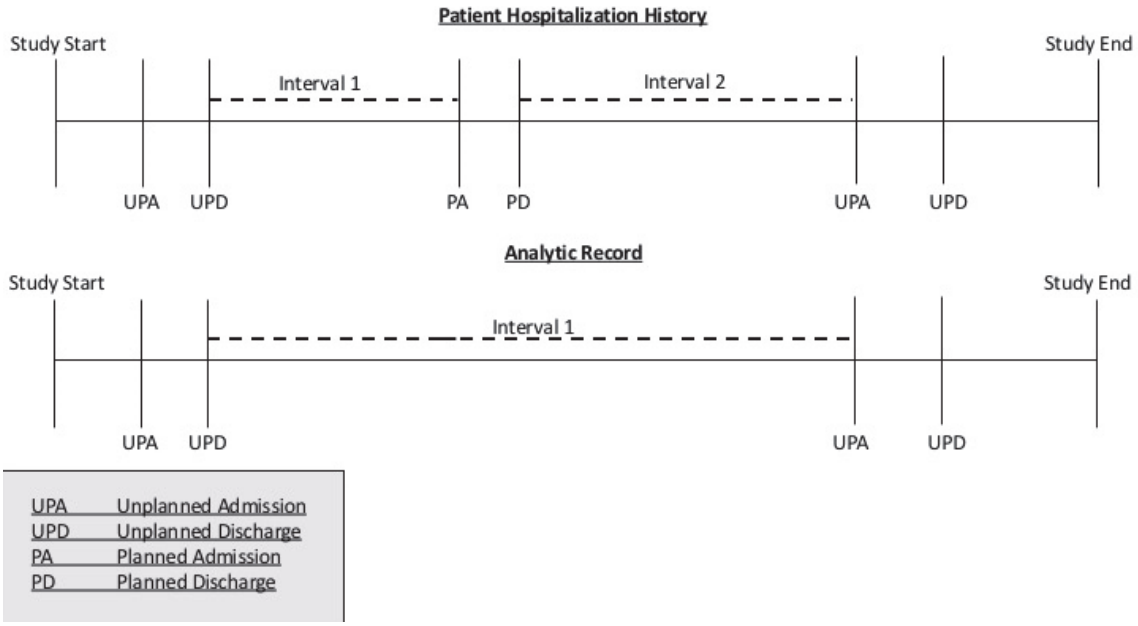
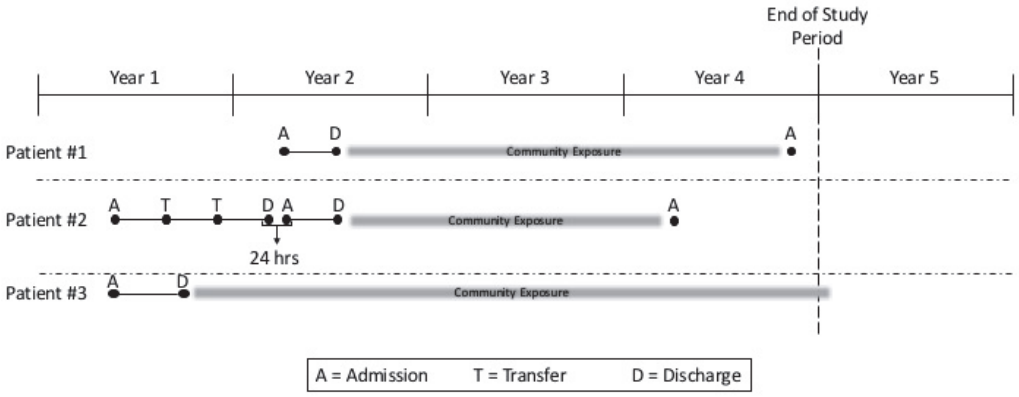


Figure 2 - Illustration of the construction of analytic records from patients' unplanned hospitalization histories*



*This figure describes how index hospitalizations and community exposure times were calculated. Patient #1 experienced an index hospitalization, was discharged and then experienced an unplanned repeat hospitalization approx. two years later. Patient #2 had an index hospitalization in year 1 that involved a series of transfers and a short discharge and re-admission before finally getting discharged in year 2. These events were all part of the same course of treatment and were grouped into one episode of care. Patient three had an index hospitalization, but never experienced a repeat hospitalization and was censored at the end of the study. Analytic records considered the 'community exposure' time between the first "index" hospitalization and a subsequent unplanned hospitalization episode.

Chapter 4

Results

As described in Table 1, our final study population consisted of 65,757 people with a valid index hospitalization. They had 36,298,688 person days of exposure, with a mean exposure time of approximately 552 days. The population was almost evenly split between males and females, and the most common age group was 60-64 years old (12.37% of the population). The most common number of chronic conditions was one (36.8% of the total population), and the most common condition was hypertension (24.4% of the population).

Our study population was discharged to 73 different FSAs (described in Table 2). Nova Scotia FSAs are demographically and socioeconomically diverse. There is wide variation in population between FSAs (41 to 40,415 people). The size of Nova Scotia's FSAs also varies dramatically across urban and rural settings - the smallest FSA is .94 sq./km and the largest is 6145 sq./km. In the average FSA, approximately one third of the population experiences low income, 22% of the population is over 65, and just under a quarter of the population has less than a grade 12 education.

Our primary analytic model suggests that that community of residence is associated with the expected case-mix adjusted time until an unplanned repeat hospitalization ($p < .0001$) (Table 3-a). Because of the large size of our sample however, even a small degree of community variation is likely to be statistically significant. Therefore, it is also

important to examine the magnitude of variation. The estimated case-mix adjusted standard deviation in acceleration factors between FSAs is 1.16 (95% CI 1.12, 1.21). This suggests that the mean time until an unplanned repeat hospitalization increases by 16% for a lower risk area which is one standard deviation from the mean. In order to account for potential biases in our data, we conducted two separate sensitivity analyses. In both instances community of residence remained highly significant ($p < 0.0001$). The first sensitivity analyses, which incorporated only members of our study population without cancer, injury, dementia or stroke, returned an estimated case-mix adjusted standard deviation in acceleration factors between FSAs of 1.15 (95% CI 1.11, 1.20). The second sensitivity analysis, looking at the last three years of our data, returned an estimated case-mix adjusted standard deviation in acceleration factors between FSAs is of 1.11 (95% CI 1.06, 1.22).

Examining estimates of acceleration factors for each FSA (Table 3-b, and Figure 3), it is clear that living in some communities is associated with a significantly higher (or lower) expected case-mix adjusted time to an unplanned repeat hospitalization than the mean time to URH for all FSAs. Of the 73 FSAs included in the primary analytical model, ten were shown to vary significantly from the provincial mean. Mapping of the communities (Figure 4) shows that FSAs with acceleration factors significantly different than the provincial mean tend to be clustered together in particular regions of the province. Nine communities were associated with a significant decrease in time to URH (acceleration factor of < 1), while only one community was associated with a significant

increase time to URH (acceleration factor of > 1). In our primary analytic model, the community with the highest statistically significant risk of experiencing an unplanned repeat hospitalization at any given point in time was North East Guysborough (B0H) with an acceleration factor of 0.733 (95% CI 0.626, 0.859). This means that someone living in North-East Guysborough will, on average, experience an unplanned repeat hospitalization in 73% of the time for the average community. Put another way, since the provincial mean time to an unplanned repeat hospital is approximately 552 days, then on average, people in North-East Guysborough return to hospital unexpectedly in 403 days. The FSA with the longest mean time to unplanned repeat hospitalization was South-Central Halifax (B3N) with an acceleration factor of 1.21 (95%CI 1.012, 1.451). In this case, since the provincial mean time to an unplanned repeat hospital is 552 days, then on average, people in South-Central Halifax would return to hospital unexpectedly in approximately 668 days.

In the communities where time to unplanned repeat hospitalization was significantly different from the mean of FSAs, the impact of community of residence on mean time to an unexpected return to hospital was quite large. Figure 5 illustrates the variation in acceleration factors in the ten areas significantly different than the mean time to URH for FSAs, as compared to the acceleration factors of some of the more common chronic conditions. For example, the adjusted acceleration factor of the FSA “B0H” was greater than the adjusted acceleration factor for diabetes. Similarly, the adjusted acceleration factor of the FSA “B0K” was greater than adjusted acceleration factor of cardiovascular

disease. The higher adjusted acceleration factors of the communities suggest living in a "B0H" will shrink the time to an unplanned repeat hospitalization more than contracting diabetes, while living in "B0K" decreases the time to repeat hospitalization more than contracting cardiovascular disease.

Certain chronic conditions also have a significant effect on the time until patient returns to hospital unexpectedly after an index discharge (Table 3-a). After adjustment, kidney disease shows the most dramatic acceleration factor (.503, 95%CI .403, .628) This means that people who have kidney disease will, on average, return to hospital unexpectedly in 50% of the time of people without kidney disease. Other conditions that reduce the time to unplanned repeat hospitalization include: asthma, cancer, and heart disease. The other variable that had a major impact on whether or not someone returned to hospital was whether or not they were in their last year of life. Being admitted to hospital in the last year of life was associated with an acceleration factor of 0.286 (95% CI 0.256,0.319).

Our work also shows that multimorbidity can play a larger role than community of residence in terms of determining time to URH. Figure 5 shows the variation in the effect of community on mean time to an URH as compared to the variation in the effect of having multiple morbidities. The graph highlights how multi-morbidities have the potential to play a much larger role in determining the time to an unplanned repeat hospitalization than community of residence. Figure 5 was designed to illustrate a very

large multimorbidity effect. Not all combinations of chronic disease will have such a dramatic impact on time to an unplanned repeat hospitalization.

Tables

Table 1 - Characteristics of the study population (n=65,757) as captured at the time of discharge from index hospitalization

Age (years)	Total (N)	% of Study Population
30-34	1869	2.84
35-39	2623	3.99
40-44	3492	5.31
45-49	4890	7.43
50-54	6145	9.34
55-59	7069	10.74
60-64	8136	12.37
65-69	7950	12.08
70-74	7147	10.86
75-79	6370	9.68
80-84	5149	7.83
85+	4957	7.53
Sex		
Male	33306	50.62
Female	32491	49.38
Disease Count		
0	22913	34.82
1	24213	36.80
2	11095	16.86
3	4616	7.02
4	1907	2.90
≥5	1053	1.60
Top 5 Most Prevalent Conditions		
Hypertension	16065	24.40
Injury	9129	13.87
Cancer	6545	9.94
Diabetes	4767	7.24
COPD/Asthma	4590	6.97
Reasons for Censoring		
Repeat Hospitalization	19269	29.27
Death	2472	3.75
Left Eligibility	608	0.92
End of Study	43448	65.99
Minimum Exposure Time (days)	1	
Maximum Exposure Time (days)	1461	
Mean Exposure Time (days)	551.67	
Median Exposure Time (days)	469	

Table 2 - Demographic characteristics of Nova Scotia's forward sortation areas

	Mean	Median	Min	Max	Q1	Q2	Q3	SD
Area (Sq/Km's) *	722.40	130.05	0.94	6145.32	24.15	126.83	548.54	1429.24
Population *1	11994.78	10277.50	41.00	40415.00	4492.00	10602.00	16997.00	9864.98
# of Private Dwellings *1	5955.43	4512.00	116.00	23597.00	1969.00	4539.00	7862.00	5181.15
% of pop. with Low Income *2	30.36	30.68	14.00	47.00	26.00	31.00	35.00	5.98
% of pop. over 65 *2	22.02	23.23	7.00	41.38	18.33	23.34	25.78	6.10
% of pop. with less than grade 12 education *2	23.15	22.08	4.34	61.91	17.09	21.63	27.75	9.24
% of pop. With single mother households *2	14.80	13.41	6.45	42.95	10.42	13.29	17.26	6.34

* = Data Drawn from Statistics Canada Forward Sortation Area Boundary File (92-179-X) - http://www5.statcan.gc.ca/olc-cel/olc.action?objId=92-179-X&objType=2&lang=en&limit=0

1 = Data Drawn from Statistics Canada - Population and Dwelling Count Highlight Tables, 2016 Census - http://www12.statcan.gc.ca/census-recensement/2016/dp-pd/hlt-fst/pd-pl/Table.cfm?Lang=Eng&T=1201&S=22&O=A

2 = Data Drawn from the Nova Scotia Health Atlas - www.healthatlas.c

Table 3 – Primary analytic model[1]
(3-a: Fixed effects portion of Primary Analytic Model)

Parameter	Acceleration Factor*	P-Value	95% Confidence Intervals	
			Lower	Upper
Male 30-54 years	1.221	0.0049	1.067	1.397
Female 30-54 years	1.196	0.0112	1.045	1.368
Female 60-64 years	0.854	0.0457	0.733	0.994
Female 65-69 years	0.749	0.0004	0.643	0.871
Female 70-74 years	0.642	<.0001	0.552	0.748
Female 77-79 years	0.643	<.0001	0.552	0.750
Female 80-84 years	0.531	<.0001	0.454	0.620
Female 85+ years	0.507	<.0001	0.435	0.591
Male 55-59 years	0.962	0.6225	0.824	1.123
Male 60-64 years	0.800	0.0036	0.692	0.925
Male 65-69 years	0.689	<.0001	0.596	0.796
Male70-74 years	0.592	<.0001	0.511	0.685
Male 77-79 years	0.528	<.0001	0.454	0.612
Male 80-84 years	0.498	<.0001	0.424	0.584
Male 85+ years	0.444	<.0001	0.374	0.527
1 chronic condition	0.972	0.7912	0.791	1.195
2 chronic conditions	0.904	0.6236	0.606	1.349
3 chronic conditions	0.903	0.7391	0.497	1.641
4 chronic conditions	0.941	0.8806	0.425	2.084
5+ conditions	0.879	0.8144	0.301	2.568
hypertentsion	0.997	0.98	0.811	1.226
cancer	0.551	<.0001	0.447	0.680
diabetes	0.753	0.0117	0.608	0.934
cardiovascular disease	0.798	0.0448	0.642	0.991
neurological disorders	0.955	0.6901	0.761	1.198
asthma	0.513	<.0001	0.415	0.634
injury	1.492	0.0004	1.209	1.840
hyperlipidemia	1.086	0.4767	0.866	1.363
heart disease	0.592	<.0001	0.476	0.736
dementia	1.523	0.0105	1.113	2.085
stroke	1.191	0.3111	0.851	1.668
anxiety	0.835	0.2236	0.625	1.114
osteoarthritis	0.931	0.589	0.719	1.205
thyroid problems	0.975	0.8376	0.763	1.245
kidney disease	0.503	<.0001	0.403	0.628
muscular problems	1.098	0.512	0.831	1.452
obesity	0.991	0.9501	0.738	1.330
stomach problems	1.039	0.7615	0.811	1.331
liver disease	0.579	0.0126	0.381	0.880
urinary	1.099	0.4908	0.841	1.438
schizophrenia	0.764	0.1342	0.540	1.082
somatoform disorders	0.980	0.9096	0.697	1.380
adjustment disorders	1.271	0.0391	1.016	1.590
End of Life	0.286	<.0001	0.256	0.319
Other computed Statistics				
Shape Parameter Estimate	0.5963	<.0001	0.5886	0.6039
Intercept	8.7172	<.0001	8.5868	8.8476
SD of variation between community acceleration factors	1.16	<.0001	1.113	1.201

[1] * The referent is female, aged 55-59 years, with no chronic conditions.
Numbers <1 indicate that the condition resulted in people returning to hospital earlier than expected, while numbers >1 indicates longer than expected time until an URH. Grey shading indicates that the acceleration factor is statistically significant.

Table 3-b – Random effects portion of primary analytic model

FSA	Acceleration Factor	P-Value	95% Confidence Intervals	
			Lower	Upper
B0H	0.735	0.00021	0.628	0.860
B5A	0.779	0.00161	0.670	0.907
B0K	0.805	0.00011	0.724	0.894
B0S	0.816	0.00642	0.706	0.943
B2H	0.831	0.01453	0.717	0.963
B2G	0.832	0.02662	0.708	0.978
B4N	0.833	0.02118	0.714	0.972
B0E	0.858	0.01357	0.760	0.968
B0C	0.876	0.24308	0.701	1.096
B0W	0.881	0.02874	0.787	0.987
B2R	0.881	0.33012	0.682	1.139
B2N	0.888	0.09924	0.770	1.023
B2V	0.914	0.34797	0.756	1.105
B2A	0.916	0.34481	0.763	1.100
B2Y	0.916	0.28235	0.780	1.076
B2Z	0.918	0.41374	0.747	1.129
B1E	0.925	0.54994	0.713	1.199
B1X	0.926	0.5823	0.702	1.222
B1A	0.931	0.32364	0.807	1.074
B0T	0.936	0.36989	0.809	1.083
B2X	0.950	0.57302	0.792	1.139
B1W	0.960	0.74245	0.749	1.230
B3J	0.963	0.7619	0.754	1.231
B4G	0.964	0.75525	0.761	1.220
B1P	0.969	0.67963	0.830	1.130
B3E	0.974	0.80825	0.784	1.210
B0V	0.975	0.81387	0.788	1.206
B3V	0.978	0.84495	0.784	1.222
B1V	0.980	0.83657	0.805	1.193
B3R	0.981	0.84266	0.811	1.187
B1C	0.981	0.88366	0.761	1.266
B1N	0.991	0.9279	0.807	1.217
B0J	0.993	0.89526	0.887	1.110
B2W	0.998	0.96942	0.879	1.132
B3A	0.999	0.9914	0.865	1.154
B1Y	1.001	0.98914	0.809	1.239
B0P	1.005	0.93853	0.890	1.134
B1J	1.006	0.96182	0.771	1.314
B1R	1.008	0.94456	0.802	1.267
B1M	1.017	0.90092	0.779	1.327
B4R	1.020	0.8801	0.791	1.315
B0N	1.020	0.73102	0.909	1.145
B3M	1.024	0.73426	0.891	1.177
B3P	1.025	0.80325	0.841	1.249
B1B	1.028	0.83024	0.798	1.324
B1G	1.028	0.82181	0.804	1.315
B3G	1.029	0.77438	0.844	1.254
B1K	1.039	0.74665	0.822	1.313
B0M	1.039	0.62011	0.891	1.212
B1S	1.048	0.63025	0.864	1.271
B9A	1.056	0.63778	0.839	1.329
B1L	1.056	0.63758	0.839	1.330
B3K	1.061	0.45061	0.908	1.241
B0A	1.063	0.63189	0.824	1.371
B0R	1.071	0.51894	0.868	1.322
B1H	1.074	0.42266	0.900	1.281
B4P	1.093	0.3914	0.890	1.341
B0L	1.094	0.47543	0.853	1.402
B3Z	1.103	0.27656	0.923	1.317
B4V	1.106	0.18175	0.953	1.284
B3L	1.110	0.22224	0.937	1.316
B6L	1.122	0.24409	0.923	1.364
B3H	1.128	0.18992	0.941	1.351
B3T	1.143	0.1456	0.954	1.370
B4C	1.143	0.09476	0.977	1.338
B4E	1.164	0.09929	0.971	1.395
B4A	1.170	0.07925	0.981	1.394
B2S	1.176	0.16465	0.934	1.479
B3S	1.192	0.07098	0.985	1.442
B4H	1.197	0.0501	1.000	1.432
B2T	1.201	0.06074	0.992	1.455
B3N	1.209	0.03864	1.010	1.447
B4B	1.211	0.08951	0.970	1.512

Figures

Figure 3 - The difference in expected time until URH, compared to the mean time to URH of FSAs[1]

[1] This caterpillar plot shows the relationship of expected time to an unplanned repeat hospitalization in each FSA as compared to the expected time to unplanned repeat hospitalization of all FSAs in Nova Scotia.

Figure 4 - Geographic distribution of communities with a probability of URH that differs significantly from the mean community time to URH

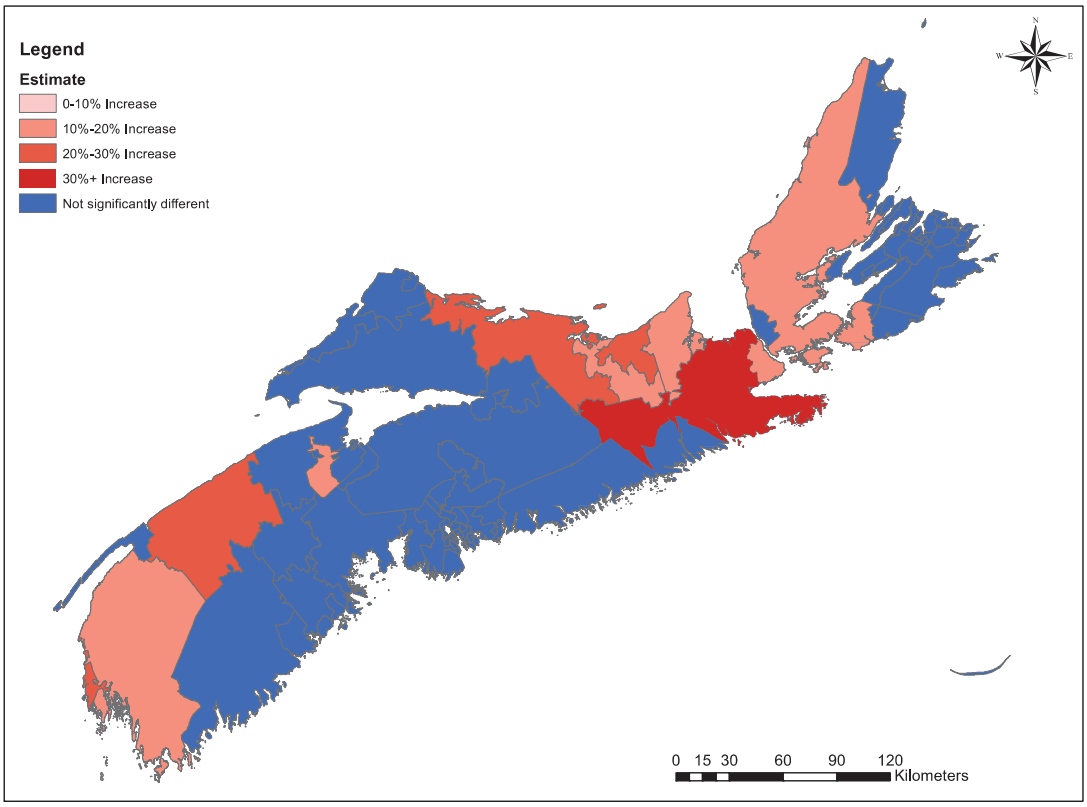
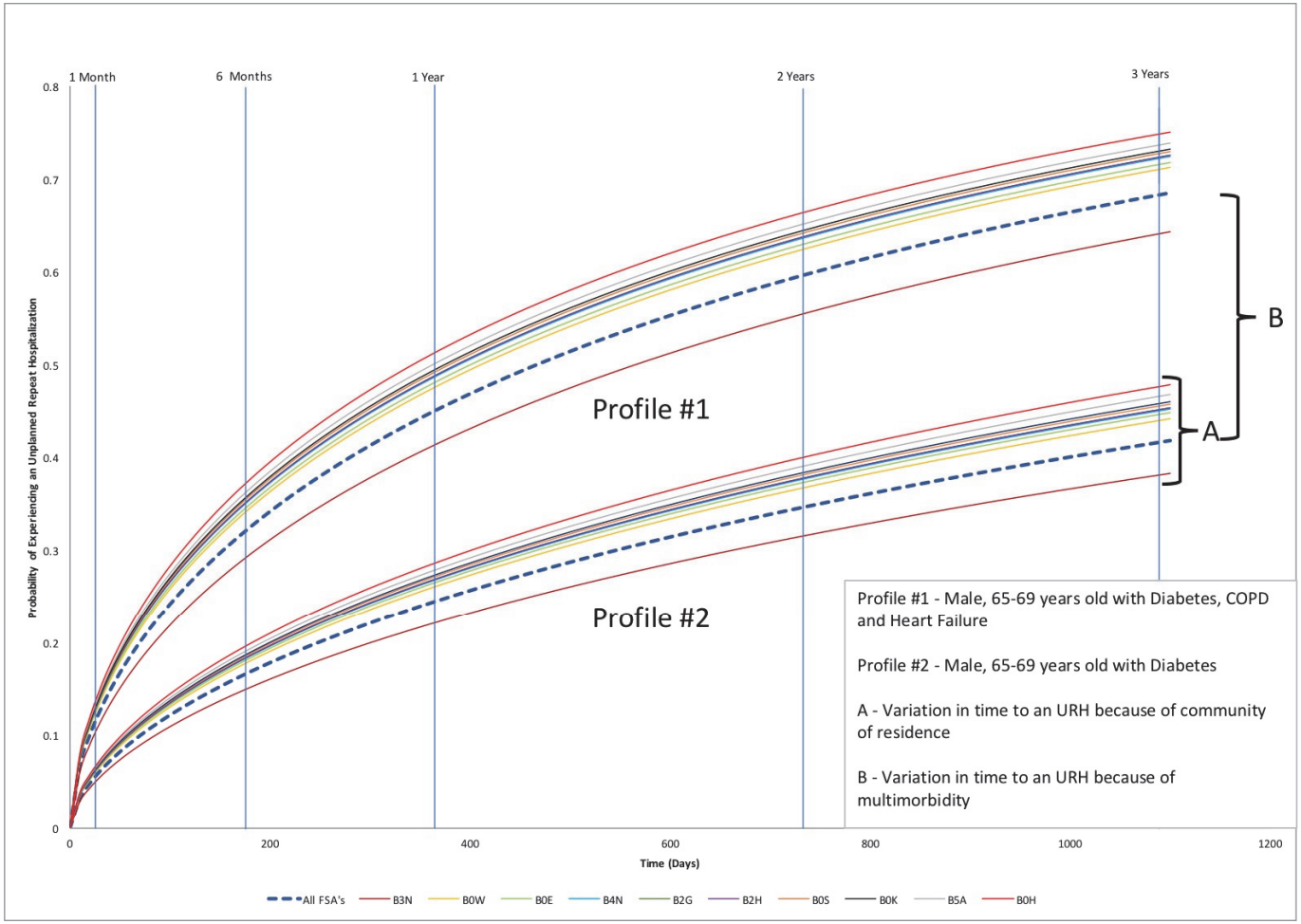
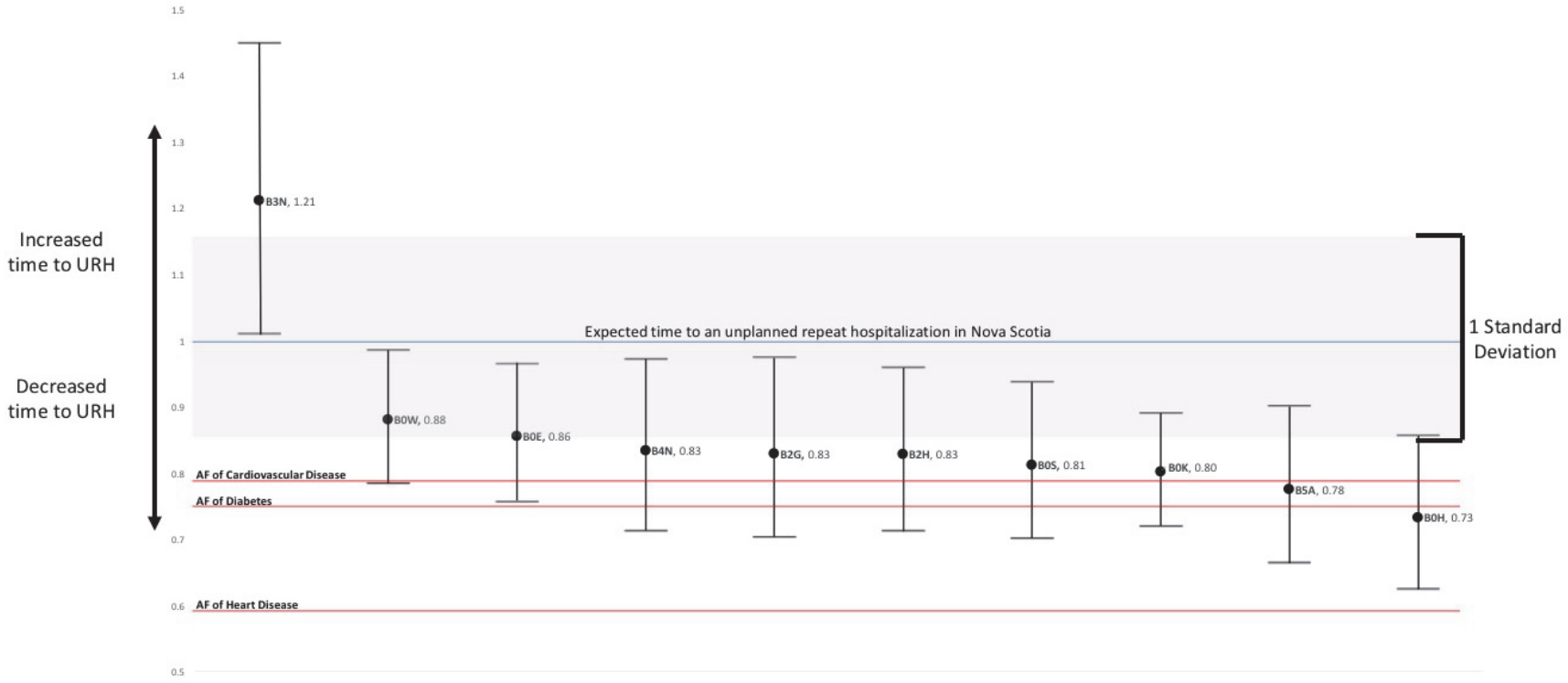


Figure 5 – Comparing the effect of area to the effect of multimorbidity[1]



[1] This graph represents the survival curves for patients with different disease profiles. Both patients are male, aged 65-69. One patient has Diabetes, COPD and heart failure, while other has Diabetes. The clusters of lines represent the variation in time to unplanned repeat hospitalization due to community of residence, while the space between clusters represents the the impact that multimorbidity has on the time until a patient experiences an unplanned repeat hospitalization. These disease profiles represent the extremes of potential variation in effect. Different profiles would likely result in smaller effects.

Figure 6 - Showing the acceleration factors of the ten statistically significant FSAs as compared to the acceleration factors of 3 major chronic conditions



Chapter 5

Discussion

Our results indicate that communities in Nova Scotia experience significant case-mix adjusted variation in the risk of unplanned repeat hospitalization. While our work does not explain the reasons for this variation, when viewed alongside existing studies of small area rate variation in health care use in Nova Scotia, it provides evidence that community based primary health care systems can have a significant effect on the performance of long-term chronic disease management strategies and interventions.

Comparison with earlier work on small area rate variation

Our analyses correlate well with earlier work done on small area rate variation in high-cost health care usage in Nova Scotia (SARV) (Figure 7). Our models indicate that the areas which differ significantly from the expected mean tend to be clustered together in particular regions of the province. Furthermore, the areas at higher risk of unplanned repeat hospitalizations in our work correspond geographically with those identified in the SARV work (Figure 8). This makes sense, as the SARV study found that hospital use is one of the primary drivers of high-cost health care use (86). Five out of the nine areas that we showed as having a significantly higher risk of unplanned repeat hospitalization than expected were also identified as areas of significant high-cost health care usage within the SARV Study (Figure 7). Our study lends credibility to the earlier SARV work and strengthens the case for pursuing further, targeted research in areas that have consistently shown themselves to have anomalous health care usage patterns.

The magnitude of community impact

Our work has shown that where one lives in Nova Scotia can have an influence on the case-mix adjusted time to an unplanned repeat hospitalization. In certain cases, the effect of living in a particular region on how long until a person returns to hospital unexpectedly is comparable to the effect of common chronic conditions. This is important, especially when we take into account the fact that our estimates of community effect size are likely conservative. Because our definition of community was based on geography designed to facilitate mail delivery, the geographic areas used in our study do not reflect the culture and community systems of the province. In Nova Scotia, there are numerous FSAs that encompass a large variety of different demographics. North End Halifax, for example, has neighbourhoods where high and low-income families live side by side. Similarly, FSA B0J encompasses both the Eastern Shore of the province as well as the South Shore. These two areas differ greatly in many aspects; however, we are forced to consider them as one "community."

The heterogeneity of populations within FSAs makes it difficult to separate overall community effects from the more localized individual effects within a particular area. It is reasonable to assume that if we re-ran our analyses using geography that was designed to be more reflective of community based primary health care systems (e.g. primary care catchment areas), that the overall community effect would increase. We have designed our analyses to accommodate this new information, should it become available in the future. Our model was designed to be as flexible as possible because,

geography aside, there were a number of assumptions that needed to be made in our analyses -- outlined below. If future research shows these assumptions to be inaccurate, then our model can be adjusted accordingly.

Analytical considerations and assumptions

We assumed that the hazard associated with community remained constant over time. This is known as the proportionality assumption and in our study, it is possible that proportionality does not hold. Hazards can change over time. Research has shown that, due to differences between the requirements of transitional and long-term care, longer time intervals from initial discharge can increase the relative importance of community-based primary health care systems in the outpatient management of chronic illness (87,88). For technical expediency, we assumed proportionality, but the AFT allows for the relaxing of the proportionality assumption should it be necessary. Since the AFT model is based on the survival curve rather than the hazard function, it is better suited to modelling data in which proportionality is in question. (89,90). Our sensitivity analysis encompassing only the last three years of study data confirms that the effect of community remains significant into the later stages of our study period, however if future analyses suggest that the effect of community is not consistent over time, then our formula can be adjusted to take that into account.

The size of our dataset means that study is highly powered to detect overall area effect, however at the FSA level, smaller populations result in our estimates being less precise.

While our fully adjusted model only found ten areas that differed significantly from the expected rate, small populations resulted in large confidence intervals. If we were able to conduct a similar study with a larger population, we anticipate that more regions would show significant variation from the expected time to unplanned repeat hospitalization.

Because of technical and time constraints, we were unable to describe the individuals in our study population at as fine a level of detail as we had initially hoped. There are many variables that could be associated with both an individual and a community that, within the limited scope of this study, are largely un-measureable. Factors like poverty, homelessness, ethnicity and even religious background all have the potential to affect our results, however we did not include them in the case-mix adjustment. These omitted variables represent a definite study limitation. Until we have a better sense of these missing factors, we will not be able to determine whether or not there are any significant interactions between fixed and random effects at the community and individual level. Similarly, by only counting emergent/urgent procedures we necessarily excluded people who identified their condition early enough to have preventative surgery. It is possible that this exclusion biases our data towards only identifying patients with more advanced forms of their specific condition. Despite these assumptions, we are confident that our model is based on sound principles with the most up-to-date and well coded data available, and provides helpful insights into the nature of unplanned repeat hospitalizations in Nova Scotia.

The benefits of the accelerated failure time model (AFT)

The AFT model can offer a number of advantages over the more common parametric proportional hazards model (91). For our purposes, the biggest advantage of the AFT is that it provides an intuitive summary statistic, the acceleration factor, which clearly shows how living in a particular community either increases or decreases the expected time until an unplanned repeat hospitalization. In contrast to the Cox Proportional Hazards Model, the AFT model can provide the mean survival times, time ratios, predicted hazard functions, acceleration factors and predicted survival functions. The intuitiveness of the AFT model becomes especially important when looking to communicate results to policymakers and other stakeholders. By providing a result that is clear and easily understood, the AFT equips us with the necessary tools to disseminate the results of our research to the general public in a way that is both easily understood and meaningful.

Policy implications

While many studies have examined unplanned repeat hospitalizations as a measure of hospital performance, this is one of the first attempts at using unexpected returns to hospital as a measure of how well community based primary health care systems can support people with complex chronic conditions. Our work shows that the responsibility for effective chronic disease management extends beyond the hospital and formal health care system. This study supports the idea that new health care policy

could benefit by taking more informal community systems into account during the design phase. The results of our work support a growing body of research into small area variation in health care service use in Nova Scotia, and similar work to ours has already been included in the policymaking process.

This study is an early step towards developing a better understanding of the role that community systems play in the duration of time before a patient experiences an unplanned repeat hospitalization. It gives us an indication of what communities stand out, but does not tell us why certain communities appear to be having more success than others when it comes to effective long-term chronic disease management. The complexity of formal and informal care systems at the community level make it difficult to determine any sort of causality through quantitative analysis alone. While we can make post hoc observations about the nature of communities with higher or lower than expected probability of repeat hospitalization, a more in-depth analysis of the communities highlighted in this work is necessary in order to determine what mechanisms are causing the increase/decrease in time to unplanned repeat hospitalization. At this stage, all we can capture is the fact that a repeat hospitalization occurred, we cannot definitively say why. To answer that question, we will need to incorporate qualitative methods and move beyond secondary data analysis based on the Discharge Abstract Database (DAD).

Figures

Figure 7 - Comparison of areas that were found to be significant in our work vs. earlier work on high-cost health care users in Nova Scotia

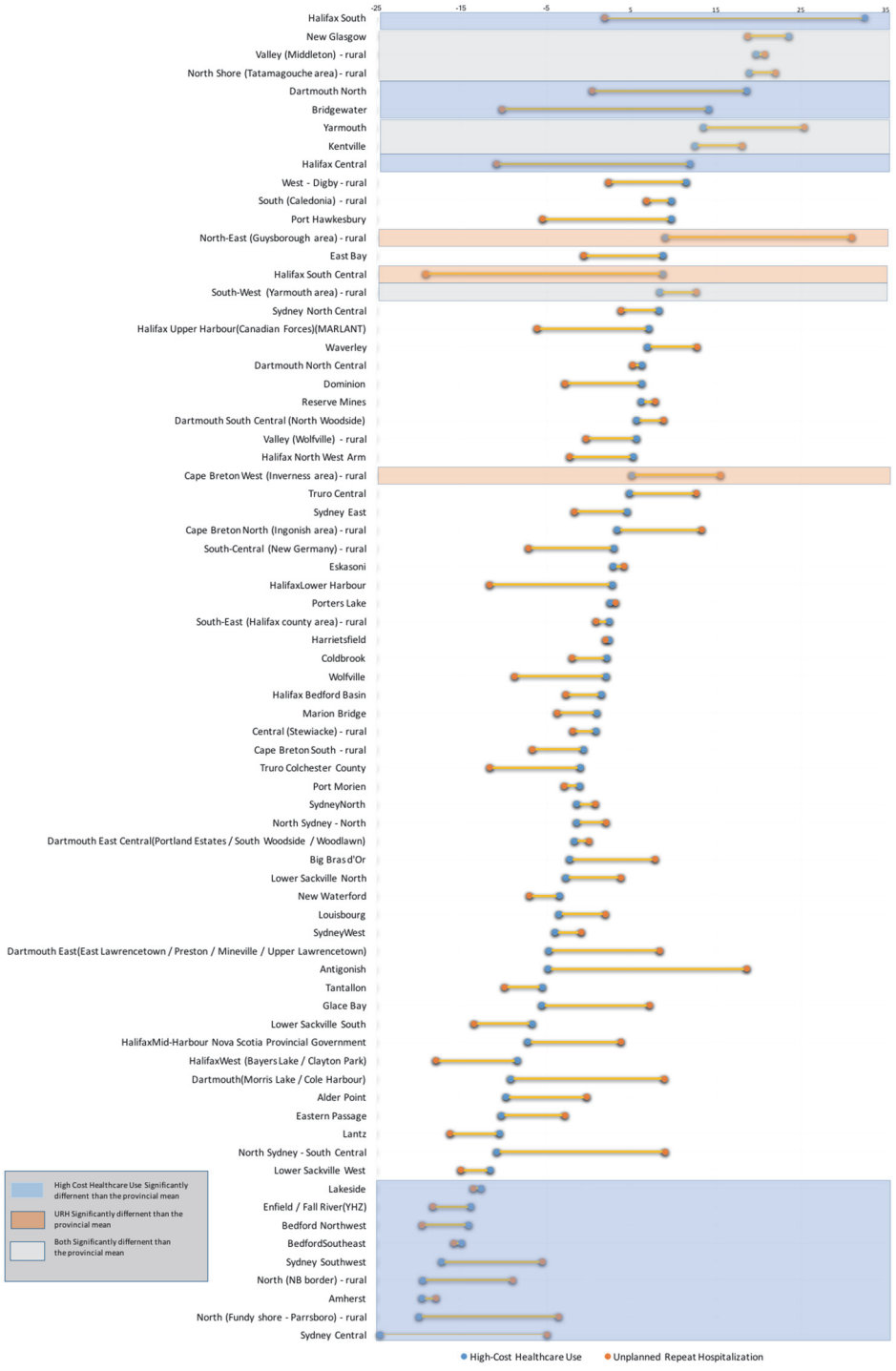
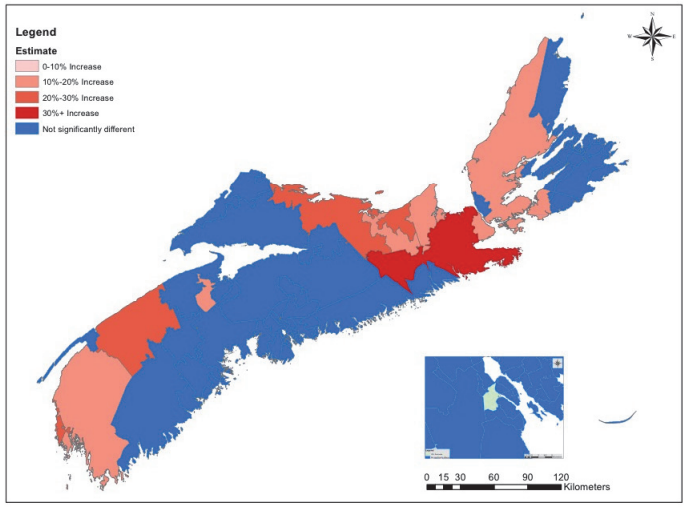
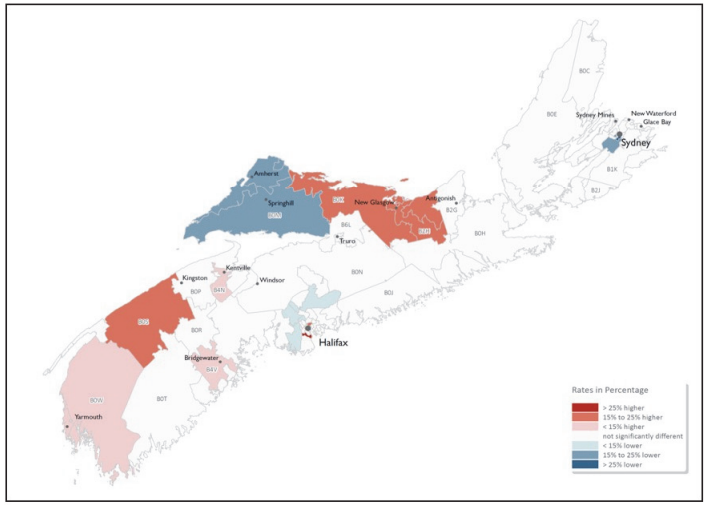


Figure 8 - A comparison of the geographic clustering of communities in our work and earlier work done on high-cost health care users in Nova Scotia[1]

Areas with Significant variation in time to URH after adjustment for demographics, disease patterns EOL and Multimorbidity



Areas with Significant variation in High-Cost Healthcare usage after adjustment for demographic and disease patterns



[1]The map on the left shows which areas of the province were found to vary significantly from the provincial mean time to unplanned repeat hospitalization. The map on the right shows the results from the earlier SARV work highlighting areas of the province with higher than expected high-cost health care use. The areas found to be significant in our work correlate very well with areas that had high-cost health care use due to chronic disease, and unexplained high cost health care use.

Chapter 6

Conclusion

Our work shows that community of residence can have an impact on the time until a patient experiences an unplanned return to hospital. As treatment patterns shift focus from acute care to long term chronic disease management, it is important to acknowledge that much of the necessary work in long-term chronic disease management is going to be done outside of the traditional primary care setting. This study serves as an important early step towards gaining a better understanding of the mechanisms that help or hinder community-based primary health care systems to support their most vulnerable members.

At this stage, our research can offer only broad insights into the effect that living in certain communities in Nova Scotia has on the time to an unplanned repeat hospitalization. The complex and interrelated nature of these communities makes a purely quantitative analysis less than ideal for determining exactly how community-based primary health care systems affect the people in a given community. By highlighting which communities have a risk of early unplanned repeat hospitalization that varies significantly from the mean expected provincial rate, however, we are now able to target more in-depth, mixed methods research.

The combination of qualitative and quantitative research can help researchers and policymakers move beyond the question of “where” and closer to answering “why”. As our understanding of community–based primary health care systems grows, we will be able to work with policymakers to develop new long-term CDM strategies that both support and enhance existing long-term CDM measures. By taking the innovative step of moving beyond the metrics of hospital performance, this study begins to contextualize unplanned repeat hospitalizations within the wider communities in which they take place. Our results will direct future research efforts on the communities that will benefit the most from improved long-term CDM strategies. We hope that the knowledge generated here can offer insight to all levels of government as well as the community-level formal and informal health care systems that are helping to keep Nova Scotians healthy, active, and happy.

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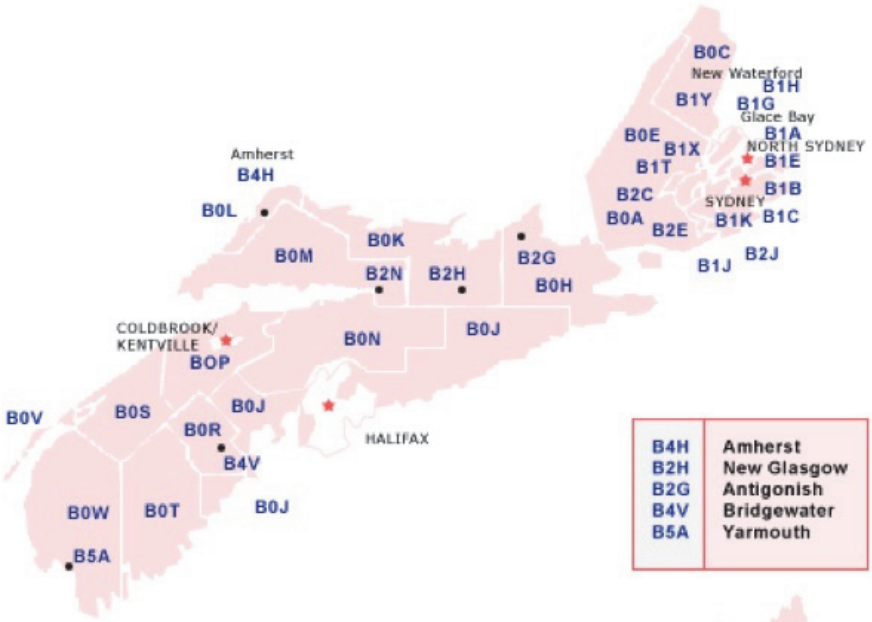
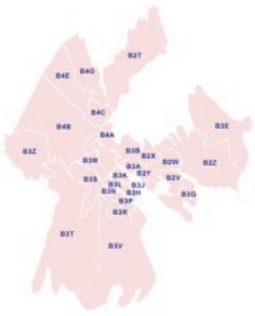
Appendix 1 – Nova Scotia's forward sortation areas



Coldbrook/Kentville



Halifax

North Sydney

Sydney

All images from: http://www.topmoving.ca/moving-tools/canada-fsas.html?prov=nova-scotia

Appendix 2 – Variables used in our analysis

NOTE: Each record is a "person-interval" describing an index "episode" of hospitalization, and the wait time until a following admission or censor time (whichever comes first). A person with multiple eligible admissions will have multiple records.

Hospital Episode Definition
Our episode definition groups sequential hospital separations which involve transfers between acute care institutions or rehabilitation facilities (based on "**institution type"** "***institution from***" and "***institution to***") fields, OR date time criteria (the time between separation and admission is less than 48 hrs.: ***admission date, admission time, separation date separation time***). In short, a readmission occurring within 48 hours is added to the standard episode definition used by HDNS. Day Surgeries will be excluded from the data set.

Unless otherwise stated in the tables, variables pertaining to episodes combine information from all separations making up an episode

"Index" Hospitalization Episode
A discharge from a hospitalization episode, which marks the beginning of an exposure period for risk of repeat hospitalization, is an "index" episode. Each record in the analytic file begins with an "index" hospitalization episode. An index episode is an *inpatient* hospitalization episode that meets the following criteria:

7. At least one of the separations is emergent/urgent (based on ***admit type***)
8. Admit to variable is not in an ER, OPD, or Day surgery
9. None of the separations are related to pregnancy or birth (***main patient service:*** 51=delivered, 52=antepartum, 53=aborted, 59=postpartum)
10. The final discharge in an episode is to a community setting (i.e. not to a LTC institution, OPD, other non-acute care institution or a psychiatric hospital). This will be based on ***institution to*** field.
11. The most responsible discharge diagnosis for any of the separations in the episode is not a psychiatric condition (**main patient service=64** OR ***most responsible Dx*** of a psychiatric condition: ICD-10 codes of F00-F99)
12. The ***discharge disposition*** variable is not 06 (sign out) or 12 (did not return from pass)

Each person will have one record for each index episode meeting the above criteria. Each record will end in either a repeat hospitalization or censor (i.e., death, end of eligibility or the end the study interval)

"Repeat" Hospitalization Episode

A repeat hospitalization episode is one that follows an index hospitalization. A repeat hospitalization episode meets the following criteria:

1. At least one of the separations is emergent/urgent (based on **admit type**)

A repeat hospitalization episode which meets the criteria for an index hospitalization episode will become the index hospitalization for the next record.

Source of Data	Variable	Notes on Variable Construction
MSI - Patient registry (MASTER): scrambled HCN	*Studyid (scrambled)*	*person*
CIHI DAD: derived (see episode definitions above)	*Index episode Sequence number*	*Person-interval*
CIHI DAD	Type of hospitalization	This is an indicator variable that will identify whether the primary reason for admission is surgical or Medical. (0=surgical, 1=medical) Based on the same definition of surgical/medical that appears in the CMG+ Documentation
CIHI DAD: separation date	Start of time interval (Index episode separation date +2)	*Day (specified as days since a fixed reference date; e.g. January 1, 2010)* since DAD is a discharge database, we will miss admissions where the discharge occurs after the end of the study interval, 2010-14. We will use DAD data for 2014-15 to capture hospitalization episodes that begin in the study period)
CIHI-DAD (admission date) and Eligibility file (fromdate, todate, tstat, dob, program)	End time of interval	*Day (specified as days since a fixed reference date; e.g. January 1, 2010)* since DAD is a discharge database, we will miss admissions where the discharge occurs after the end of the study interval, 2010-14. We will use DAD data for 2014-15 to capture hospitalization episodes that begin in the study period. The end of a time interval will occur if the following conditions occur: Repeat admission, death, patient leaves eligibility, patient leaves registry, or end of study.
CIHI-DAD (see repeat hospital episode definition above) and Eligibility file (fromdate, todate, tstat)	Event/censor type	1 – Repeat Hospitalization 2 - Death 3- Patient Leaves Eligibility 4 – End of Study
CIHI DAD: (admission date/time, separation date time)	Index episode: LOS (total days length of stay of separations comprising episode)	Days grouped. Final grouping will be decided based on distribution to ensure adequate cell size by group. Anticipate 5-10 groups Length of stay will be based on all hospitalizations in each episode of care

CIHI DAD: adjusted ALOS and calculated LOS (from admission date/time, separation date time)	Index episode: Ratio of total observed length of stay to total expected length of stay for each episode	Will be grouped into about 5 levels based on examination of distribution to ensure adequate cell size by group Adjusted length of stay will be based on all hospitalizations in each episode of care Both the Max expected LOS and the Last expected LOS will be calculated.
CIHI-DAD: institution number	Index episode: Hospital of discharge from index hospitalization	This is a de-identified indicator variable of hospital (i.e. numbered 1 – N)
CIHI-DAD: derived. See episode definition above)	Index episode: Number of separations comprising the episode	Integer (# of hospitalizations in an episode)
CIHI-DAD: postal code	Index hospitalization: FSA of residence	First three digits of postal code Interval start date in fiscal 13 post dataset
Derived using start date and end date (see above) and eligibility file (todate, tstat)	Proximity to end of life	The proportion of the final interval (end date – start date) that falls in the last year of life (range: 0-1, 2 decimal points of precision)
CIHI DAD: dxcode1-dxcode25	Diabetes	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD : dxcode1-dxcode25	Hypertension	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Chronic bronchitis, Chronic COPD, or Asthma	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes

CIHI DAD: dxcode1-dxcode25	Injury	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Hyperlipidemia	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Heart failure	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Osteoporosis	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Cancer	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Dementia	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Stroke or Transient Ischemic attack	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Anxiety or Depression	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Osteoarthritis or Rheumatoid arthritis	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Thyroid Problem	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Chronic kidney disease or failure	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Chronic Musculoskeletal problem	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Obesity	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Cardiovascular Disease	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Stomach Problem	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Colon Problem	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Chronic Liver Disease	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Chronic Urinary Problem	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Neurologic Conditions	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Schizophrenia/psychosis	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Neurotic/Somatoform Disorders, Personality disorders	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	Adjustment Reaction/attempted self-harm/other mental disorders	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
CIHI DAD: dxcode1-dxcode25	No specific diagnosis	coded in each year as a dichotomous (Y/N) variable. See attached Xcel Sheet for ICD-10 codes
Derived variable from chronic condition dummy variables	Number of chronic conditions	Number of unique chronic disease codes from previous variable

Registration and eligibility file (age)	Age as of index episode discharge	5-year age groups, with 1 group for age 85+ age is defined as the age at the end of each index episode of care
Registration/Eligibility file (sex)	Sex	Male/female
CIHI DAD: dxcode1-dxcode25	Elixhauser Comorbidity Index Score	Total Elixhauser Score based on comorbidities
CIHI DAD: dxcode1-dxcode25	Charlson Comorbidity Index (CCI) Score	Total CCI score based on comorbidities
CIHI-DAD: derived	Excluded Episode within Interval	Yes/No indicator for whether or not there was an excluded episode within a given interval.

Appendix 3 – SAS code used in our primary analytical model

```
proc nlmixed data=work.fuddummy cov ;

bounds pp > 0;

linp = b0 + yngmale*age_sex1 + yngfemale*age_sex2+ f6064*age_sex4+
f6569*age_sex5+ f7074*age_sex6+ f7579*age_sex7+ f8084*age_sex8+
f85plus*age_sex9+ m5559*age_sex10+ m6064*age_sex11+ m6569*age_sex12+
m7074*age_sex13+ m7579*age_sex14+ m8084*age_sex15 + m85plus*age_sex16 +
cc1*cc_catnum1 + cc2*cc_catnum2 + cc3*cc_catnum3 + cc4*cc_catnum4 +
cc5plus*cc_catnum5 + hypert*hypert_bi + cancer*cancer_bi + diabetes*diabetes_bi +
cardio*cardio_bi + neuro*neuro_bi + asth*asth_bi + injury*injury_bi + hyperl*hyperl_bi
+ heart*heart_bi + dementia*dementia_bi + stroke*stroke_bi + anxiety*anxiety_bi +
osteoa*osteoa_bi + thyroid*thyroid_bi + kidney*kidney_bi + muscu*muscu_bi +
obesity*obesity_bi + stomach*stomach_bi + liver*liver_bi + urinary*urinary_bi +
schiz*schiz_bi + somato*somato_bi + adjust*adjust_bi + EOL*end_life + u0;

alpha = exp(-linp);


G_t = exp(-(alpha*exposure)**pp);

g = pp*alpha*((alpha*exposure)**(pp-1))*G_t;

ll = (rep_hosp_bi=1)*log(g) + (rep_hosp_bi=0)*log(G_t);

model exposure ~ general(ll);

random u0 ~ normal(0,exp(2*logsig)) subject=pc_regress out=reffectfixed;

run;
```

Appendix 4 – Measuring multimorbidity

Adjusting for type and number of comorbidities is a common and important element of performance benchmarking and risk prediction (92). It is also a complex undertaking (93). Some of the more common indices include: a simple disease count, the Elixhauser index, variants of the Charlson Index, Chronic Disease Score/Rx Risk, Adjusted Clinical Group system, the Cumulative Index Illness rating scale and the Duke Severity of Illness Checklist (92,94). These are just a few of a wide variety of specific multimorbidity indices available, many of which have been calibrated and validated for a particular target population.

It was essential that we picked a measure suited to repeat hospitalizations, rather than the disease characteristics of the study population. Quail et al. found in a study that examined five different multimorbidity measures, that the optimal multimorbidity measure depends on the health outcome being measured and not on the disease characteristics of the study population (95). Huntley et al. concluded that more complicated measures do not necessarily perform significantly better than the simpler methods such as disease counts (94). This is important because the results from this study should be translatable into practical recommendations. By using simple disease counts we avoided the "black box" effect that is inherent with some of the more complicated risk adjustment methods.

We based the chronic disease categories used in our model on the work of the Patient-Centered Innovations for Persons with Multimorbidity (PCIPM) group, a Canadian Institutes of Health Research (CIHR) funded research group based out of The University of Western Ontario and The Université de Sherbrooke Quebec. Their team has developed and validated a list of 20 common chronic diseases that we included as dummy variables to adjust for common chronic diseases (80). We modified the list through the addition of disease codes which are not covered by the PCIPM list but are likely to be influenced by community factors. This expanded list includes categories for: diseases of the nervous system, schizophrenia/psychosis, neurotic/somatoform disorders, personality disorders, and adjustment reaction/attempted self- harm/other mental disorders. While relatively rare in Nova Scotia, these diseases tend to result in more complex episodes of care and need to be taken in to account (96). Our final list included 26 different categories that were used in our adjustment. This strategy allowed us to capture the effect of not only the total number of chronic conditions, but also provided insight into the effect that specific chronic conditions had on the overall equation.

Conditions Included in our Analyses.

1. Hypertension	2. Osteoporosis
3. Obesity	4. Dementia
5. Diabetes	6. Musculoskeletal Problems
7. COPD/Asthma	8. Stomach Problems
9. Hyperlipidemia	10. Colon Problems
11. Cancer	12. Liver Disease
13. Cardiovascular Disease	14. Urinary Problems
15. Heart Failure	16. Stroke/TIA

17. Thyroid Problem	18. Kidney Disease/Failure
19. Osteo/Rheumatoid Arthritis	20. Anxiety/Depression
21. Diseases of the Nervous System	22. Schizophrenia/Psychosis
23. Neurotic/Somatoform Disorders	24. Personality Disorders
25. Adjustment Reaction/ attempted self-harm/ other mental disorders	26. Injury

* Items 1-20 were developed as part of a CIHR-funded CBPHC Signature Initiative called the Patient-Centred Innovations for Persons with Multimorbidity Team or PACE in MM Team *(The short form of PACE in MM can be used if needed; Co-Principal Investigators are Dr. Moira Stewart and Dr. Martin Fortin. The website for the PACE in MM Team is http://www.paceinmm.recherche.usherbrooke.ca/*

**Dr. Martin Fortin (Professor, Universite de Sherbrooke) was the primary creator of this list, its categories and associated diagnostic codes

***The original reference can be found at: Nicholson K, Terry AL, Fortin M, Williamson T, Bauer M, Thind A. Examining the prevalence and patterns of multimorbidity in Canadian primary health care: a methodologic protocol using a national electronic medical record database. Journal of Comorbidity 2015; 5: 150-161.

ICD-10 Codes used in Analysis:

1. Hypertension	I10, I15.0, I15.8,
2. Obesity	E66.01, E66.9,
3. Diabetes	E10.10, E10.11, E10.21, E10.29, E10.311, E10.319, E10.36, E10.39, E10.40, E10.51, E10.618, E10.620, E10.621, E10.622, E10.628, E10.630, E10.638, E10.641, E10.649, E10.65, E10.69, E10.8, E10.9, E11.00, E11.01, E11.21, E11.29, E11.311, E11.319, E11.36, E11.39, E11.40, E11.51, E11.618, E11.620, E11.621, E11.622, E11.628, E11.630, E11.638, E11.641, E11.649, E11.65, E11.69, E11.8, E11.9,
4. Chronic Obstructive Pulmonary Disease or Asthma	J41.0, J41.1, J41.8, J42, J43.9, J44.0, J44.1, J44.9, J45.20, J45.21, J45.22, J45.901, J45.902, J45.909, J45.990, J45.991, J45.998,
5. Hyperlipidemia	E78.0, E78.1, E78.2, E78.3, E78.4, E78.5,
6. Cancer	C00-C14, C15-C26, C30-C39, C40-C41, C43-C44, C50, C51-C58,
7. Cardiovascular Disease	I20, I20.1, I20.8, I20.9, I25.2, I48.91, I48.92, I70,
8. Heart Failure	I05.0, I05.1, I05.8, I06.1, I06.2, I06.8, I06.9, I50,
9. Anxiety or Depression	F32.0, F32.1, F32.2, F32.3, F32.4, F32.5, F32.9, F33.9,

10. Osteoarthritis or Rheumatoid Arthritis	M05.00, M05.30, M05.60, M06.1, M06.9, M15, M16, M17, M18, M19,
11. Stroke or Transient Ischemic Attack	G45.0, G45.1, G45.8, G45.9, I63.30, I63.40, I63.50, I66.09, I66.19, I66.29, I66.9, I67.848,
12. Thyroid Problem	E00-E07
13. Kidney Disease or Failure	N17 (Inclusive), N18, N18.1, N18.2, N18.3, N18.4, N18.5, N18.6, N18.9, N 19(Inclusive)
14. Osteoporosis	M80 (inclusive) 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,
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, K58.9,
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, 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, 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, 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. Schizophrenia and other psychosis	F05, F20-F29
23. Neurotic disorders and somatoform disorders, depressive disorder	F32-34, F38-F39, F40, F42, F43.1, F44-F50, F54, F59, F99
24. Personality disorders:	F60-F69
25. adjustment reaction, , other mental disorder, Attempted self-harm,	R4020, R404, R403, R400, R401, R440, R442, R443, R55, R5600, R5601, R561, R569, R42, F518, R5382, R532, R531, R5381, R5383. R61, R6812, R6811, R412, R413, R6881, R4583, R52, R4182, R4584, R6889, R4181, R450, R454, R4587, R4586, R453, R4589 R457, F430, F4320-25, F4329, F4312, F438, F4310, F4390, F43948, E950-E959, T36-50, X60-X84, F985, F5000, F959, F950-52, F984, F509, F502, F983, F9821, F508, F9829, F980, F981, F4541, F4542, F633, R451, F51-F53, F55-F59,F99, V11,V61,V62,R40-R46,R69,T74.1,T74.2,T74.9,T88.7,Y07.0,Z03.2,Z55,Z56,Z59,Z60-Z65,Z72.8
27. 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

Appendix 5 – Constructing episodes of care

Hospitalization events often involve transfers between hospitals. For example, a patient may be admitted to one hospital and then transferred to another to obtain necessary services. These two admissions are normally coded as 2 separate hospitalizations; however, they are both part of the same episode of care. Episodes of care are defined as: "a block of one or more medical services received by an individual during a period of relatively continuous contact with one or more providers of service, in relation to a particular medical problem or situation (97)." Failure to account for episodes of care properly can result in inaccurate assessment of important parameters such as admission rates, readmission rates, mortality, and lengths-of-stay. Similarly, erroneously combining entries that represent separate episodes of care will also produce inaccurate results (98).

How to appropriately combine different hospitalizations into one episode of care is subject to debate. Hellsten et al. point out that constructing episodes of care results in challenges stemming from data requirements, complexity, time and resources necessary and methodological issues (99). Peng et al. suggest the use of a time gap of 9 hours between 2 hospitalizations to define hospital transfer in inpatient databases and group those records together. They add that when admission or discharge time is not available in the database, a time gap of same day (up to 24 hours) can be used (100). CIHI suggests combining records if re-admission occurs within six hours of a previous

discharge, or up to twelve hours if one of the institutions codes the transfer (101). Fransoo et al. (98) compared 5 different methods for constructing episodes of care: Method one ignored transfers, while methods 2-5 considered the time gap between successive entries (≤1 day vs. ≤2 days), with or without use of data fields indicating inter-hospital transfer. They concluded that the details of the method used to identify transfers, at least among the variations they tested, made relatively little difference (98). Research on ICU patients has shown that the interval of two full calendar days strikes a good balance between readmissions that are the result of discharge decisions, minimizing readmissions due to patient factors, and avoiding artificial associations between night time discharges and readmissions (102).This being the case, and since repeat hospital admissions within 48 hours are generally considered very early and are often associated with premature discharge from hospital (103) and not community systems, we combined all repeat hospitalizations that occurred under 48 hours into one episode of care.