Spatiotemporal dynamics of urban processes in a university town: Neighbourhood change, transit development, and crime

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

This doctoral thesis was completed in the manuscript format. I, Renan Cai, am the sole author of *Chapters 1*, *5*, and *6*, and the lead author of the three manuscript chapters (*Chapters 2*, *3*, and *4*). All three manuscripts were co-authored with Dr. Su-Yin Tan. As first author for all manuscripts, I conceptualized the studies, designed the methodology, conducted data collection and analysis, prepared the results, and drafted and revised the manuscripts. Dr. Tan contributed to the manuscripts by providing feedback and revising the drafts.

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Abstract

Neighbourhood change, reflecting shifts in physical, social, economic, and demographic characteristics, is a central concern in cities worldwide. It encompasses a range of processes that unfold differently across local contexts. Among these processes, gentrification, commonly understood as the influx of middle-class residents into previously low-income neighbourhoods, has been the most extensively studied. In university towns and knowledge economy regions, studentification and youthification, referring to the concentration of post-secondary students and young adults, respectively, also represent important forms of change. These processes may overlap, while also exhibiting distinct characteristics and outcomes, leaving substantial room for research and policy consideration. This research examines neighbourhood processes in Kitchener–Waterloo, Canada, a mid-sized urban region that functions as a prominent university town and an important knowledge economy node.

This dissertation includes three manuscripts to address distinct but interconnected topics using Bayesian spatiotemporal modelling approaches. The first manuscript investigates the relationship between light rail transit development and gentrification. It argues that the association between transit development and neighbourhood change is spatiotemporally varying, rather than uniform across areas served by a transit line or across different stages of its development. The second manuscript examines the spatiotemporal patterns of post-secondary students, university graduates, and young adults between 2011 and 2021, a period marked by both development and disruption. The results identify shared neighbourhoods among these sociodemographic groups around campuses and along the central transit corridor, where high-density and high-cost rental housing may create barriers for other groups such as working-class families. The third manuscript analyzes the relationship between studentification and crime and disorder. The findings demonstrate varying relationships across the academic calendar and dependent on both crime types and measures of studentification, highlighting the need for targeted crime and disorder control in studentified neighbourhoods to promote community safety. In addition, a supplementary study

critically reflects on the use of official statistics in the manuscripts by examining how neighbourhood-level indicators relate to residents' lived experiences and perceptions of wellbeing.

Overall, this dissertation advances understanding of neighbourhood processes, public transit development, and environmental criminology by addressing research questions that are either highly debated or underexplored in the existing literature. It adopts a spatiotemporal perspective, an important yet underutilized lens in neighbourhood change research, and extends the application of advanced spatiotemporal models to this field. The findings also provide insights for planning and policymaking by identifying where and when important neighbourhood change may occur and highlighting implications for community inclusiveness, safety, and wellbeing.

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List of Abbreviations

BRT	Bus Rapid Transit
CBD	Central Business District
CI	Credible Interval
CIW	Canadian Index of Wellbeing
CT	Census Tract
CTC	Central Transit Corridor
DA	Dissemination Area
DIC	Deviance Information Criterion
GIS	Geographic information system
GTWR	Geographically and Temporally Weighted Regression
HMOs	Houses in Multiple Occupation
ICAR	Intrinsic Conditional Autoregressive
INLA	Integrated Nested Laplace Approximation
LQ	Location Quotient
LRT	Light Rail Transit
MAUP	Modifiable Areal Unit Problem
MTUP	Modifiable Temporal Unit Problem
ON-Marg	Ontario Marginalisation Index
PBSA	Purpose-Built Student Accommodation
PCA	Principal Component Analysis
RW1	Random Walk 1
TOD	Transit-Oriented Development
WAIC	Watanabe–Akaike Information Criterion

Chapter 1
Introduction

1.1 Context

Urban neighbourhoods are never static. Homes rise and fall, residents arrive and depart, and these continuous shifts steadily transform places that once felt familiar. As the physical, social, economic, and demographic characteristics of a neighbourhood evolve, some residents benefit while others face new challenges and stressors. Neighbourhood change occurring around the world has become a central concern for urban planners and policymakers seeking to promote inclusive, equitable, and sustainable communities, and it has also provided abundant opportunities for academic research to deepen understanding of neighbourhood dynamics and support decision-making.

Neighbourhood change is a complex process for which no single theory adequately explains why neighbourhoods evolve differently over time. Early ecological theories conceptualize neighbourhood change as a natural and deterministic process driven primarily by broader socioeconomic forces, with limited roles for individual agency. One foundational model is Burgess's (1925) invasion-succession model, which explains neighbourhood change as an inevitable outcome of competition for urban space, whereby new socioeconomic groups invade neighbourhoods and gradually succeed previous residents as cities expand outward. Building on this perspective, subsequent ecological theories argue that neighbourhoods progress through predictable life cycles, with decline resulting from housing aging and investment shifting to newer developments (Temkin & Rohe, 1996). Other theories emphasize that neighbourhood trajectories are shaped by the decisions and interactions of multiple actors, including residents, governments,

developers, landlords, investors, and other institutions. These perspectives recognize that neighbourhood change reflects interactions among housing markets, public policies, capital investment, social networks, place attachment, and community identity, while also acknowledging that unequal access to economic resources and decision-making power constrains residential choices and contributes to socioeconomic sorting and spatial inequalities (Bourne & Hulchanski, 2020).

In terms of the neighbourhood sociodemographic dynamics, Van Ham et al. (2012) group the main drivers into three broad categories. The first involves changes in neighbourhood composition through residential mobility, as households move into and out of neighbourhoods according to their preferences, opportunities, and constraints. The second reflects demographic and socioeconomic changes among residents who remain in place, including changes associated with aging, household composition, and socioeconomic status. The third comprises external forces, such as neighbourhood regeneration, gentrification, institutional interventions, and wider economic restructuring, that reshape neighbourhood populations and the built environment. Regardless of its underlying causes or trajectories, neighbourhood change is an inherent feature of urban development rather than a problem in itself. It becomes a concern when it intensifies existing inequality, marginalization, and polarization (Bourne & Hulchanski, 2020).

Among the many forms of neighbourhood change, gentrification has attracted particular attention in both public policy discussions and scholarly debates. Sociologist Ruth Glass (1964) first used the term “gentrification” to describe middle-class residents occupying inner-city working-class districts in London, UK, a process that can rapidly reshape neighbourhood social and housing compositions. Causes of gentrification have long been debated, with early studies contrasting demand-side and supply-side explanations. Supply-side theories focus on capital flows, suggesting that redevelopment occurs when a widening rent gap between potential ground rent values and depreciating actual values makes investment increasingly profitable (N. Smith, 1979, 1987). Demand-side theories emphasize population flows, linking middle-class movement to city centres to demographic change, economic shifts, and preferences for urban living (Ley, 1986, 1994).

Gentrification brings physical and socioeconomic improvements to a neighbourhood, and many original residents who remain, including some lower-income residents, may benefit from reduced neighbourhood poverty and rising housing values (Brummet et al., 2019). However, these benefits rarely extend to everyone, with displacement being a common outcome. Displacement occurs when conditions within a dwelling or its surrounding environment make it impossible, unsafe, or unaffordable for a household to continue occupancy (Grier & Grier, 1978). In an early effort to comprehensively conceptualize displacement, Marcuse (1985) defined four categories as direct last-resident displacement, where occupants are forced out by physical or economic conditions; direct chain displacement, which recognizes prior households pushed out by earlier deterioration or rent increases; exclusionary displacement, where comparable households are prevented from moving in after a household leaves; and displacement pressure, where residents, seeing their neighbourhood become increasingly unfamiliar, feel compelled to move before they are formally forced out. Despite the ongoing debate about gentrification-induced displacement, there is broad agreement that gentrification at least produces exclusionary displacement, where in-movers have higher socioeconomic status than those leaving (Zuk et al., 2018).

As neighbourhoods constantly transform, the literature on neighbourhood change continues to grow. Since Glass's initial definition, gentrification has evolved to capture a broad middle-class reshaping of neighbourhoods, encompassing new-build development, retail and commercial change, and cultural shift, and extend well beyond traditional city centres (Shaw, 2008). Research has increasingly emphasized a holistic understanding of gentrification that integrates supply-side and demand-side perspectives and jointly accounts for broader sociodemographic shifts, resident preferences, private investment, and public policies (Hwang & Lin, 2016; Slater, 2006; Zuk et al., 2018). Empirical studies have examined a variety of specific drivers of gentrification, such as attractive parks (e.g., Rigolon & Németh, 2020), high-performing schools (e.g., Wu et al., 2016), and public transit stations (e.g., Bardaka et al., 2018). A wide range of societal outcomes of gentrification beyond its direct impacts on housing and social composition have also been explored, such as population health (e.g., Schnake-Mahl et al., 2020), education (e.g., Keels et al., 2013), and crime (e.g., Barton, 2016).

While gentrification continues to dominate discussions of neighbourhood change, it is far from the only transformation shaping urban areas. A growing set of related concepts, stemming from gentrification studies yet defined by their own causes, processes, and impacts, has emerged to capture the diverse ways neighbourhoods evolve. Whether it is touristification in major tourist destinations (Cocola-Gant, 2023), studentification in university towns (D. P. Smith, 2005), or youthification in amenity-rich urban centres (Moos, 2016), these processes can displace long-term residents or generate displacement pressures. Although each develops through distinct pathways and produces its own specific outcomes, they may also intersect with one another and with gentrification, intensifying displacement risks.

Just as Glass's foundational work focused on gentrification in London, many case studies of neighbourhood change based on world cities and major metropolitan regions have since emerged. However, processes of urban transformation are not limited to large cities and also occur in mid-sized and small cities, peri-urban areas, and formerly rural towns. Importantly, these processes are always shaped by regional contexts. For example, neighbourhood change in many American cities cannot be understood without acknowledging historic racial residential segregation patterns (Wyly & Hammel, 2004). Likewise, neighbourhood dynamics in European historic cities are often connected to heritage management and tourism (Bobic & Akhavan, 2022), while in China, transformations often stem from state-led projects across cities of various sizes (S. He, 2019). In the Canadian context, Bourne and Hulchanski (2020) note that neighbourhood change reflects broader structural changes, including economic restructuring, immigration, demographic transitions, and technological change, while the ways these processes unfold differ across cities according to their local histories, geographies, politics, and demographics. With diverse neighbourhood change patterns across the world, region-specific empirical studies that examine neighbourhood change pathways and their links to contextual factors can both deepen general understandings of urban transformation and inform local policymaking.

This dissertation focuses on Kitchener-Waterloo, a mid-sized urban region in Canada. Kitchener-Waterloo is unique for its distinctive mix of rapid population growth, higher-education expansion, a thriving technology sector, and the development of new light rail transit (LRT) system. These characteristics also position it as a valuable case for advancing broader understandings of

neighbourhood change in comparable mid-sized cities, university towns, knowledge economy centres, and regions with urban rapid transit systems around the world. More specifically, this dissertation explores how LRT development is associated with neighbourhood change, how sociodemographic groups associated with studentification, gentrification, and youthification intersect within the university town and knowledge economy context, and how studentification is connected to crime and disorder. Although each of these topics has been examined to some extent in previous research, important gaps remain, particularly regarding how these patterns and associations vary across space and time (see *Section 1.3*). This dissertation seeks to provide novel insights, particularly from a spatiotemporal perspective, and to contribute to understanding neighbourhood dynamics in Kitchener-Waterloo as well as to the broader neighbourhood change literature.

1.2 Background

This section provides an overview of the important concepts, theories, current debates, and research gaps relevant to this research. Although each manuscript chapter includes its own background section that reviews literature leading to its specific research questions and design, this section serves as a general knowledge foundation for defining the overall scope, goals, objectives, and methodological approach of the dissertation.

1.2.1 Conceptualization and operationalization of neighbourhood change

Neighbourhood change, the central focus of this dissertation, seems straightforward, yet neither "neighbourhood" nor "change" has a universally accepted definition. A neighbourhood can be conceptualized as a "bundle of spatially based attributes associated with clusters of residences, sometimes in conjunction with other land uses" (Galster, 2001, p. 2112). These attributes are diverse, encompassing the physical, social, economic, demographic, and sentimental dimensions, and some, such as building type, the quality of education, and air pollution, operate at markedly different spatial scales (Galster, 2001). As a result, it is impractical to delineate unambiguous neighbourhood boundaries that simultaneously account for all attributes.

Despite the conceptual challenges, the need to define neighbourhoods remains critical in place-based planning and research. For planners and policymakers, the concept of neighbourhood is fundamental for local policy interventions and contemporary urban designs (Minnery et al., 2009). Its importance lies in recognizing the distinctive characteristics of small areas and enabling targeted responses to local issues, such as poverty, crime, and health (Foster et al., 2010; Musthafa et al., 2015; Rohe, 2009; Sandel et al., 2016). Minnery et al. (2009) identify two main approaches to conceptualizing neighbourhoods in planning practice: the first views the neighbourhood as a place with identifiable boundaries (e.g., administrative boundaries based on streets) that coordinate the actions of various parties, while the second defines neighbourhood boundaries using planning criteria such as walking distance and school catchment limits. However, planners' hope to identify consistent and meaningful neighbourhood boundaries for developing useful indicators and interventions is often disrupted by differing perceptions among actors and stakeholders (Galster, 2001). In particular, it is important to acknowledge the perspectives of residents, yet even individuals living in close proximity may perceive neighbourhood boundaries differently, further complicating efforts to define neighbourhoods (Coulton et al., 2013).

For neighbourhood change research, the definition of neighbourhoods directly shapes analytical frameworks, data selection, and the interpretation of findings. Despite the complexity of conceptualizing neighbourhoods, quantitative studies using official data sources are typically constrained by the administrative boundaries associated with the data. Since census datasets are most used, census geographic units are often operationalized as proxies for neighbourhoods. These artificial spatial units rarely correspond accurately to planning neighbourhoods, where local redevelopment areas are implemented, or to residents' perceptions of the neighbourhoods in which they live. In the absence of alternative data and given the infeasibility of defining universally accepted neighbourhood boundaries, administrative units remain the most practical and commonly used in empirical research, despite their well-recognized limitations.

The choice of spatial unit of analysis is subject to the modifiable areal unit problem (MAUP), which recognizes that analytical results may vary depending on the scale and configuration of geographic units (Fotheringham & Wong, 1991; Openshaw, 1984). Among census geographic units, the census tract (CT) is often used as the neighbourhood unit of analysis by

default (Finio, 2022; Sperling, 2012). In Canada, a CT is a relatively small and stable census geographic unit, typically containing a population size typically under 7,500, and CT boundaries must follow easily recognizable physical features (Statistics Canada, 2022a). Despite its common use, reliance on CTs in Canadian neighbourhood research can mask important fine-scale variation in socioeconomic characteristics that can be observed at the dissemination area (DA) level (Prouse et al., 2014). The DA is the smallest standard census geographic unit for which sociodemographic data are available, with population sizes typically ranging from 400 to 700, and DAs are fully nested within CTs (Statistics Canada, 2022b).

Alongside the challenges of defining neighbourhoods, the concept of change further complicates the analysis of neighbourhood dynamics. From a broad conceptual perspective, neighbourhood change encompasses a range of observable and measurable changes in the physical and social environment of a neighbourhood (Temkin & Rohe, 1996). Such changes may be identified in dwelling and other built environment characteristics, as well as in the socioeconomic and demographic composition of the population. Changes can include in-situ transitions within the non-mobile population, such as shifts in socioeconomic conditions as unemployed residents enter the workforce, and population movements, such as changes in demographic composition resulting from inter-neighbourhood migration (Lupton & Power, 2004). The latter often raises concerns about the displacement of existing residents.

Neighbourhood change is multidirectional. The deterioration of neighbourhood physical, economic, and social conditions is generally referred to as neighbourhood downgrading or decline, while the improvement of neighbourhood characteristics is generally referred to as neighbourhood upgrading or ascent. Earlier research has predominantly focused on neighbourhood decline and related issues such as inner-city poverty, while more recent research has been paying increasing attention to neighbourhood ascent or revitalization (Zuk et al., 2015). Gentrification is the most extensively researched form of neighbourhood upgrading in the literature, and it can be generally understood as "the transformation of a working-class or vacant area of the central city into middle-class residential and/or commercial use" (Lees et al., 2008, p. XV). Due to its displacement effects, it is distinct from other forms of upgrading, particularly incumbent upgrading, where existing residents remain and benefit from neighbourhood improvements (Zuk et al., 2018).

Gentrification processes around the world have evolved over time, as have the terms used to conceptualize them (Lees et al., 2008). While the original concept of gentrification focused on low-income areas in central cities, subsequent variants have extended it to broader contexts, including super-gentrification in already gentrified neighbourhoods in world cities, rural gentrification driven by the influx of middle-class residents and new investment in rural areas, new-build gentrification associated with high-end developments on vacant land, and commercial gentrification involving transformations in retail environments and the loss of affordable options (Davidson & Lees, 2010; Lees, 2003; Phillips, 2010; Rankin & McLean, 2015). These concepts have extended the scope of gentrification research and highlighted the diverse forms and contexts in which neighbourhood upgrading and displacement may occur.

Additional concepts related to but distinct from gentrification have emerged to describe a range of neighbourhood transformations occurring under specific physical and sociodemographic conditions. One concept that has gained increasing attention over the past two decades is studentification, a neighbourhood process observed in university and college towns, typically in areas near campuses. It is characterized by the in-movement and concentration of post-secondary students in neighbourhoods previously occupied by long-term residents (D. P. Smith, 2005). Another neighbourhood process characterized by a distinct in-mover profile is youthification, which refers to the increasing concentration of young adults aged 25-34 in central-city neighbourhoods, attracted by affluent amenities and urban lifestyles (Moos, 2016). These concepts are rooted in the gentrification literature but differ from class-based gentrification processes, as in-movers are not necessarily middle class or of higher socioeconomic status than existing residents.

To empirically examine these neighbourhood change processes, it is often necessary to operationalize them using quantifiable indicators. Ideally, processes involving population movements could be measured using data on the number and characteristics of residents moving across neighbourhoods, yet such data are often unavailable. For example, gentrification may be captured using displacement data, but due to their limited availability, quantitative studies typically operationalize gentrification using census-based indicators such as income, ethnicity, property values, and socioeconomic status (Bardaka, 2024, Finio, 2022). Similarly, in the absence of direct measures of student populations and their movements, empirical research has operationalized

studentification using census-based measures of student-aged residents or proximity measures to post-secondary campuses (Foote, 2017; Moos, Revington, et al., 2019; Revington et al., 2023). While imperfect, these proxy measures provide a practical means to systematically examine neighbourhood change processes and, when combined with knowledge of local contexts, can offer important implications for understanding displacement risks.

1.2.2 Neighbourhood change associated with public transit development

Neighbourhood change does not occur in isolation and is shaped by a range of contextual factors. Key determinants of neighbourhood change include population movements, public policies and investments, and private capital flows, whose influences are mutually dependent (Zuk et al., 2015). While the neighbourhood change literature has traditionally focused on private investment, the role of public investment has received increasing attention. Governments can shape residential patterns through housing policies and programs. Although these interventions are often intended to alleviate poverty and promote social mixing, they have also been widely criticized for contributing to gentrification and displacement (Bridge et al., 2011; Goetz, 2011; Mösgen et al., 2019).

While housing projects represent a more direct form of public intervention in neighbourhood change, infrastructure investment operates more indirectly yet remains important in shaping neighbourhood processes. Public transit, as a fundamental component of urban infrastructure, plays an influential role in shaping neighbourhood change, particularly in the case of rail transit, due to its fixed infrastructure, high capital investment, and associated commercial activity (Zuk et al., 2015). Public transit systems are typically designed to provide affordable and environmentally sustainable mobility, and by enabling car-less individuals to access employment, services, and essential goods, they play a critical role in promoting social equity. These goals are frequently advanced through transit-oriented development (TOD), which promotes walking, cycling, and public transit by developing moderate- to high-density, mixed-use, and walkable communities around transit nodes (Singh et al., 2017). The introduction of new transit systems or stations often produces substantial physical transformation, such as transit construction and

station-area redevelopment, while also potentially reshaping neighbourhood sociodemographic composition.

Increasing the supply of affordable housing is often articulated as an expected outcome in TOD initiatives, such as Ontario's Transit Oriented Communities program (Infrastructure Ontario & Metrolinx, 2022). However, this intended benefit has been widely questioned as studies have linked TOD to unaffordable housing and gentrification (Padeiro et al., 2019). Researchers caution that this raises a fundamental question about who benefits from transit-oriented planning, warning that transit investment may displace low-income residents who are most dependent on public transit when affordability is not well addressed (Immergluck & Balan, 2018; Kramer, 2018). Nonetheless, empirical studies have not reached a consensus on whether and to what extent public transit is linked to gentrification (Padeiro et al., 2019).

1.2.3 The town-gown relationship and studentification in university towns

Neighbourhood change must be understood within its local context, as the processes, drivers, and outcomes can vary substantially across different regional settings. In university towns, the relationship between academic and non-academic communities, known as the town-gown relationship, plays a significant role in shaping neighbourhood dynamics. Universities contribute substantially to attracting and developing talent, as well as producing and disseminating knowledge, thereby benefiting the economies of host cities, especially in knowledge economy regions where growth depends more on intellectual capacity than on physical resources (Bejinaru, 2017; Bramwell & Wolfe, 2008; Temple, 2012). Moreover, post-secondary campus development is often associated with urban revitalization and economic growth, yet it can also drive gentrification and displace low-income residents, creating conflicts with non-academic communities (Addie et al., 2015; Ehlenz, 2019; Jolivet et al., 2023).

Alongside higher education expansion and related redevelopment, studentification has also become a prominent dimension of town–gown tensions. Studentification is often associated with the degradation of neighbourhood environments and the disruption or displacement of long-term residents, as a result of student lifestyles such as late-night noise, frequent social gatherings, and property neglect, as well as the transformation of local housing, services, and commercial activities

toward student-oriented uses (Munro & Livingston, 2012; Sage et al., 2012a; D. P. Smith et al., 2014). Studentification is also a manifestation of residential segregation, particularly in the form of purpose-built student accommodation (PBSA), which can create student-only "enclaves" (D. P. Smith & Hubbard, 2014). Such student-dominated neighbourhoods may foster specific social problems, including crime and disorder, due to students' higher involvement in deviant behaviour and their limited capacity for guardianship (Gregory, 2022; Woldoff & Weiss, 2018). Furthermore, despite the segregated nature of studentification, studentification, gentrification, and youthification may overlap or transition into one another, intensifying displacement pressures on disadvantaged populations in university towns (Moos, Revington, et al., 2019).

1.2.4 GIS-based approaches and spatial statistics in neighbourhood change research

Regardless of the specific neighbourhood processes being examined, neighbourhood change is essentially a problem of how people, capital, social resources and physical environment features are distributed across space. Understanding these distributions requires the use of spatially referenced data that capture not only the attributes of neighbourhoods but also their geographic location and spatial relationships. Geographic Information Systems (GIS) are instrumental in creating spatial data and variables, such as neighbourhood housing and sociodemographic conditions, for the analysis of neighbourhood change patterns (Delmelle, 2022).

In addition to collecting and managing spatial data, GIS-based methods are widely used for analysis and visualization. Choropleth mapping involves GIS thematic maps that shade or colour geographical areas according to a quantitative data variable, making it a valuable tool for visualizing neighbourhood conditions (Stewart & Kennelly, 2010). The variables represented in such maps may be directly obtained from neighbourhood-level aggregate data, such as average income or the percentage of low-income residents from census data. They have also been used in combination with derived indices, among which commonly used examples include the location quotient (LQ) and principal component analysis (PCA). The LQ is calculated for each neighbourhood as the ratio of the proportion of a group within the neighbourhood to its proportion in the overall study area, and can, for example, represent the concentration of young adults to

indicate youthification (Moos, Revington et al., 2019). PCA is a dimensionality reduction technique used when multiple variables are involved, and can be applied, for example, to derive an index of gentrification based on a combination of sociodemographic variables (Walks & Maaranen, 2008).

While choropleth maps of neighbourhood variables and derived indices provide a straightforward way to identify areas with noteworthy characteristics and visualize spatial patterns, they may lead to biased interpretations of neighbourhood processes by overlooking spatial interdependence between nearby neighbourhoods, namely spatial autocorrelation. Spatial autocorrelation describes the systematic variation in a variable across space, with positive autocorrelation indicating clustering of similar values and negative autocorrelation indicating clustering of dissimilar values (Haining, 1990). Neighbourhood change often exhibits positive spatial autocorrelation, as the factors driving changes are spatially clustered and changes can spill over from one neighbourhood into adjacent areas (Jun, 2017). Spatial autocorrelation may also arise from misalignments between the artificial neighbourhood unit and the actual geographic scale of urban processes. Ignoring spatial autocorrelation and treating neighbourhood values as independent observations can obscure the true scale and intensity of neighbourhood processes.

To account for spatial autocorrelation and to assess spatial structures, a range of spatial methods can be applied, including cluster detection techniques such as local indicators of spatial association (LISA) which identify locations of significant spatial dependence (Anselin, 1995), and spatial modelling approaches, such as the Besag–York–Mollié (BYM) model, which decomposes a spatial variable into random and spatially structured components (Besag et al., 1991). Cluster detection methods are useful for identifying and mapping the locations and spatial extent of significant clustering, such as groups of neighbourhoods with similar socioeconomic conditions, housing characteristics, or gentrification scores, thereby aiding the interpretation of neighbourhood processes (Corrigan et al., 2021; Lee & Newman, 2021). Spatial modelling approaches smooth neighbourhood-level variables, such as gentrification scores, by incorporating information from nearby neighbourhoods, reducing abrupt changes at administrative boundaries and sensitivity to how spatial units are defined (Johnson et al., 2022).

In addition to mapping spatial variables, many neighbourhood change studies aim to understand the associations between different variables. Common methods include bivariate correlation and multiple regression. Depending on the variable settings, different regression models (linear regression, logistic regression, quantile regression, etc.) have been employed to identify predictors of neighbourhood change (e.g., Chapple et al., 2017, Ding et al., 2016). Regression analysis is also widely used to assess the dependence of neighbourhood or individual outcomes (socioeconomic characteristics, health, crime, etc.) on neighbourhood processes (e.g., Barton, 2016; Tran et al., 2020). The issue of spatial autocorrelation also applies to these multivariate analyses. When spatial dependence is present, non-spatial multivariate methods, such as classical regression models that assume spatial randomness, can yield biased estimates (Anselin, 1988). For example, a regression coefficient may be insignificant in a non-spatial model but become significant in a spatial model that correctly accounts for spatial dependence, and interpretations based on non-spatial model results may therefore be misleading. Although accounting for spatial autocorrelation through spatial regression models that include additional terms to capture spatial dependence, is well established in fields such as epidemiology and criminology, these approaches remain less commonly applied in neighbourhood change research.

Neighbourhood change is not only spatial but also spatiotemporal in nature. Neighbourhoods evolve continuously over time, and transformations such as gentrification do not occur abruptly but unfold through gradual processes of investment, construction and renovation, and population movements. In practice, however, empirical research typically relies on discrete temporal snapshots, such as census years. When data are available, incorporating multiple time points can more accurately reflect neighbourhood change than relying on a single snapshot. Traditional GIS-based mapping methods have therefore often used maps at different time points to represent variations in neighbourhood conditions across both space and time (e.g., Delmelle, 2015; Foote, 2017). While such approaches provide useful descriptive insights, they may fail to fully capture the continuous nature of neighbourhood change and the interconnections between spatial and temporal processes. Similar to spatial dependence, neighbourhood conditions and changes across time should not be treated as independent observations, since temporal autocorrelation often exists (Andrienko et al., 2010). This temporal dependence may arise because

conditions in one period influence those in subsequent periods, or because the temporal units of analysis do not align with the actual temporal scale at which neighbourhood change occurs.

In addition to mapping spatiotemporal snapshots, multivariate analyses of neighbourhood change over longer periods also benefit from drawing on data from multiple time points, as this strengthens the interpretation of long-term patterns or reveals relationships that change over time (e.g., Chapple et al., 2017; Zhang & Wu, 2025). Failing to account for temporal dependence in such analyses can lead to biased parameter estimates and misleading conclusions. To properly address neighbourhood change as a spatiotemporal problem, studies need to account for both spatial and temporal dependence to avoid unreliable interpretations of neighbourhood change patterns and relationships. Although advanced spatiotemporal methods, such as Bayesian hierarchical models, are well developed and widely applied in fields such as disease mapping (Lawson, 2018), they remain rarely used in neighbourhood change research, despite the inherently spatiotemporal nature of neighbourhood dynamics. These models explicitly account for spatial and temporal dependence and are well suited to analyzing neighbourhood change at fine spatial scales (*see Section 1.4*).

1.3 Research gaps, goals, and objectives

Although neighbourhood change has been extensively studied over the past few decades, important uncertainties and gaps remain in the literature that warrant further investigation. This dissertation specifically focuses on the processes of gentrification, studentification, and youthification. These processes are of particular concern because they may reshape neighbourhood socioeconomic and demographic composition, influence housing affordability and residents' ability to remain in their neighbourhoods and contribute to broader social and spatial inequalities. In addition, they are closely interconnected and should be understood through an integrated perspective that recognizes their shared drivers, interrelationships, and combined implications for neighbourhood outcomes and policy.

This research identifies several specific gaps related to gentrification, youthification, and studentification and seeks to advance their conceptual and empirical understanding. First,

empirical evidence on the relationship between public transit development and gentrification remains inconclusive. Despite diverse research settings, quantitative studies have typically assumed a homogeneous effect of transit development on neighbourhood change across space and time, potentially masking localized and temporally specific associations. Second, although the spatial overlap of gentrification, studentification, and youthification, as well as their associated population groups, has been examined using correlation-based approaches, existing research has not identified the specific locations where these processes or groups co-occur or exhibit distinct spatial patterns, how these patterns evolve over time, or the underlying factors shaping their dynamics. Third, very limited research has formally investigated the relationship between studentification and crime or disorder in off-campus residential neighbourhoods, despite its direct relevance to town–gown relations and social safety and stability.

Recognizing these research gaps, this dissertation includes three manuscripts, each addressing one of the identified gaps. Furthermore, spatiotemporal methods have rarely been applied in past neighbourhood change research, even though a spatiotemporal perspective is essential for formally investigating spatiotemporal patterns and for identifying when and where associations between different neighbourhood phenomena emerge, intensify, or diminish. Each manuscript therefore applies a spatial or spatiotemporal modelling approach that appropriately accounts for autocorrelation and is tailored to the specific research context to achieve the research goals and objectives.

The first manuscript (*Chapter 2*) aims to contribute to the debate on the association between public transit development and gentrification. The main objectives are to:

1) Propose the concept of analyzing the relationship between transit and neighbourhood change as a spatiotemporally variable phenomenon.
2) Using the LRT in Kitchener-Waterloo as a case study, examine when and where transit development is associated with neighbourhood upgrading, particularly gentrification, from the planning to opening phases of the line.

The second manuscript (*Chapter 3*) aims to investigate the co-occurrence of post-secondary students, university graduates, and young adults across space and time in the knowledge economy context. Using Kitchener-Waterloo as a case study, the main objectives are to:

1) Identify neighbourhoods that serve as shared spaces for students, university graduates, and young adults, as well as those exhibiting distinct spatial concentrations of these groups.
2) Identify neighbourhoods that experience notable temporal shifts in the concentrations of the three groups, during a ten-year period (2011-2021) of development and disruption.
3) Identify factors influencing the spatiotemporal patterns of these processes.

The third manuscript (*Chapter 4*) explicitly examines the associations between studentification and crime and disorder. Using Kitchener-Waterloo as a case study, the main objectives are to:

1) Determine whether expressive crime, acquisitive crime, and disorder are spatially associated with studentification by testing multiple indicators of studentified neighbourhoods, including campus proximity, student-oriented housing, and student-aged population.
2) Assess how the associations are temporally influenced by the academic calendar, including academic terms and breaks and business days and non-business days.

In addition to the three manuscripts, this dissertation includes a supplementary study (*Chapter 5*) that addresses a key limitation of many quantitative studies, including the three manuscripts in this dissertation: the reliance on official datasets that may not capture residents' lived experiences, an important dimension of neighbourhood change. This study explores the use of wellbeing survey data as an alternative data source and compares perceived wellbeing with neighbourhood indicators derived from census data and police-reported crime records to assess the extent to which official datasets reflect residents' perceptions of wellbeing, while also identifying directions for future data collection and analytical frameworks.

1.4 Methodology

The primary statistical approach adopted in this dissertation is Bayesian hierarchical modelling. In contrast to classical frequentist statistics, which treat parameters as fixed but unknown constants,

Bayesian statistics view parameters as random variables and provide probabilistic statements about their values by combining prior knowledge with observed data through Bayes' theorem (Bolstad & Curran, 2016). Bayesian models are well suited to addressing key challenges in the analysis of spatiotemporal data, including spatial and temporal autocorrelation, spatiotemporal heterogeneity in underlying processes, uncertainties and measurement errors in data collection, and data sparsity (Haining & Li, 2020). Bayesian modelling is particularly advantageous for small-area analysis because it can incorporate prior knowledge, flexibly implement complex model structures, handle both continuous and discrete data, and mitigate the small numbers problem, where limited sample sizes yield unstable estimates (Law et al., 2014). As a result, Bayesian modelling approaches have gained increasing popularity for analyzing data at fine spatial and temporal resolutions, particularly in the public health domain, and have been extended to other areas such as the analysis of crime and socioeconomic disadvantage.

The Bayesian models used in this dissertation are specified within a hierarchical framework consisting of the following levels:

1) Data level: A data model is used to describe how the observed outcome variable is generated from an underlying process and account for measurement errors.
2) Process level: A process model is employed to represent the underlying level of the outcome as a function of spatial random effects, temporal and spatiotemporal random effects (where applicable), and relevant covariates.
3) Parameter level: Prior distributions are assigned to all model parameters.
4) Hyperparameter level: Hyperpriors are specified for the hyperparameters that define the prior distributions.

Based on this framework, a variety of advanced Bayesian spatial and spatiotemporal models have been developed in the literature, such as models that allow covariate effects to vary across space and time and those that enable the joint modelling of multiple outcome variables. This research applies different models tailored to specific objectives, with model specifications described in detail in each manuscript chapter. All models are implemented using the Integrated Nested Laplace Approximation (INLA) approach through the latest R-INLA package (www.r-inla.org), which provides a computationally efficient method for Bayesian inference (Rue et al.,

2009, 2017). These Bayesian models were tailored to the spatiotemporal characteristics of the data and the objectives of each study, providing methodological advantages over conventional mapping, clustering, and frequentist statistical methods.

The first study employs a Bayesian spatiotemporally varying coefficient model, allowing the relationship between LRT development and neighbourhood change to vary across neighbourhoods and stages of LRT development. Unlike conventional regression models that estimate a single global coefficient under the assumption of stationarity, this method provides a more realistic representation of spatially and temporally heterogeneous processes. A similar objective can be achieved using geographically and temporally weighted regression (GTWR; Fotheringham et al., 2015; Huang et al., 2010), a frequentist method to estimate local regression coefficients using observations weighted by their spatial and temporal proximity. Extensions such as mixed GTWR allow selected covariates to have global effects while others vary locally (Liu et al., 2017), while multiscale GTWR accounts for different scales of nonstationarity across variables (Wu et al., 2019). Although both the Bayesian approach and GTWR model spatiotemporal nonstationarity in regression coefficients, GTWR estimates a separate local regression for each location-time combination by borrowing nearby observations through a spatiotemporal kernel, making the results sensitive to bandwidth specification. In contrast, the Bayesian approach estimates coefficients for the entire study region using a full-map modelling strategy, explicitly modelling spatial and temporal dependence through structured prior distributions that allow neighbouring spatial and temporal units to borrow strength from one another (C. Song et al., 2020). Furthermore, while GTWR estimates a unique coefficient for each spatiotemporal observation, Bayesian spatiotemporally varying coefficient models can flexibly decompose coefficient variation into fix components, spatially varying, temporally varying, and space-time interaction, depending on the research objective, computational constraints, and policy needs (C. Song et al., 2019, 2020; I. Song & Luan, 2022).

The second study employs a Bayesian spatiotemporal joint modelling approach with a spatial shared component to estimate the underlying spatial patterns shared between different neighbourhood processes. Alternative approaches have been used to combine multiple neighbourhood variables in previous studies. For example, clustering methods such as k-means

have been widely applied to classify neighbourhoods into typologies based on various sociodemographic characteristics and to examine transitions between neighbourhood types over time (Foote, 2017; Mikelbank, 2011). However, these approaches produce discrete neighbourhood categories rather than continuous measures of neighbourhood conditions or the strength of underlying processes. Another commonly used approach is to standardize multiple variables and combine them using weighted or unweighted sums to construct composite indices (Preis et al., 2021). The results are straightforward to interpret but typically rely on subjective weighting schemes and do not account for correlations among variables. PCA provides a more data-driven approach by reducing multiple correlated variables into a smaller number of composite components, with variable contributions determined by the underlying covariance structure (Bereitschaft, 2020; Walks & Maaranen, 2008). However, the derived components are often difficult to interpret because they represent mathematical combinations of variables that may not correspond to theoretically meaningful or policy-relevant neighbourhood dimensions (Demšar et al., 2012). In contrast, the Bayesian joint modelling approach allows shared components to be specified according to the underlying theoretical framework and policy objectives through appropriate model and prior specifications, while flexibly estimating both shared and outcome-specific spatial, temporal, and space-time interaction components to address different analytical and policy purposes (Quick & Luan, 2020).

The third study employs a Bayesian spatial regression model that allows the relationship between studentification and crime to vary across different day categories. Crime analyses have progressively shifted towards finer spatial units to better identify crime hotspots, capture relatively homogeneous neighbourhood conditions, and examine localized risk factors (Oberwittler & Wikström, 2009). However, small-area crime data present several methodological challenges, including spatial uncertainty arising from both the geocoding errors and intentional offset of police-reported crime locations for privacy protection, the small number problems caused by low crime counts and excess zeros, and strong spatial dependence among neighbouring areas (Law et al., 2015; Quick et al., 2017). Compared with conventional frequentist spatial regression models, such as spatial lag or spatial error models, Bayesian hierarchical models address these challenges by borrowing strength from neighbouring areas to produce more stable estimates while providing

a flexible framework for modelling count data, multiple time periods, and complex dependence structures (Law et al., 2014; Quick et al., 2018). The model used in this study further allows the effect of the covariate of interest to vary across day categories while estimating common effects for socioeconomic and built environment control variables, category-specific spatial patterns, and correlated random effects across day categories (Gruenewald et al., 2023). These modelling choices reflect criminological theories and the characteristics of the data to best address the research objectives.

1.5 Study area

The study area comprises the adjacent cities of Kitchener and Waterloo, located within the Region of Waterloo, Ontario, Canada. Due to their close proximity and interconnected urban functions, the two cities are commonly referred to collectively as Kitchener-Waterloo. Kitchener-Waterloo is a mid-sized urban area within the Great Lakes megalopolis, situated approximately 100 kilometres west of Toronto, the country's largest city. It has a land area of 201 km² and a census residential population of around 378,000 in 2021, increasing from approximately 277,000 in 2001 and 318,000 in 2011.

Kitchener-Waterloo has a strong technology and service-based economy and is internationally recognized as a cluster of high-tech firms, particularly those specializing in information and communication technology. Waterloo is home to the main campuses of two renowned universities, the University of Waterloo and Wilfrid Laurier University, which attract talent from around the world and drive innovation at both local and global scales. The study area also hosts Conestoga College, a polytechnic institution with campuses operating in both cities. Together, the strong presence of higher education institutions and advanced technology industries has established Kitchener-Waterloo as a leading knowledge economy hub with global influence. With increasing numbers of professionals and students moving to the region, Kitchener–Waterloo is among the fastest-growing regions in Canada. There were approximately 72,400 full-time post-secondary students in the Region of Waterloo in 2020 (Region of Waterloo, n.d.). According to the Town and Gown Committee (2023), there were about 51,000 post-secondary students (including

undergraduate, graduate, and local co-op students) residing in the City of Waterloo, of whom approximately 35,360 potentially required off-campus rental housing.

Kitchener-Waterloo has a dense local bus transit network and an LRT line with 19 stations that began operation in 2019. The LRT line connects two major shopping centres, passes by the university main campuses, and links the two city centres, Uptown Waterloo and Downtown Kitchener. The line is planned to extend to Cambridge, another city within the Region of Waterloo, but the extension has experienced delays and uncertainties. TOD in the study area is strongly focused along the LRT corridor, with ongoing investment and development concentrated around station areas (Region of Waterloo, 2023). Figure 1-1 presents a study area context map, showing the LRT line and post-secondary campus locations[1], as well as the study area's relative location to nearby major cities.

Previous research on neighbourhood change in this study area has primarily focused on gentrification and studentification. Early signs of gentrification have been identified along the LRT corridor even prior to its opening (Doucet, 2021; Ellis-Young & Doucet, 2024). Gentrification processes in Downtown Kitchener have also been documented (e.g., Davies, 2016). As higher education enrolment has expanded in recent decades, studentification has emerged as a growing concern in the City of Waterloo (e.g., Revington, 2022). These studies are mainly qualitative, and there remains a gap for quantitative research to comprehensively examine the spatiotemporal patterns of neighbourhood change and systematically identify the factors associated with these processes and their outcomes.

[1] In addition to the post-secondary campuses shown on the map, several small satellite campuses are located in the Kitchener city centre (Downtown Kitchener). The influence of these campuses is not considered in the analyses due to their small scale or is treated as part of the broader Downtown Kitchener effect.

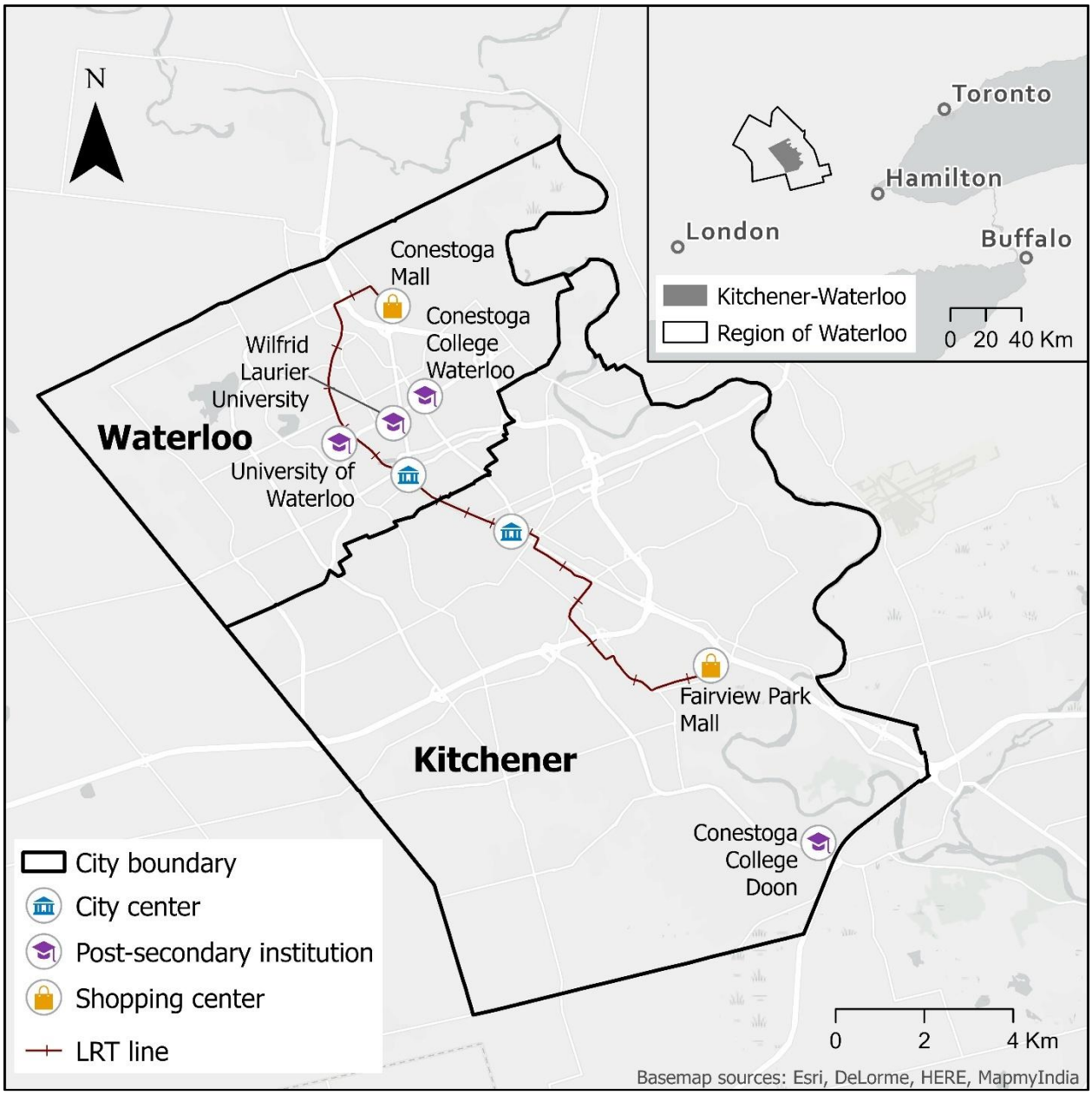


Figure 1-1: Kitchener-Waterloo: Study area context map.

1.6 Data sources and spatial unit of analysis

Table 1-1 summarizes the datasets used in this research. The primary data source is the census, which provides sociodemographic variables used across all studies. Local built environment data (locations of parks, bus stops, and business areas, etc.) are incorporated into the statistical models as explanatory variables for sociodemographic processes. Public transit routes and schedules are used to calculate public transit travel times between locations in *Chapter 3* and *Chapter 4*. In *Chapter 4*, crime and disorder are quantified using police-reported occurrence data, and the Ontario Marginalisation Index (ON-Marg) is used to derive control variables. In *Chapter 5*, the Canadian Index of Wellbeing (CIW) dataset is tested as an alternative data source that captures residents' perceptions.

Table 1-1: Data summary table

Dataset	Source	Format/spatial unit	Reference year/period
Census	Statistics Canada	Dissemination area	2021, 2016, 2011, 2006, 2001
Built environment	Region of Waterloo	Georeferenced points/polygons	Matched census years
Public transit routes and schedules	OpenMobilityData TriTAG Labs	General Transit Feed Specification	Matched census years
Police-reported occurrences	Waterloo Regional Police	Georeferenced points	2015-2019
Marginalisation Index	Public Health Ontario	Dissemination area	2016, 2021
Wellbeing survey results	Canadian Index of Wellbeing	Region of Waterloo neighbourhood	2018, 2022

To capture high-resolution spatial variation using census data, the DA is adopted as the neighbourhood spatial unit of analysis, except in *Chapter 5*, where wellbeing survey data are not available at the DA scale. *Chapter 2* and *Chapter 3* use the 2021 DAs to examine neighbourhood change, with all earlier census data harmonized to the 2021 boundaries. *Chapter 4* uses 2016 DA boundaries, as crime and disorder are analyzed over the 2015–2019 period in order to avoid the influence of the COVID-19 pandemic. Figure 1-2 illustrates the DA boundaries for all census years included in this research. Over the two decades, DA boundaries have undergone some substantial changes. To ensure the most accurate alignment of sociodemographic data across census years, a

longitudinal census data matching method adapted from Allen and Taylor (2018) is applied, as detailed in *Appendix A*.

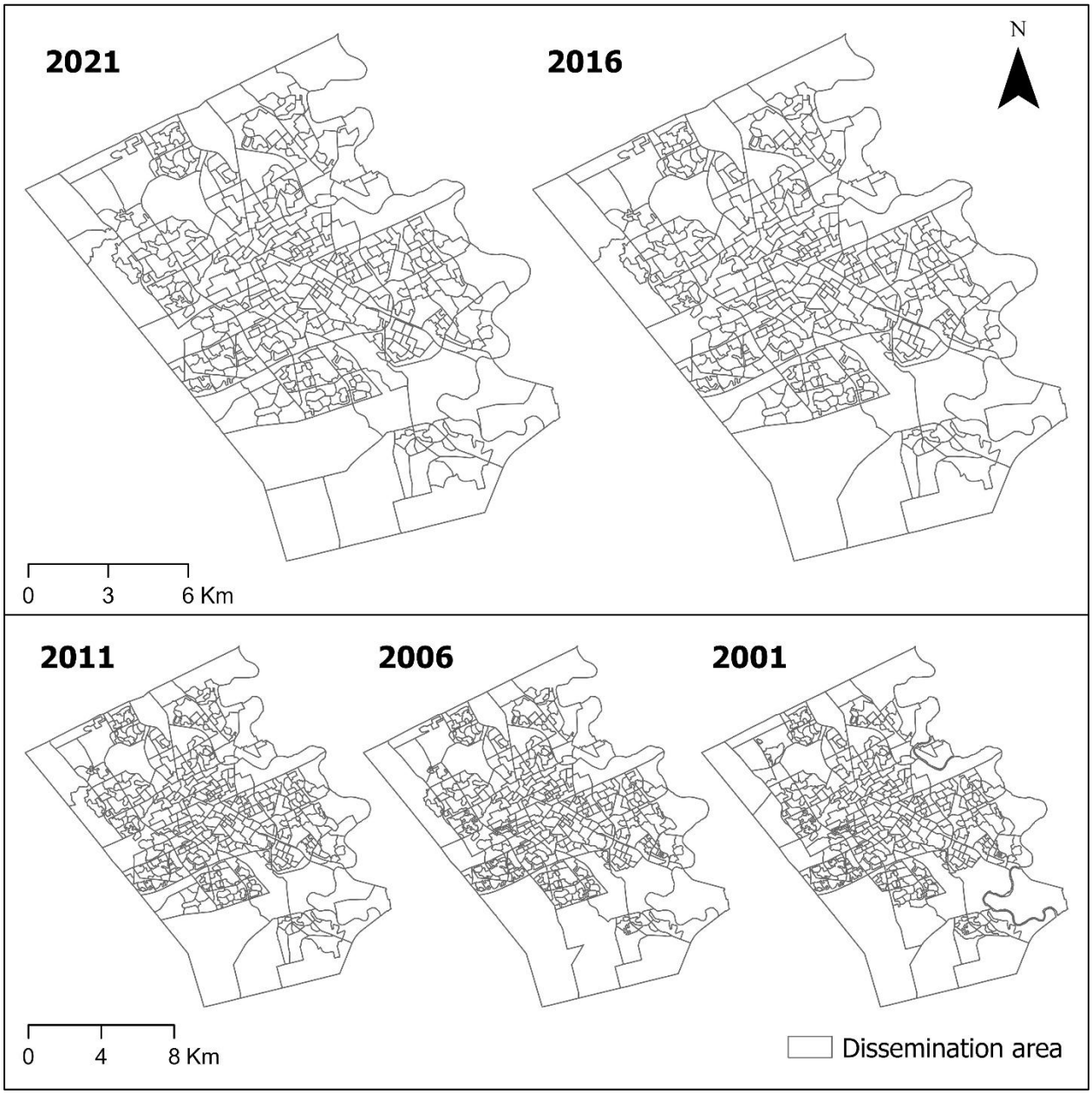


Figure 1-2: Dissemination areas in Kitchener-Waterloo in 2021, 2016, 2011, 2006, and 2001.

As described in *Section 1.2.1*, DAs were selected as the primary spatial unit of analysis because they are better suited than larger census units, such as CTs, for capturing localized variation in neighbourhood conditions. Previous research has shown that important sociodemographic patterns and relationships between neighbourhood variables may differ when analyzed at the CT and DA levels (Cai & Tan, 2025b; Chu et al., 2021). The choice of DAs does not eliminate the MAUP, nor do DAs necessarily correspond to "true" neighbourhoods (see *Section 6.3.1* for further discussion). Nevertheless, from a practical perspective, the research questions examined in this dissertation involve highly localized neighbourhood processes. For example, the influence of LRT development is expected to be concentrated in neighbourhoods with access to stations, while a single CT may include both transit-accessible and transit-inaccessible areas. Similarly, studentification patterns and student housing development in Kitchener–Waterloo are highly clustered, meaning that larger spatial units may combine neighbourhoods with very different levels of student concentration. Given the available data, DAs therefore provide the most appropriate balance between capturing fine-scale neighbourhood variation and maintaining consistent sociodemographic information for analysis, while also supporting more spatially targeted planning and policy interventions.

1.7 Dissertation structure

This dissertation examines neighbourhood change in Kitchener-Waterloo and is organized into six chapters following a manuscript style, with three standalone research articles that share a common theme and study area. This introductory chapter has explained the research context and key terms, described the research background and gaps, defined the research scope and objectives, summarized analytical methods, and described the study area and data sources. *Chapter 2* presents the first manuscript, titled. **"The spatiotemporally varying relationship between LRT development and gentrification: Evidence from a mid-sized urban area in Canada"**. Chapter 3 presents the second manuscript, titled "**Urban change in a university town: Spatiotemporal patterns of post-secondary students, university graduates, and young adults during a period of development and disruption"**. *Chapter 4* presents the third manuscript, titled

"**Neighbourhood safety in a university town: The associations between studentification and crime and disorder"**. *Chapter 5* presents a supplementary study that explores the relationship between individual-level perceptions and neighbourhood-level indicators derived from official statistics. Although not a standalone research article, it complements the main research, which relies on census and other official data sources, and highlights potential future research possibilities using alternative data sources. *Chapter 6* concludes the dissertation, summarizing key findings, contributions, and limitations, and identifying future research directions. Together, these chapters offer novel perspectives on neighbourhood process analysis, provide new insights into neighbourhood change patterns in Kitchener–Waterloo, and contribute to the broader neighbourhood change literature.

Chapter 2
The spatiotemporally varying relationship between LRT development and gentrification: Evidence from a mid-sized urban area in Canada

Summary

Urban rapid transit systems, such as light rail transit (LRT), may be associated with gentrification. Previous quantitative studies have adopted various analytical methods and reported mixed findings. However, they have often failed to differentiate gentrification from other forms of neighbourhood change or assumed a homogeneous transit-gentrification relationship across space and time. This study argues that the relationship between transit and neighbourhood change can vary across different zones and time periods within the urban area served by a transit line. A Bayesian modelling approach was employed to examine the spatiotemporally varying association between distance to LRT and neighbourhood change from the planning to opening stages of the LRT line in Kitchener-Waterloo. Income improvement associated with LRT predominantly occurred in the opening stage of the transit line, while dwelling value growth related to LRT mainly occurred in the planning and construction stages. Neighbourhoods showing significant associations between LRT and increases in income or dwelling value were found around central business district stations and near the northern and southern terminals. Some of these changes might be categorized as LRT-related gentrification. The research framework and advanced modelling approach presented in this study, as well as the novel concept of analyzing the relationship between transit and neighbourhood change as a spatiotemporally variable phenomenon are valuable for transportation and gentrification research.

2.1 Introduction

In recent decades, light rail transit (LRT) development has expanded globally in both large and mid-sized cities. As an urban rapid transit solution balancing capacity, speed, and flexibility, LRT is expected to enhance mobility and promote walkable communities. It is also advocated as a catalyst for economic growth and city image enhancement, particularly within transit-oriented development contexts (Ferbrache & Knowles, 2017; Olesen, 2020).

Despite the expected benefits of LRT, concerns have emerged about its potential links to gentrification, an extensively researched and often controversial form of neighbourhood upgrading. While neighbourhood upgrading generally involves improvements in socioeconomic characteristics and the physical environment and is usually viewed as beneficial, gentrification often excludes low-income residents from these benefits (Walks & Maaranen, 2008). Gentrification is generally understood as the transformation of central city neighbourhoods from working-class or vacant areas to middle-class spaces, often displacing low-income groups (Lees et al., 2008). Transit development may attract investments, raise property prices, and displace disadvantaged residents, but empirical evidence on transit-related gentrification remains inconclusive (Padeiro et al., 2019).

Previous quantitative studies have employed diverse gentrification measures, statistical methods, timeframes, and spatial scales. However, many have failed to distinguish gentrification from other forms of neighbourhood upgrading. Even when this distinction was made, existing studies have predominantly assumed a consistent relationship between a transit line and gentrification across all stations and focused only on opening phases. Nonetheless, uncertainties exist regarding the timing and spatial patterning of transit-related gentrification, meaning that the transit-gentrification relationship may vary across different time periods and zones within the urban area served by a transit line.

This paper seeks to contribute to the ongoing debate on transit-related gentrification by presenting a comprehensive spatiotemporal study of LRT-related neighbourhood change. The key question is when and where LRT development is associated with neighbourhood upgrading, particularly gentrification. Answering this question can help identify or anticipate neighbourhood

change during LRT development and determine the times and locations for addressing gentrification if it is deemed undesirable. An advanced Bayesian spatiotemporal model with a varying regression coefficient is used to capture the spatiotemporal variability in the relationship between LRT and neighbourhood change. This modelling framework, initially developed in the public health domain (e.g., C. Song et al., 2019; I. Song & Luan, 2022), has yet to be used for analyzing gentrification.

The study area is Kitchener-Waterloo, a rapidly growing mid-sized urban area in Canada. The findings offer valuable insights for urban areas globally, especially mid-sized cities that have recently implemented or are planning LRT systems. The modelling approach is applicable to other case studies, with flexibility to be further modified. The concept of analyzing the spatiotemporally varying relationship is essential for accurately understanding transit-related gentrification in future research. This novel approach helps to mitigate overgeneralization, which often arises when neighbourhood change patterns are averaged across transit stations and time periods, masking critical localized variations.

2.2 Background

2.2.1 Linking public transit to gentrification

Gentrification literature has continually evolved, with ongoing debates on its definitions, causes, and impacts (Lees et al., 2008). As a process involving the influx of more affluent residents, gentrification is viewed by some as beneficial for fiscal revenue and social diversity, while others highlight its negative effects, such as the loss of affordable housing (Atkinson & Bridge, 2004). Displacement is central to discussions about gentrification, as most studies confirm that in-movers are often wealthier, whiter, and more educated than out-movers (Zuk et al., 2018). When public transit contributes to gentrification and displacement, its intended benefits are called into question.

Gentrification is often explained from supply-side (N. Smith, 1979) and demand-side (Ley, 1986) perspectives, both of which provide theoretical links to transit. From the supply-side perspective, new transit development enhances accessibility and enables more intensive land use, thereby increasing potential ground rent and attracting investments (Revington, 2015). From the

demand-side perspective, transit is a desirable urban amenity that attracts higher-income in-movers by enhancing connectivity with jobs and other destinations (Zuk et al., 2018).

Ecological gentrification offers an additional theoretical lens, showing how transit development within broader sustainability strategies may drive gentrification. Along with the concepts of environmental and green gentrification, it demonstrates how urban environmental sustainability improvements attract investments and wealthier residents, displacing disadvantaged groups (Checker, 2011; Dooling, 2009; Gould & Louis, 2012). In North America, transit is frequently integrated with densification planning under the "sustainability-as-density" approach, which promotes high-density housing in transit-accessible neighbourhoods and has been linked to rising housing prices and displacement (Quastel et al., 2012). As eco-friendly living gains popularity, higher-income professionals, particularly in creative and technology sectors, are increasingly attracted to transit-oriented high-density communities in city centres, exacerbating ecological gentrification (Rice et al., 2020).

Despite the theoretical links between transit and gentrification, quantitative studies have shown mixed findings. Empirical evidence of transit-induced gentrification has been associated with various forms of urban rapid transit, including bus rapid transit (BRT; e.g., Brown, 2016), LRT (e.g., Bardaka et al., 2018), and metro systems (e.g., J.-J. Lin & Chung, 2017). Others found little to no evidence of transit-related gentrification (e.g., Deka, 2017; Dong, 2017). Furthermore, some studies reported differing results across regions or transit lines, highlighting the importance of local geographical contexts (e.g., Baker & Lee, 2019; Grube-Cavers & Patterson, 2015).

Inconsistencies in how transit and gentrification were measured may explain some of the divergence in findings. Transit influence was measured relatively consistently by proximity, including distance to the nearest station (e.g., J.-J. Lin & Chung, 2017) or binary indicators based on station buffer zones (e.g., Brown, 2016). Gentrification, however, has been measured using diverse indicators, including income, ethnicity, education, and housing prices (Padeiro et al., 2019). These census-based indicators primarily capture socioeconomic upgrading but not displacement, an essential yet difficult-to-measure aspect of gentrification (Bardaka, 2024). Displacement is best identified using population movement data, such as eviction records (Delmelle et al., 2021), which are often unavailable. Due to data constraints, this study continues to rely on census-based

indicators, while acknowledging their limitations and interpreting gentrification-related findings with caution.

2.2.2 Spatiotemporal variability in transit-related gentrification

Empirical studies have employed diverse statistical methods, including various forms of difference-in-differences analysis (e.g., Bardaka et al., 2018; Dong, 2017) and regression modelling (e.g., Chapple et al., 2017; J.-J. Lin & Chung, 2017). However, existing studies have either not captured or only partially addressed the spatiotemporal variability in transit-related gentrification. This concerns how the transit-gentrification relationship varies across space and time, as well as spatial and temporal autocorrelation, where changes in a neighbourhood during one time period influences other neighbourhoods or time periods.

Gentrification studies often emphasize that it can only occur in gentrifiable neighbourhoods, typically defined by income levels below the regional average or similar socioeconomic criteria (e.g., Chapple, 2009; Freeman, 2005; Grube-Cavers & Patterson, 2015). However, gentrifiability has not always been addressed in studies about transit-related gentrification (Padeiro et al., 2019). Without defining gentrifiability, analytical results might be masked by non-gentrifiable neighbourhoods. For example, Baker and Lee (2019) found stronger transit effects when only gentrifiable neighbourhoods were included, compared to when all neighbourhoods were considered. Nevertheless, gentrifiability, defined to some degree arbitrarily and inconsistently across studies, may also introduce uncertainties. Furthermore, gentrifiability essentially divides neighbourhoods into two categories, assuming transit has distinct effects on each. However, transit effects are more complex in reality and can vary significantly even within gentrifiable areas, making this dichotomy potentially misleading.

Small census units like census tracts are common neighbourhood proxies in gentrification studies (Finio, 2022). Positive spatial autocorrelation is expected at this scale, meaning that nearby neighbourhoods tend to exhibit similar changes. This may arise from discrepancies between the analytical units and the actual change areas, or from spillover effects, where the interconnected nature of small neighbourhoods allows changes in transit-served neighbourhoods to influence proximate neighbourhoods (Bardaka et al., 2018; Brown, 2016; Grube-Cavers & Patterson, 2015).

A small proportion of studies have used spatial methods to account for spatial autocorrelation, such as spatial difference-in-differences analysis (Bardaka et al., 2018) and spatial autoregressive models (Baker & Lee, 2019).

The temporal and spatial dimensions of neighbourhood change are equally important. Previous studies have used temporal units of analysis ranging from several years to several decades (Padeiro et al., 2019). Most studies have focused on a single period for each transit line, examining the effects of its opening. However, a new transit line can influence nearby neighbourhoods before it opens due to investments during planning and construction stages (Ellis-Young & Doucet, 2024; Golub et al., 2012). There could also be a significant delay between a transit line's opening and gentrification (Dong, 2017).

The transit-gentrification relationship may not remain constant over a long-term study period. Studies analyzing multiple time periods have found varying effects of the same transit system on gentrification over time (Chapple, 2009; Chava & Renne, 2022). However, these studies assessed each period separately without treating neighbourhood change as a continuous process. Similar to the spatial dimension, positive temporal autocorrelation is likely, as changes in one period influencing the next (e.g., gentrifying neighbourhoods attracting more higher-income in-movers), and the key neighbourhood transformation period may not align with the temporal unit of analysis. Overlooking the spatial and temporal structures of neighbourhood change may lead to unreliable results.

Considering the spatiotemporal variability, we propose that an analytical framework for studying transit-related gentrification should: 1) account for the spatiotemporal variations in the relationship between transit and neighbourhood change and minimize uncertainties from arbitrarily defining gentrifiability, 2) select an appropriate spatial unit of analysis and properly handle spatial autocorrelation, and 3) choose a suitable temporal unit, examine multiple time periods, and account for temporal autocorrelation. With these aspects being carefully addressed, the timing and spatial patterning of transit-related gentrification may be better assessed.

2.2.3 Study area: Kitchener-Waterloo

The LRT under examination is ION LRT, serving Kitchener and Waterloo, two adjacent cities within the Region of Waterloo, Ontario, Canada. These cities are often collectively referred to as "Kitchener-Waterloo" and are considered "twin cities". This mid-sized urban area, with a population of around 378,000 in 2021, is among the fastest-growing regions in the country. As a globally recognized innovation hub, Kitchener-Waterloo hosts numerous technology firms, including major multinationals like Google, and two renowned universities that draw students and researchers globally.

Figure 2-1 presents a map of ION LRT with its development timeline and key destinations within the study area, a map of the relative location of Kitchener-Waterloo, and a map outlining the spatial unit of analysis. The neighbourhood spatial unit is the dissemination area (DA), the smallest census geographic unit for sociodemographic data. The DA helps to capture local variations in sociodemographic characteristics more precisely, which might be masked at the larger census tract level.

ION LRT began operating a single route with 19 stations in Kitchener-Waterloo in 2019. It runs between two vibrant shopping centres, passing by two universities, the regional train station, and two central business districts (CBDs), known as Uptown Waterloo and Downtown Kitchener. Qualitative research that employed field observations and interviews has identified signs of gentrification and displacement related to ION LRT even before its opening, including the loss of affordable housing, the rise of exclusionary neighbourhood cultures, and distress among original residents due to changes in neighbourhood physical and social environments (Doucet, 2021; Ellis-Young & Doucet, 2024). A gap remains in quantitative research using statistical modelling to systematically analyze LRT-related neighbourhood change in Kitchener-Waterloo.

This study examines neighbourhood change at five-year census intervals between 2001 and 2021, during which Kitchener-Waterloo experienced significant population growth and sociodemographic shifts. The first two periods (2001-2011) correspond to the LRT planning stage, during which its arrival was expected but not assured. The third period (2011-2016) covers the approval of LRT and the beginning of construction, while the final period (2016-2021) includes the opening phase of LRT.

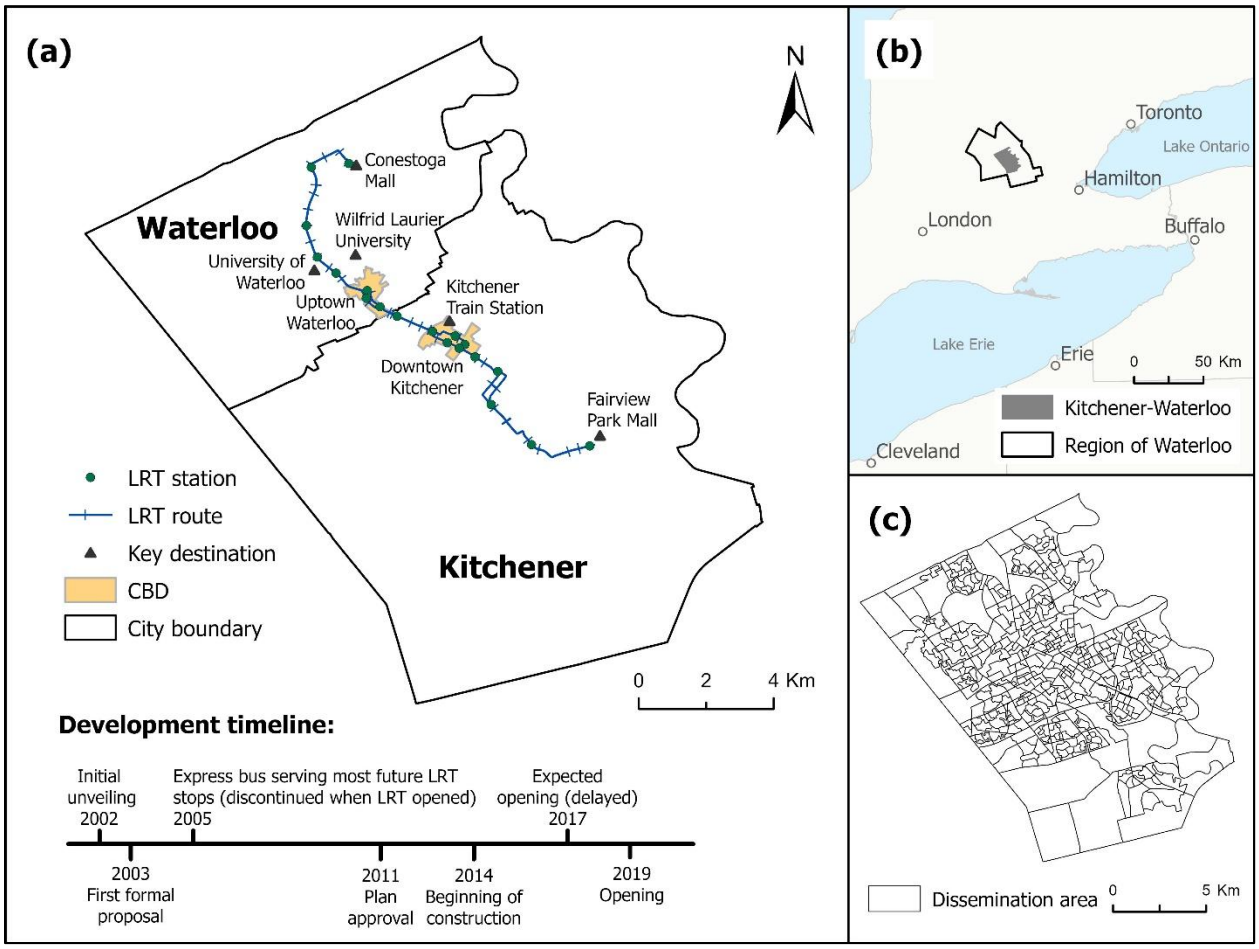


Figure 2-1: Maps of (a) ION LRT with its development timeline and key destinations, (b) relative locations of Kitchener-Waterloo and the Region of Waterloo to Toronto and other cities, and (c) dissemination areas within Kitchener-Waterloo.

2.3 Methodology

This study employed a Bayesian spatiotemporal regression model that allows the association between neighbourhood change and distance to LRT to vary across time and space, while effectively addressing spatial and temporal autocorrelation in neighbourhood change. Unlike past studies that relied on predefined gentrifiability to isolate the transit-gentrification relationship from transit effects on other neighbourhoods, this approach avoids such dichotomies. By examining each individual neighbourhood in each time period, it captures where and when significant transit

influences occur without pre-grouping neighbourhoods. Gentrification status was only assessed after identifying neighbourhoods with significant associations.

2.3.1 Variables and Data

Income and dwelling value were measured as indicators of neighbourhood change, representing demand and supply aspects, respectively (Finio, 2022). Rent was also considered but excluded due to insufficient data. Specifically, this study used average income, defined as average total income for persons with income, and dwelling value per room, calculated by dividing average dwelling value by average number of rooms. The use of dwelling value per room enables more meaningful temporal comparisons by accounting for possible housing size changes and aligns with measures used in previous Canadian research (e.g., Moos, Revington, et al., 2019). Changes in the two indicators over five-year periods were used to represent neighbourhood change and operationalized as dependent variables in regression modelling. These indicators also served as explanatory variables for their changes, based on the hypothesis that changes depend on initial conditions. Both indicators were adjusted to 2021 dollars and log-transformed, following common practices (Baker & Lee, 2019; Bardaka et al., 2018; Bunten et al., 2024; Chapple et al., 2017).

The key explanatory variable was distance to LRT, measured in kilometres from each DA's population-weighted centroid to the nearest station using road networks. This variable was held constant, assuming residents anticipated future LRT stations due to its early unveiling and an express bus roughly following the planned route. A series of sociodemographic, dwelling, and built environment variables were included as control variables. Table 2-1 presents descriptions and summary statistics for all regression variables. More explanatory variables (e.g., visible minorities, parks, and university-proximate neighbourhoods) were tested but excluded due to a lack of significant associations.

Datasets from the 2001, 2006, 2011, 2016, and 2021 censuses by Statistics Canada were used to derive sociodemographic and dwelling variables. All census data were harmonized to 2021 DA boundaries. Out of 476 DAs in Kitchener-Waterloo, 34 and 43 were excluded from modelling income changes and dwelling value changes, respectively, due to insufficient census data. These primarily consisted of sparsely populated or newly developed areas with little or no population in

2001, as well as several university-adjacent neighbourhoods dominated by students, with insufficient reporting on incomes and dwelling values. Additional datasets from Region of Waterloo Open Data were used to identify CBDs, bus stops, and LRT stations. Census-based explanatory variables were measured at the start of each five-year period. Bus accessibility was measured within each period in a year with available data, while CBD was held constant.

Table 2-1: Summary statistics for variables used in this study.

Variable	Mean	S.D.	Min	Max
Dependent variable				
Change in average income (2021 dollars; log difference)	0.03	0.18	-0.75	0.85
Change in dwelling value per room (2021 dollars; log difference)	0.28	0.23	-0.73	1.33
Explanatory variable				
Distance to LRT (kilometre)	2.85	1.63	0.10	7.21
Average income (2021 dollars; log-transformed)	10.77	0.28	9.65	12.17
Dwelling value per room (2021 dollars; log-transformed)	10.74	0.30	9.96	11.96
Children: % of population aged 0-14	17.32	6.07	0.00	36.92
Youths: % of population aged 15-24	14.57	6.04	3.09	81.13
Renters: % of dwellings that are occupied by renters	28.69	28.28	0.00	100.00
Low-income population: % of population in low income	11.53	10.80	0.00	69.00
Movers: % of residents that moved in the past five years	42.38	18.08	0.00	100.00
Population density: Thousand residents per square kilometre	3.34	2.22	0.01	22.25
Apartments: % of dwellings categorized as apartments	25.57	29.23	0.00	100.00
Attached dwellings: % of dwellings categorized as single dwellings attached to other dwellings or buildings	17.05	21.45	0.00	100.00
Dwelling in disrepair: % of dwellings that need major repair	4.81	5.47	0.00	38.10
New dwellings: % of dwellings built in the past five years	6.49	17.02	0.00	97.67
CBD: Binary (DAs that intersect with a CBD are assigned a value of one) [1]	0.07	N/A	N/A	N/A
Bus accessibility: Number of bus stops per square kilometre [2]	15.97	13.33	0.00	68.49

1 Distance to CBD was also tested but no significant associations were found.

2 The study area has a dense bus network, making density a more suitable measure than a binary or distance variable.

2.3.2 Spatiotemporal modelling

A Bayesian hierarchical spatiotemporal model specified in the equation below was fitted for each dependent variable. Unlike conventional regression models that assume fixed relationships between the dependent and explanatory variables, this approach allows the effect of distance to LRT on neighbourhood change to differ by DA and year, making it well-suited to the objectives of this study.

$$
\begin{aligned}
&Data\ model\text{: } Y_{i,j} \sim N(\theta_{i,j}, \tau_{\epsilon}^{-1}) \\
&Process\ model\text{: } \theta_{i,j} = \mu_{i,j} = \alpha + \upsilon_i + \nu_j + \delta_{i,j} + \sum_{k=1}^{14} \beta_k X_{k,i,j} + \lambda_{i,j} X_{1,i,j} \\
&Random\ slope\text{: } \lambda_{i,j} = \psi_i + \gamma_j + \omega_{i,j}
\end{aligned}
\tag{2-1}
$$

The dependent variable $Y_{i,j}$ in DA i and period j, was modelled as a normal distribution, commonly used for continuous variables. An identity link function connected $\theta_{i,j}$, the expected value of $Y_{i,j}$, to μ_{ij}, parameterized as the sum of an intercept term (α), a spatial effect term (υ_i), a temporal effect term (ν_j), a space-time interaction term ($\delta_{i,j}$), a fixed effect term for all explanatory variables ($\sum_{k=1}^{14} \beta_k X_{k,i,j}$), and a random slope term for the first explanatory variable ($\lambda_{i,j} X_{1,i,j}$). $X_{k,i,j}$ measured the k^{th} explanatory variable and β_k was the regression coefficient. Excluding the random slope term would result in a common Bayesian hierarchical spatiotemporal regression model (Haining & Li, 2020). The random slope term added a spatiotemporally varying component ($\lambda_{i,j}$) to the regression coefficient for the first explanatory variable (distance to LRT). Following Song and Luan (2022), $\lambda_{i,j}$ was further parameterized as the sum of a spatial term (ψ_i), a temporal term (γ_j), and a space-time interaction term (ω_{ij}). This allowed the relationship between distance to LRT and neighbourhood change, represented by $\beta_1 + \lambda_{i,j}$, to vary across different DAs and time periods.

Each unknown parameter must be assigned a prior distribution in Bayesian modelling. In the absence of sufficient prior knowledge, commonly used vague or weakly informative priors were applied, as specified in the equation below.

$$\alpha \sim U(-\infty, \infty), \beta_k \sim N(0, 10^3)\ for\ k = 1,2,\ldots 14$$

$$\upsilon_i = s_i + u_i, s_i \sim ICAR(W, \tau_s^{-1}), u_i \sim N(0, \tau_u^{-1}), \nu_j - \nu_{j-1} \sim N(0, \tau_\nu^{-1}), \delta_{i,j} \sim N\left(0, \tau_\delta^{-1}\right)$$

$$\psi_i \sim ICAR\left(W, \tau_\psi^{-1}\right), \gamma_j - \gamma_{j-1} \sim N\left(0, \tau_\gamma^{-1}\right), \omega_{i,j} \sim N(0, \tau_\omega^{-1})$$

$$W_{ii} = 0, W_{ic} = 1\ if\ DAs\ i\ and\ c\ share\ an\ edge\ or\ vertex, W_{ic} = 0\ otherwise$$

$$log\left(\tau_p\right) \sim loggamma(0.001{,}0.001) for\ p \in \{\epsilon, s, u, v, \delta, \psi, \gamma, \omega\}$$

(2-2)

α was assigned a uniform distribution. Each regression coefficient (β_k) was assigned a normal distribution. The spatial effect (υ_i) was assigned a Besag-York-Mollié (BYM) prior, consisting of a structured effect component to capture spatial autocorrelation and an unstructured effect component to capture uncorrelated errors (Besag et al., 1991). The structured effect component followed an intrinsic conditional autoregressive (ICAR) prior, defined by a weight matrix (W) to specify spatial adjacency. The temporal effect (ν_j) was given a first-order random walk (RW1) prior, modelling ν_j as the sum of ν_{j-1} and random errors. The space-time interaction term was independent and identically distributed (IID), with each $\delta_{i,j}$ following a normal distribution with the mean of 0 and the same precision, reflecting a Type I space-time interaction (Haining & Li, 2020; Knorr-Held, 2000). Assuming that the random slope varied but remained similar in nearby space and time, ψ_i, γ_j and $\omega_{i,j}$ were given ICAR, RW1, and IID priors, respectively. An hyperprior of $loggamma(0.001, 0.001)$ was used for log-precision terms. Other hyperpriors were tested to ensure the findings were not affected by the choice of hyperparameters.

Several tests were conducted to verify the model, with results provided in Appendix B. First, Moran's I statistics were computed to confirm spatial autocorrelation in each dependent variable. Second, variance inflation factors were calculated to ensure no significant

multicollinearity among explanatory variables. Third, posterior predictive checks were conducted to validate the current model. Last, the deviance information criterion (Spiegelhalter et al., 2002) and Watanabe–Akaike information criterion (Watanabe, 2009) were used to compare the model with alternatives, including a base model without the random slope term and models incorporating Types II, III, and IV space-time interactions described in Knorr-Held (2000). The current model outperformed all tested alternatives.

2.4 Results

Significant associations with the dependent variables were found for most control variables. As they are not the focus of this study, their results and possible explanations are summarized in Table 2-2 without further discussion. Figure 2-2 and Figure 2-3 illustrate the main results of this study, showing regression coefficients associated with distance to LRT. Without further investigation of gentrification status, the regression coefficients reflect associations with neighbourhood upgrading, defined here as improvements in income and dwelling value in any neighbourhood type.

Table 2-2: Posterior means and 95% credible intervals (in parentheses) of regression coefficients for control variables, along with possible explanations.

Dependent / Explanatory	Change in average income	Change in Dwelling value per room	Possible explanation
Intercept	0.031 (0.015, 0.045) *	0.271 (0.260, 0.281) *	Overall, both income and dwelling value increased over the study period.
Average income	-0.238 (-0.261, -0.214) *		A lower initial condition allowed for greater potential relative growth.
Dwelling value per room		-0.183 (-0.211, -0.159) *	
Children (aged 0-14)	-0.021 (-0.035, -0.008) *	0.008 (-0.003, 0.019)	Neighbourhoods with larger dependent or transient populations tended to experience lower income growth.
Youths (aged 15-24)	-0.021 (-0.033, -0.010) *	-0.001 (-0.010, 0.008)	
Movers	-0.019 (-0.033, -0.005) *	-0.003 (-0.016, 0.010)	
Renters	-0.012 (-0.034, 0.010)	0.060 (0.042, 0.078) *	Dwelling value increases in renter-oriented areas were driven by rising demand and rental prices.
Low-income population	0.014 (0.001, 0.027) *	-0.014 (-0.024, -0.003) *	Low-income areas allowed greater potential relative income growth but remained less attractive in the housing market.
Population density	-0.006 (-0.018, 0.007)	-0.030 (-0.039, -0.021) *	Dwelling value increased more in lower-density areas, where larger dwellings or lower dwelling densities created greater potential for upgrading or new development.
Apartments	-0.081 (-0.106, -0.056) *	0.023 (0.004, 0.042) *	Apartment prices rose faster but they did not always house higher-income residents. Neighbourhoods with more attached housing or dwellings in disrepair were less likely to upgrade, while new-built housing was typically linked to upgrading.
Attached dwellings	-0.051 (-0.066, -0.037) *	-0.029 (-0.039, -0.018) *	
Dwelling in disrepair	-0.008 (-0.017, 0.000) *	-0.003 (-0.011, 0.004)	
New dwellings	0.017 (0.005, 0.029) *	0.019 (0.008, 0.031) *	
CBD	0.021 (0.003, 0.039) *	0.023 (0.011, 0.034) *	CBDs have undergone more rapid advancement in urban prosperity compared to other areas.
Bus accessibility	-0.018 (-0.029, -0.008) *	-0.008 (-0.016, 0.000) *	Conventional bus transit is often linked to poverty concentration and discourages higher-income in-movers (Pathak et al., 2017).

* Significant (i.e., have consistent signs) at the 95% credible interval.

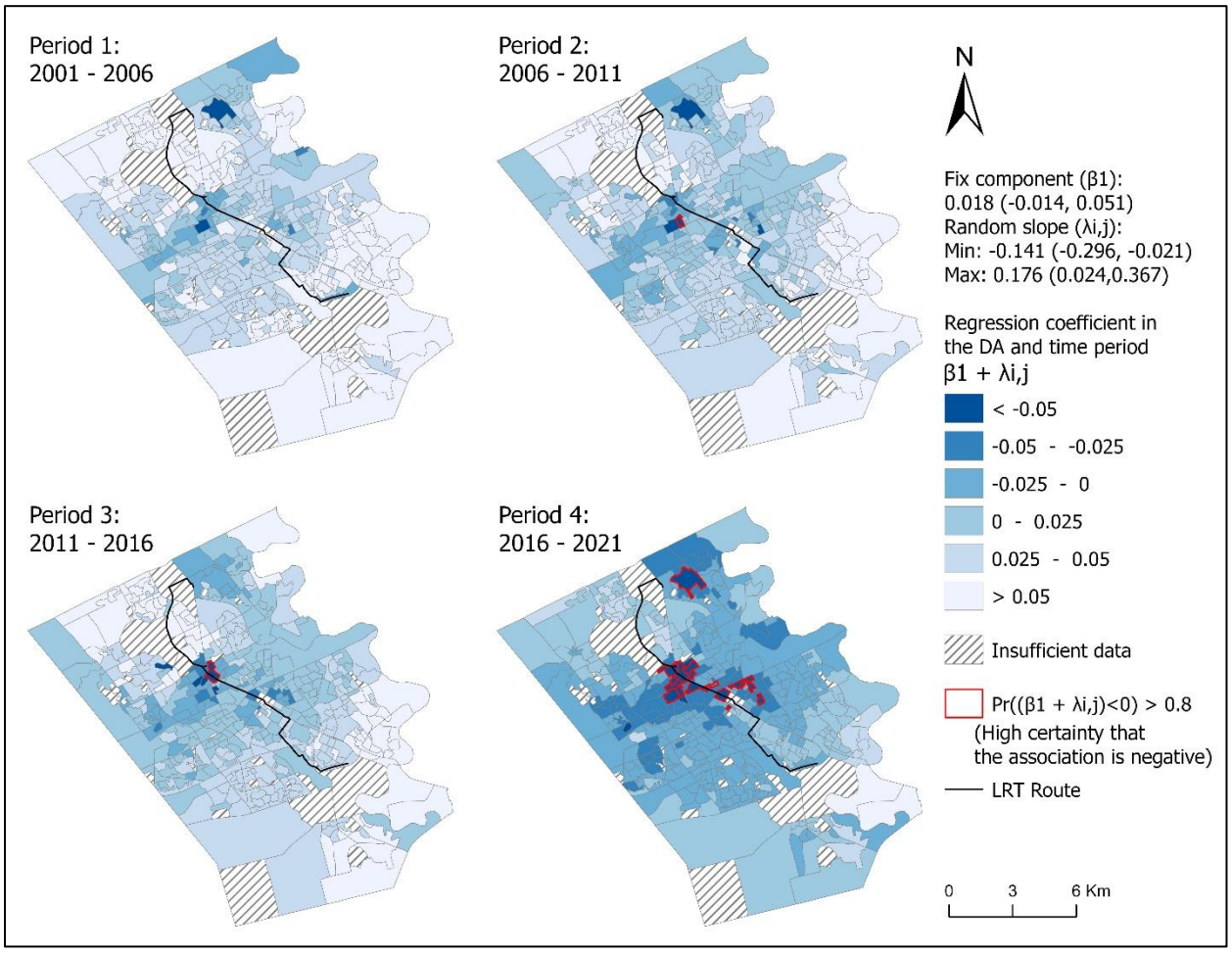


Figure 2-2: Spatiotemporally varying relationship between distance to LRT and the change in average income.

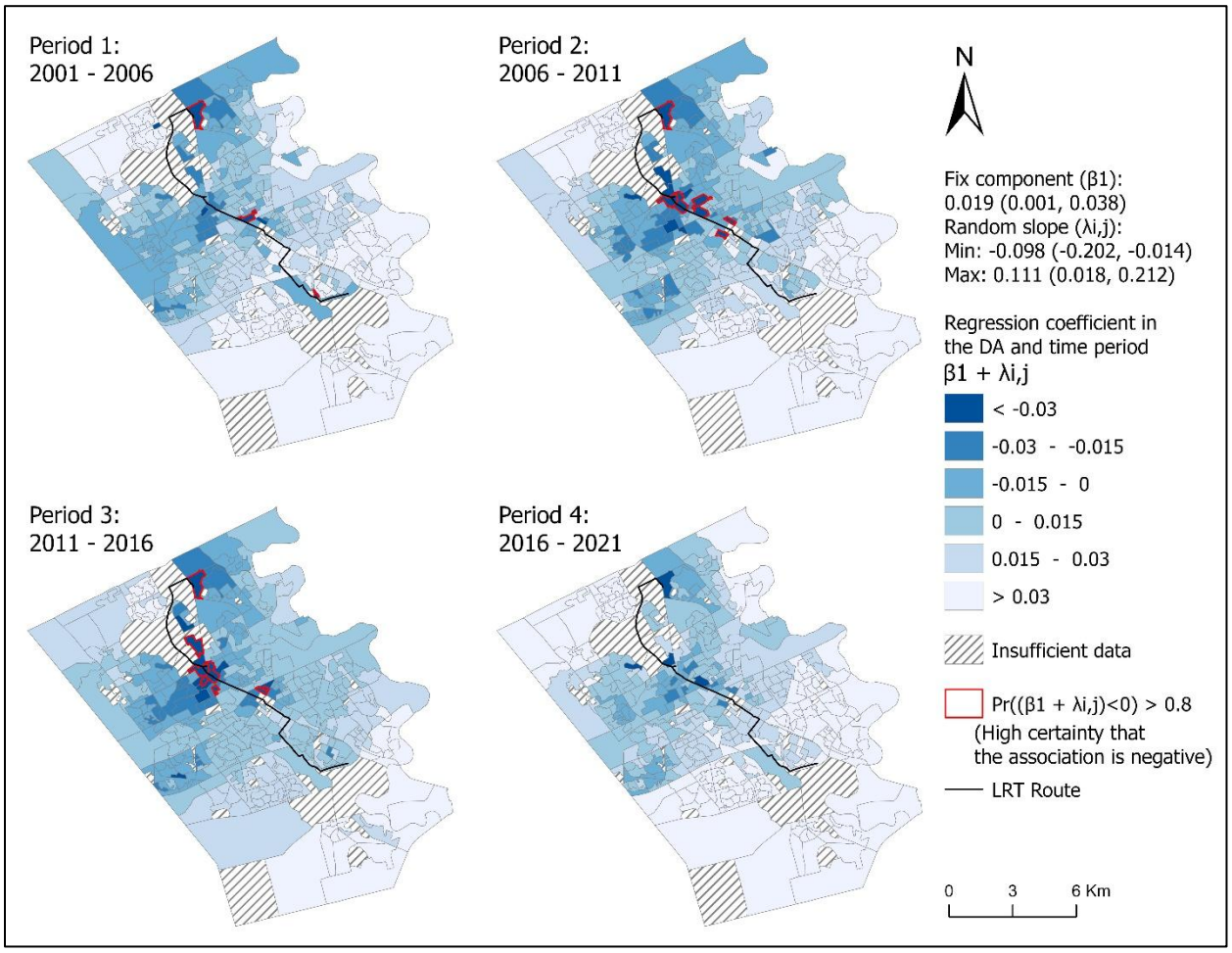


Figure 2-3: Spatiotemporally varying relationship between distance to LRT and the change in dwelling value per room.

Focusing on the fixed component (β_1), it is not significant for the change in average income but is significant for the change in dwelling value per room at the 95% credible interval, with a posterior mean of 0.019. This indicates that, on average, across the entire study area and the 20-year study period, being one standard deviation (1.63 kilometres) farther from LRT stations was associated with a 1.92% increase in dwelling value per room over a five-year period ($e^{0.019} - 1 \approx 0.0192$). The random slope ($\lambda_{i,j}$), which captures how the local regression coefficient for a specific DA and period deviates from the fixed component, indicates substantial spatiotemporal variability. For the change in average income, the random slope values range from -0.141 to 0.176, corresponding to a -13.15% to 19.24% five-year change in average income for each standard

deviation increase in distance to LRT. Similarly, the random slope values for the change in dwelling value per room range from -0.098 to 0.111, equivalent to a -9.34% to 11.74% change.

The local relationship is represented by the posterior mean of the sum of the fixed component and the random slope of the regression coefficient ($\beta_1 + \lambda_{i,j}$), with negative values indicating associations between proximity to LRT stations and income or dwelling value increases. To further assess the certainty of local associations, posterior probabilities of negative regression coefficients were computed. A threshold of 0.8, commonly used in Bayesian spatiotemporal analyses to identify significant random effects, was used to define high posterior probabilities (Cai & Tan, 2025a; Li et al., 2014; Richardson et al., 2004; I. Song & Luan, 2022).

For average income (Figure 2-2), the number of neighbourhoods with negative coefficients gradually grew over time, and a few neighbourhoods in the central and northeastern zones showed high posterior probabilities of negative coefficients in the fourth period, indicating a significant link between proximity to stations and income growth during the LRT opening stage in these areas. High posterior probabilities were also found with two of these neighbourhoods in earlier periods. As for dwelling value per room (Figure 2-3), negative coefficients with high posterior probabilities appeared in some neighbourhoods in the central and northeastern zones during the first three periods, particularly in the second and third periods. To focus only on neighbourhoods with LRT-related upgrading for further discussion, the locations of neighbourhoods identified with significant associations (i.e., high posterior probabilities of negative regression coefficients) are summarized in Figure 2-4. Table 2-3 details LRT-related upgrading in each of these neighbourhoods. Average incomes and dwelling values per room at the start and end of the study period, in comparison to the regional average, are included in the table to help discuss possible gentrification.

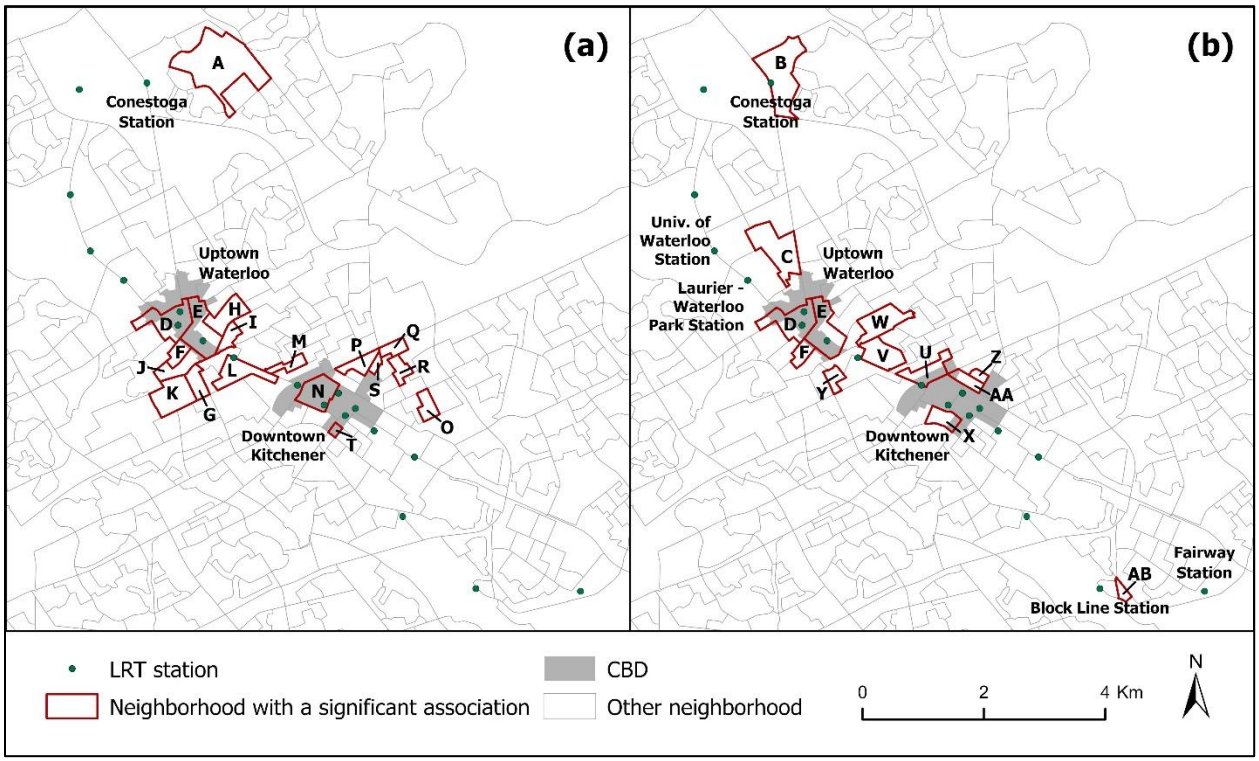


Figure 2-4: Maps of (a) neighbourhoods with a significant association between average income improvement and proximity to LRT, and (b) neighbourhoods with a significant association between dwelling value growth and proximity to LRT.

Table 2-3: Neighbourhoods with significant associations between proximity to LRT and upgrading: Timing, locations, incomes, and dwelling values (bolded incomes and dwelling values are lower than the regional average; bolded percentage changes are higher than the regional average).

ID[1]	Neighbourhood change associated with proximity to LRT and the timing	Proximate stations(s)[2]	Average income 2001 $	Average income 2021 $ and % change	Dwelling value per room 2001 ($)	Dwelling value per room 2021 ($) and % change
A	Income 2016-2021	Conestoga	105,473	121,005 (15%)	49,085	125,474 (156%)
B	Dwelling value 2001-2006 & 2011-2016		57,172	57,187 (0%)	96,659	214,634 (122%)
C	Dwelling value 2011-2016	CBD & university	**27,952**	**25,382** (-9%)	37,928	115,789 (**205%**)
D	Income 2016-2021; Dwelling value 2006-2016	CBD	61,818	90,754 (**47%**)	46,075	153,191 (**232%**)
E	Income 2011-2021; Dwelling value 2006-2016		50,254	74,903 (**49%**)	57,077	165,000 (189%)
F	Income 2016-2021; Dwelling value 2011-2016		79,376	86,195 (9%)	41,286	136,508 (**231%**)
G	Income 2006-2011 & 2016-2021		79,845	78,736 (-1%)	**37,084**	**108,219** (192%)
H	Income 2016-2021		**48,189**	82,466 (**71%**)	**29,723**	125,806 (**323%**)
I			**47,641**	64,232 (**35%**)	46,692	141,667 (203%)
J			70,574	110,230 (**56%**)	39,722	142,466 (**259%**)
K			94,394	109,816 (16%)	47,819	148,913 (**211%**)
L			**41,276**	72,934 (**77%**)	**29,006**	116,667 (**302%**)
M			**34,253**	60,710 (**77%**)	**31,052**	134,091 (**332%**)
N			**40,702**	69,412 (**71%**)	43,766	150,667 (**244%**)
O			68,846	173,012 (**151%**)	**36,072**	**107,368** (198%)
P			50,064	85,988 (**72%**)	**29,800**	117,143 (**293%**)
Q			**47,706**	69,619 (**46%**)	**34,149**	114,615 (**236%**)
R			48,852	64,232 (**31%**)	**30,009**	**98,551** (**228%**)
S			**47,887**	92,411 (**93%**)	46,671	**95,238** (104%)
T			**35,759**	63,403 (**77%**)	40,301	139,024 (**245%**)
U	Dwelling value 2001-2006		**34,082**	**47,034** (**38%**)	**32,664**	134,694 (**312%**)
V	Dwelling value 2006-2011		**35,485**	**43,719** (**23%**)	44,649	190,244 (**326%**)
W			**37,696**	57,394 (**52%**)	**34,732**	**101,786** (193%)
X			**40,467**	**45,584** (13%)	38,245	182,609 (**377%**)
Y	Dwelling value 2011-2016		**46,410**	**53,872** (16%)	48,683	185,366 (**281%**)
Z			**46,477**	**44,755** (-4%)	49,735	148,936 (199%)
AA			**32,661**	**44,134** (**35%**)	59,254	204,878 (**246%**)
AB	Dwelling value 2001-2006	Block Line & Fairway	**33,942**	No Data	**29,110**	**96,000** (**230%**)
Region of Waterloo average			48,263	56,721 (18%)	37,760	114,531 (203%)

1 Neighbourhood IDs are labelled on the maps in Figure 2-4.

2 University of Waterloo Station and Laurier-Waterloo Park Station are grouped into university stations, and stations in neighbourhoods intersecting CBDs are grouped into CBD stations.

2.5 Discussion

2.5.1 LRT-related neighbourhood upgrading

Focusing on the spatial patterns of neighbourhood with significant LRT-related upgrading (Figure 2-4), several key findings stand out. First, neighbourhoods showing significant LRT-related income improvement and dwelling value increase were found in similar but not entirely consistent locations. Second, the population-weighted centroids of all these neighbourhoods lie within 1.5 kilometres of the stations via road networks, implying that the LRT's influence was mostly limited to walkable areas from stations. This also aligns with previous studies that used predefined transit influence zones based on fixed buffers, typically ranging from 0.5 to 1 mile (Bardaka et al., 2018).

Furthermore, three of these neighbourhoods were found near the northern or southern LRT terminals, with the rest clustered around the two CBDs. By incorporating spatial variability into modelling, this finding provides valuable insight into the specific locations where transit-related neighbourhood change occurred. This level of spatial detail has rarely been captured in previous quantitative studies, which often generalized results at the city or transit-line level. Nonetheless, the observed patterns align with gentrification theories and some qualitative research. Neighbourhoods near LRT terminals may have attracted greater residential demand due to improved access to city centres, which concentrate jobs and commercial activity. As for CBD stations, CBDs were already included as a control variable, but proximity to LRT possibly added additional value. This may reflect major investments along the LRT corridors within CBDs, including the development of high-end condominiums that increased housing prices and attracted higher-income residents (Doucet, 2021; Ellis-Young & Doucet, 2024).

Temporally, as summarized in Table 2-3, LRT-related dwelling value increase mainly occurred in the second and third periods (2006-2016), while LRT-related income improvement predominantly occurred in the fourth period (2016-2021). Although both indicate neighbourhood change status, income reflects the current status, while dwelling value represents anticipated future changes (Bunten et al., 2024). Investors may drive up housing prices during LRT planning and construction, anticipating future demand, while higher-income residents often move in only after LRT service begins. This is evident in two neighbourhoods (D and E) which showed LRT-related

income improvements following dwelling value increases. Some argue that housing prices, driven by speculation after the transit project announcement, may not accurately reflect actual neighbourhood sociodemographic change in analyses comparing periods before and after LRT opening (D. He et al., 2024; Melser, 2020). However, this study's inclusion of temporal variability addresses this concern by capturing when different types of change occur, reconfirming that neighbourhood change may occur in stages, with sociodemographic shifts typically following changes in dwelling value.

2.5.2 Possible gentrification

Recognizing that gentrification typically involves socioeconomic upgrading driven by investments and demographic shifts, but that not all upgrading is equivalent to gentrification, LRT-related gentrification should be identified within neighbourhoods exhibiting LRT-related upgrading. Table 2-3 shows that six neighbourhoods (L, M, Q, U, W, and AB) had both income and dwelling value below the regional average in 2001, signalling underinvestment and the presence of lower-income population before LRT development. By a conventional definition, these areas were gentrifiable, meaning that their upgrading might be classified as possible gentrification. All six experienced faster growth in at least one indicator compared to the regional average, and five (excluding AB), located near CBD stations, had at least one indicator over the regional average by 2021, suggesting signs of gentrification.

Due to data limitations, this research did not directly measure displacement when defining gentrification. However, the criteria used for identifying gentrification can be flexibly adjusted. Thresholds used to define gentrifiability and fast growth can be modified, and additional variables may be incorporated to suit different research or planning contexts. Since this approach narrows the assessment of LRT-related gentrification to neighbourhoods where LRT-related upgrading occurred, complementary qualitative methods such as field investigations may become more manageable for assessing gentrification, although this is beyond the scope of the current study.

Although this study did not directly confirm displacement, the observed increases in dwelling values related to LRT, particularly those outpacing the regional average, raise concerns about the loss of affordable housing, a common gentrification-related outcome. The Region of

Waterloo (2023) has already reported declines in affordable housing along the LRT corridor, especially after 2016. In addition to value increases of existing units, in the CBDs, this problem has been driven by the demolition and renovation of affordable units and the construction of high-end units, contributing to both direct and exclusionary displacement (Doucet, 2021). While government-led transit infrastructure is often framed as advancing equity, transit-served areas often become less affordable, excluding the populations most dependent on transit (Kramer, 2018). Cities planning or implementing transit projects should therefore monitor where and when these impacts occur and take proactive steps to ensure that transit investments benefit disadvantaged populations.

2.6 Limitations and future research

Several limitations of this research are worth noting. This study only analyzed changes in income and dwelling value, while other indicators, such as education, demographic compositions, and social status could be explored to better understand patterns of neighbourhood change. Where available, variables that directly capture displacement should also be incorporated as dependent variables.

It should also be noted that census-reported dwelling values may not reflect actual market prices, which were unavailable for this study. Although commonly used in relevant studies, self-assessed home value indicators often lag behind market-based measures, underestimate shifts during rapid changes, and are influenced by neighbourhood sociodemographic characteristics and changes in the housing compositions (Immergluck & Hollis, 2024). Nevertheless, such measures remain meaningful as they capture residents' perceptions, an essential aspect of gentrification as a social and psychological process that shapes living experiences and housing decisions. To partially address this limitation, this study calculated dwelling value per room and included control variables to account for housing composition shifts and reporting biases among population groups. Where market-based data are available, future research could benefit from comparing both indicators to enhance the robustness of findings.

While distance to LRT was used as the transit variable, it may not fully capture the added value of LRT. Future research could incorporate other variables, such as improved walkability scores or accessible areas resulting from LRT, if quantifiable. Also, more control variables, such as job concentrations could be included if available. Furthermore, this study used the DA as a neighbourhood proxy, but other spatial units (e.g., planning neighbourhoods and census tracts) could be examined. Similarly, examining different temporal units and timeframes could provide further insights. This study included four time periods, with only one corresponding to the LRT's opening, since ION LRT was newly developed. There could be a time lag between LRT opening and the occurrence of gentrification.

Finally, LRT may also have contributed to other forms of neighbourhood change that warrant further investigation. Gentrification is not an isolated process, particularly in a region shaped by a strong technology sector and two universities, where the knowledge economy can drive gentrification, youthification (influx of young adults aged 25–34), and studentification (influx of post-secondary students) simultaneously (Moos, Revington, et al., 2019). Future research could explore the spatiotemporal patterns of all these processes in relation to LRT.

2.7 Conclusion

Urban rapid transit systems like LRT could contribute to neighbourhood change, including gentrification, potentially displacing disadvantaged residents. Previous empirical research has reported mixed results. We argue that the relationship between LRT and neighbourhood change may vary spatially across the urban area it serves and temporally from the planning to opening stages of a transit line. This study analyzed the spatiotemporally varying relationship between distance to LRT and neighbourhood change in Kitchener-Waterloo with a Bayesian modelling approach. LRT-related upgrading, including increases in income and dwelling value, was evident in some neighbourhoods around CBD stations and near the northern and southern terminals. LRT-related dwelling value increased mainly occurred during LRT planning and construction phases, while LRT-related income improvement was predominantly found during the opening stage.

Moreover, upgrading in some neighbourhoods, mainly located near CBD stations, could be classified as gentrification related to LRT development.

Overall, this study confirms the spatiotemporal variability in LRT-related neighbourhood upgrading and gentrification. While the debate over whether transit projects are associated with gentrification continues and findings remain mixed, this research offers a distinct perspective with empirical evidence: the outcome largely depends on the specific locations and time periods examined within a transit project. Analyses assuming a consistent relationship between transit and neighbourhood change over a long time period or across all station areas of the same line, or distinguishing only between gentrifiable and non-gentrifiable neighbourhoods, could yield misleading results. This highlights the need for theoretical frameworks that conceptualize LRT-related gentrification as a spatiotemporally dynamic and context-dependent process, as well as for empirical research worldwide that captures local spatiotemporal variation to accurately and precisely identify transit-related gentrification.

The research framework and advanced modelling approach presented here, as well as the novel concept of examining transit-related neighbourhood change as a spatiotemporally variable phenomenon, could aid future research in understanding the relationship between public transit and gentrification. While the case study presented focused on a mid-sized city in Canada, the approach is adaptable to a range of urban contexts and those implementing different forms of transit system; for example, BRT, which has become increasingly popular in the Global South (Venter et al., 2018). As more evidence is gathered worldwide and as understanding grows regarding where, when, and why transit projects contribute to gentrification, it will become increasingly possible to determine when and where concerns should be addressed, and how transit projects can be designed to minimize negative impacts on disadvantaged residents. These insights can help planners and policymakers around the world integrate transport services and land development for long-term sustainable and equitable cities.

Chapter 3
Urban change in a university town: Spatiotemporal patterns of post-secondary students, university graduates, and young adults during a period of development and disruption

Summary

Studentification is an important component of urban change in university towns and is often embedded within broader sociodemographic transformations in the knowledge economy context. This study applied a Bayesian hierarchical modelling approach to investigate the spatiotemporal patterns of post-secondary students, university graduates, and young adults in Kitchener-Waterloo between 2011 and 2021, a period marked by both development and disruption. Shared neighbourhoods between the three population groups were primarily located near post-secondary campuses and central business districts and were associated with public transit influences. During the COVID-19 pandemic, studentified neighbourhoods near campuses saw a notable increase in university graduates and young adults, particularly the latter, suggesting a shift toward increasing youthification as studentification slowed. University graduates and young adults were also linked to transit-oriented development, with youthification intensifying especially along the newly opened light rail transit line between 2016 and 2021, a trend that warrants further examination using post-pandemic data. High-density and high-cost rental housing in neighbourhoods occupied by students, university graduates, and young adults may have created barriers for other sociodemographic groups, such as working-class families. This raises concerns about whether current neighbourhood planning and transit-oriented development initiatives are achieving their intended goals of fostering inclusive communities.

3.1 Introduction

Universities, colleges, and their students have emerged as key actants in urban change in their host cities. A prominent manifestation of this influence is studentification, characterized by the influx and concentration of post-secondary students (hereafter students) and the resulting physical and social transformations of neighbourhoods near campuses (D. P. Smith, 2005). Initially examined in the UK, studentification has since been documented globally (e.g., Fincher & Shaw, 2009; S. He, 2015; Holton & Mouat, 2021; Revington et al., 2020). While earlier studentification was predominantly linked to low-quality and high-density housing, recent trends reflect growing demand for and supply of higher-cost options, including purpose-built student accommodation (PBSA; Kinton et al., 2018). Regardless of its specific form, studentification plays a crucial role in reshaping the social, economic, and demographic structures of university and college towns.

Urban change processes rarely occur in isolation, and studentification is no exception. Within studentifying neighbourhoods, the growing student population often drives shifts in demographic and housing market composition, reconfigures local services and amenities, and can contribute to the degradation of the local living environment (D. P. Smith et al., 2014). As students share neighbourhood spaces with other sociodemographic groups, studentification may coincide with other urban processes such as gentrification and youthification, producing complex transformations in areas surrounding post-secondary campuses (Moos, Revington, et al., 2019). Beyond these neighbourhoods, studentification is embedded in socioeconomic shifts across the urban landscape, particularly in cities that function as knowledge nodes within the global economy, where innovation and technology drive economic growth (Foote, 2017). These patterns underscore the importance of examining studentification while considering broader sociodemographic transformations and contextual changes from the global to the local scale that shape urban development.

This research investigates the geographies of students in tandem with the spatial distributions of two other important sociodemographic groups in the knowledge economy context:

university graduates and young adults. The increasing share of highly educated residents often signals neighbourhood sociocultural uplift, and university graduates constitute an important component of Ley's (1996) concept of the new middle class in urban gentrification. Young adults play an important role in shaping urban spaces as increasingly "generationed," and the growing concentration of residents aged 25 to 34 in central city neighbourhoods is defined as youthification (Moos, 2014, 2016). Although previous studies have analyzed the spatial correlations between these population groups or the associated urban processes (Moos, Revington, et al., 2019; Revington et al., 2023), their spatiotemporal dynamics remain underexplored. Examining how students, university graduates, and young adults overlap or diverge across space and time can contribute to theoretical understanding of the convergence of studentification with other urban change processes and inform local policy responses to neighbourhood transformation. Specifically, this study addresses the following research questions: 1) How do the spatial patterns of students, university graduates, and young adults overlap and diverge within a university town and knowledge economy city? 2) How do these shared and group-specific spatial patterns evolve over time during a period of urban development and disruption? 3) What broader urban processes and neighbourhood characteristics help explain the observed spatiotemporal patterns, and what are their implications for community inclusiveness?

To answer these questions, this study analyzes the spatiotemporal patterns of students, university graduates, and young adults in Kitchener-Waterloo, Canada, between 2011 and 2021 using a Bayesian modelling approach. The study area is a mid-sized urban region that functions as a prominent university town and knowledge economy node, characterized by three post-secondary institutions and a thriving technology sector. The study period is marked by both development and disruption. Notably, steady expansion of higher education enrolment, a surge in PBSA development, and the implementation of a new light rail transit (LRT) system occurred during the study period, all of which may have influenced studentification and other urban change patterns. Moreover, the onset of the COVID-19 pandemic toward the end of the study period provided a natural experiment in which studentification and other urban processes were disrupted.

The contribution of this research is threefold. Theoretically, it contributes to a more nuanced understanding of how interconnected urban sociodemographic and neighbourhood

change processes unfold across space and time in the knowledge economy context. Methodologically, this study moves beyond the simple correlation approaches used in previous research by applying joint modelling to provide more spatiotemporally detailed examination of overlapping and group-specific neighbourhood change patterns. Practically, the findings highlight potential challenges related to community inclusiveness and housing accessibility in Kitchener-Waterloo, while also offering broader policy implications for other university towns and knowledge economy cities globally.

3.2 Background

3.2.1 Spaces of students, university graduates, and young adults: Segregated, overlapping, or transitioning?

Studentification typically reflect residential segregation through all five spatial dimensions defined in the classic work by Massey and Denton (1988): uneven distribution across the city (evenness), limited interaction with non-students (exposure), concentration in a few areas (concentration), proximity to campuses or city centres (centralization), and formation of clustered student neighbourhoods (clustering). Segregated student spaces may emerge due to student preferences to live near campuses, housing sub-markets targeting students, and urban planning that facilitates student-oriented neighbourhood developments (Fincher & Shaw, 2009; Hubbard, 2009; Kinton et al., 2018; Miessner, 2021; Revington et al., 2020; Sage et al., 2013). The rise of PBSA has further reinforced this segregation by fostering "student enclaves" (D. P. Smith & Hubbard, 2014).

Despite its segregated nature, studentification is not isolated from other forms of urban change. Earlier research often framed studentification within the context of gentrification, which is commonly understood as the process in which middle-class in-movers occupy previously lower-income neighbourhoods (Lees et al., 2008). Studentification research notes that students from middle-class backgrounds share characteristics with gentrifiers, both gentrification and studentification can displace existing residents, and living in studentified areas may prepare students to become potential gentrifiers after graduation (D. P. Smith, 2005; D. P. Smith & Holt, 2007). Nevertheless, the growing socioeconomic diversity of student populations has complicated

this narrative, making the transition from students to gentrifiers increasingly difficult to trace (Nakazawa, 2017). Although studentification is not equivalent to gentrification, it can intertwine with gentrification in neighbourhoods near campuses. Post-secondary campus development is frequently tied to urban revitalization investments that raise property values, drive gentrification, and displace low-income residents (Addie et al., 2015; Ehlenz, 2019; Jolivet et al., 2023). The influx of students can heighten housing competition, redirect local services toward student needs, and foster exclusive sociocultural environments, potentially creating tensions with or displacing long-term residents (Gu & Smith, 2020; S. He, 2015; Lager & Hoven, 2019; Sage et al., 2012a).

Studentification may coincide with the increasing presence of university graduates and young adults in such neighbourhoods, further intensifying displacement pressures on disadvantaged populations. The increasing concentration of university graduates in city centres in recent decades has contributed significantly to urban gentrification (Couture & Handbury, 2023). From a demand-side perspective of gentrification, this trend reflects the growing preference of university-educated individuals and those in professional or managerial occupations for urban living, driven by access to economic opportunities and urban amenities in city centres (Ley, 1986, 1994). Similarly, in the youthification process, the concentration of young adults in urban centres is typically associated with high-density housing and convenient access to urban amenities such as public transit (Moos, 2014, 2016).

Shared neighbourhoods among students, university graduates, and young adults, particularly recent graduates and young professionals, may emerge due to their similar demands for affordable housing, amenity-rich settings, and vibrant sociocultural environments in campus-proximate neighbourhoods (S. He, 2015; Moos, Filion, et al., 2019). It is also important to note that the empirical definitional boundaries among the three are often blurred. Older students, particularly graduate students, may be included in the young adult group, although studentification conventionally focuses on undergraduates (Moos, Revington, et al., 2019; Revington et al., 2023). Many young adults are also university graduates, and studies from across the world have identified well-educated young adults as important drivers of urban gentrification (Couture & Handbury, 2020; Hochstenbach, 2019; Inzulza-Contardo, 2016; J. Zhang et al., 2020). Nonetheless, youthification spans a broader range of social classes and not all young in-movers in gentrifying

neighbourhoods are university graduates or possess the socioeconomic characteristics typically associated with gentrifiers. Some lower-income young adults, often living with roommates, may still displace family households by outbidding them for housing and eventually contributing to gentrification (Moos, 2016; Moos, Revington, et al., 2019). These patterns highlight the complex relationships between the three groups and the associated urban processes, which can occur concurrently or independently.

Despite such interconnections, research on the spatial convergence of students, university graduates, and young adults remains limited. Moos, Revington, et al. (2019) introduced a conceptual framework linking the processes of studentification, gentrification, and youthification and examined the relationships between proximity to post-secondary campuses, the economic indicator (dwelling value) and sociocultural index (combining university graduates and occupation data) of gentrification, and the geographies of young adults in the knowledge economy context. Revington et al. (2023) extended the analysis to American legacy cities and explicitly considered neighbourhood shares of students, university graduates, and young adults. However, these studies relied on correlation coefficients that do not reveal where exactly such groups or urban processes co-occur or diverge geographically. Spatially explicit insights are essential for researchers and planners to identify affected neighbourhoods and tailor appropriate interventions. Moreover, such correlation analyses may yield biased results as they ignore the presence of spatial autocorrelation, which is the tendency for nearby areas to exhibit similar indicator values (Haining, 1990). Spatial autocorrelation may arise from misalignments between the spatial unit of analysis and the actual geographic scale of urban change, such as redevelopment projects spanning multiple census tracts. It may also result from spatial spillover, where conditions in one neighbourhood influence changes in adjacent areas (Jun, 2022).

Studentification and related urban processes may also unfold as transitioning or sequential processes. Although Moos, Revington, et al. (2019) focused their empirical analysis on geographic overlap, they also theorized potential temporal transitions, such as studentification following gentrification as students drawn to already-gentrified areas. Foote (2017), while not explicitly focused on this triad, categorized neighbourhood typologies and demonstrated neighbourhood transitions in knowledge economy cities, such as shifts from middle-class to elite areas. Revington

et al. (2023) incorporated a temporal dimension by analyzing correlations between changes in students, university graduates, and young adults, revealing tendencies for the same spaces to exhibit similar or divergent trajectories across different urban processes. Again, this correlation approach does not identify the specific locations where these patterns occur. Further research is needed to investigate the spatial and temporal patterns of students, university graduates, and young adults, particularly to understand where, when, and how their residential spaces are segregated, overlapping, or transitioning. This could further the understanding of how different urban processes unfold and how they are shaped by contextual factors across space and time, while also providing detailed insights into when and where policy interventions may be needed.

3.2.2 Urban change within the contexts of knowledge economy, transit-oriented development, and beyond

Urban change processes do not occur in a vacuum. Neighbourhood change in university towns is often embedded within the broader context of the knowledge economy, where economic growth is driven by intellectual capabilities rather than physical resources, emphasizing continuous innovation and the exchange of knowledge at local and global scales (W. W. Powell & Snellman, 2004; Simmie, 2003). Universities play a central role by generating, applying, and disseminating knowledge, fostering industry collaboration, attracting talent, and commercializing research to support regional economic development (Bejinaru, 2017; Bramwell & Wolfe, 2008; W. W. Powell & Snellman, 2004).

The rise of the knowledge economy has redefined urban change, while raising concerns about growing inequality and displacement. In addition to reshaping neighbourhoods near campuses, the knowledge economy can contribute to gentrification and socioeconomic polarization by attracting highly educated and skilled professionals to city centres and directing investment to innovation districts, thereby raising housing costs and heightening displacement pressures on disadvantaged groups (Edlund et al., 2022; Morisson & Bevilacqua, 2019; Stehlin, 2016). Youthification is also linked to the knowledge economy, as young adults, compared to previous generations, are in high demand as skilled labour and are drawn to central areas that offer employment opportunities and urban amenities (Lee, 2022; Vinodrai, 2017).

Parallel to the expansion of the knowledge economy, many cities promote transit-oriented development (TOD), as a key strategy aligned with knowledge-based urban growth (Zandiatashbar et al., 2019). Transit accessibility and walkability are critical for attracting knowledge-intensive firms and highly skilled professionals (Zandiatashbar & Hamidi, 2018, 2022). Nevertheless, the influx of higher-income professionals in creative and technology sectors within TODs may intensify gentrification under the banner of sustainability (Rice et al., 2020). Regardless of its association with the knowledge economy, TOD may contribute to gentrification through its role in attracting investment, raising property values, and displacing disadvantaged residents, although empirical evidence on these effects remains inconclusive (Padeiro et al., 2019). TOD may also influence youthification and studentification as young adults often prefer transit-accessible neighbourhoods (Moos, 2014, 2016), and improved transit infrastructure may potentially help redistribute student populations across the city (Revington et al., 2023).

Other forces can also shape neighbourhood change in cities hosting post-secondary institutions. A recent and notable example was the COVID-19 pandemic. The shift to online teaching disrupted studentification by temporarily reducing student populations and altering housing demand near campuses, with potential long-term impacts on post-pandemic studentification patterns (Prada-Trigo et al., 2022, 2024; Revington & Benhocine, 2023). It may also alter other neighbourhood change patterns; for example, remote work could motivate some young adults to relocate to suburban areas (Lee, 2022) and increase demand for housing near green infrastructure, driving up housing prices (Broitman, 2023). The pandemic is certainly not the only event capable of disrupting urban transformation. Institutional-level trends such as enrolment dynamics, municipal-level planning such as urban redevelopment initiatives, and national-level shifts such as changes in immigration policy, along with other planned or unforeseen events and disruptions, can all contribute to neighbourhood change. This emphasizes the importance of considering local conditions and their influence across spatial and temporal contexts when analyzing neighbourhood dynamics in university towns and knowledge economy regions.

3.3 Methodology

3.3.1 Study area and data

The study area includes the twin cities of Kitchener and Waterloo in the Region of Waterloo, Ontario, Canada, commonly referred to as "Kitchener-Waterloo." Located about 100 kilometres west of Toronto, this fast-growing mid-sized urban area with a strong industrial heritage has evolved into a leading innovation hub with a diverse economy spanning advanced manufacturing, biotechnology, finance, education, and high-tech industries, especially information and communication technology (Bramwell et al., 2008). The presence of multinational firms, including Google's largest Canadian research and development office, further embeds the region within the global knowledge economy.

Waterloo hosts the main campuses of the University of Waterloo and Wilfrid Laurier University, as well as a campus of Conestoga College, a polytechnic institution. Kitchener hosts another Conestoga College campus and smaller satellite campuses of both universities. This concentration of higher education institutions is central to the region's knowledge economy, with the University of Waterloo standing out as a model innovation university known for its strong connections to local industries (Addie et al., 2015; Bathelt et al., 2011; Bramwell & Wolfe, 2008). However, rapid enrolment growth since the early 2000s has raised concerns over studentification (Revington, 2022).

Kitchener-Waterloo is served by a dense bus network and an LRT system that was approved in 2011, began construction in 2014, and launched in 2019. The LRT line connects key destinations, including the two universities, major shopping malls, the regional train station, and two central business districts (CBDs), known as Uptown Waterloo and Downtown Kitchener. Both CBDs offer a vibrant mix of restaurants, bars, and cultural venues, while Downtown Kitchener also features an innovation district for technology firms. TOD in the study area focuses on the central transit corridor (CTC), which is the area within 800 metres of LRT stations, where ongoing investment and development have driven significant neighbourhood change (Region of Waterloo, 2023). An express bus route previously served roughly the same corridor before the LRT.

With its concentration of post-secondary institutions, high-tech industries, and recent transit investment, Kitchener-Waterloo presents an ideal case for analyzing neighbourhood change within the contexts of the knowledge economy and TOD. While previous studies have focused on large metropolitan areas (Moos, Revington, et al., 2019) and legacy cities (Revington et al., 2023), this dynamic mid-sized urban region can provide further insights to broaden the understanding. Figure 3-1 shows maps of the study area, including the major post-secondary campus locations (two university satellite campuses in Downtown Kitchener are not considered due to their small sizes), CBDs, the LRT line with key destinations, the study area's relative location, and the neighbourhood unit of analysis. The dissemination area (DA), the smallest geographic unit for census sociodemographic data, was selected to support detailed analysis of neighbourhood change.

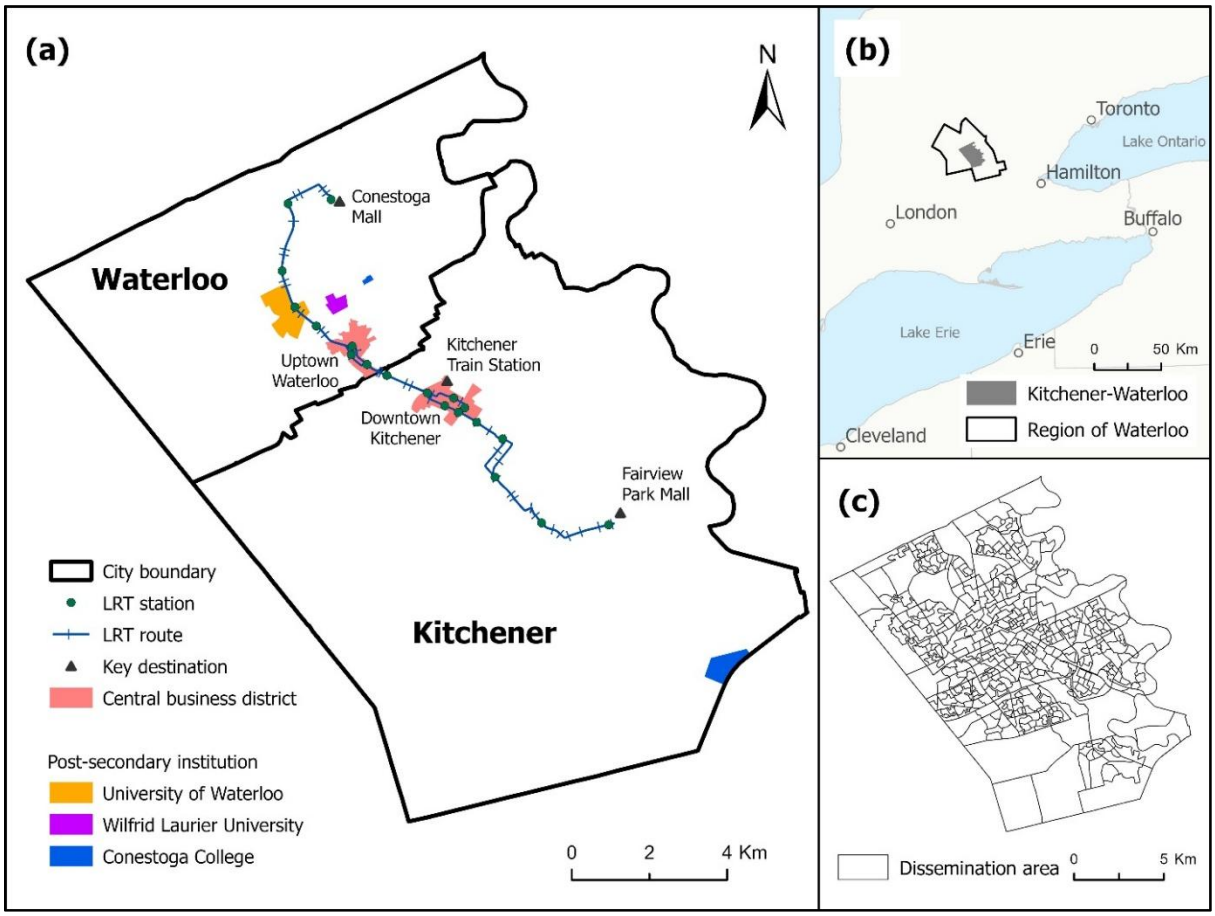


Figure 3-1: Locations of major post-secondary campuses, central business districts, and the LRT line with key destinations (a), the relative location of Kitchener-Waterloo (b), and DAs within Kitchener-Waterloo (c).

This study used census data from 2011, 2016, and 2021 to examine the geographies of students, university graduates, and young adults at five-year intervals. All data were harmonized to 2021 DA boundaries. Of the 476 DAs in the study area, four were excluded due to insufficient data. Additionally, General Transit Feed Specification (GTFS) data were used to identify transit stop locations and calculate transit times. GTFS files for 2016 and 2021 were retrieved from OpenMobilityData (transitfeeds.com), while 2011 files were downloaded from the GitHub repository of TriTAG Labs (github.com/TriTAG).

To analyze the spatial patterns of each population group, DA-level population shares were computed. The DA share of students was proxied by the percentage of individuals aged 18–24, as

the census does not directly identify students, and was used to reflect the intensity of studentification (Foote, 2017; Revington et al., 2023). The DA share of university graduates was measured as the percentage of individuals aged 25 to 64 with a bachelor's degree. The DA share of young adults was represented by the percentage of individuals aged 25–34, following the definition of youthification (Moos, 2016). Table 3-1 presents summary statistics for the shares of the three groups. To identify broader trends, study area-level values are also included. The DA-level values exhibit high variability, and the Moran's I values, a common measure of spatial autocorrelation, indicate strong spatial clustering of similar neighbourhood shares for each group in each year.

Table 3-1: Summary statistics for the DA shares of students, university graduates, and young adults.

Variables	Study area-level value	Mean	S.D.	Min	Max	Moran's I
2011 (total population = 317,933)						
% Students	10.70	11.35	6.70	3.64	77.97	0.57 ($p < 0.001$)
% University graduates	31.43	30.19	17.65	0.00	86.96	0.59 ($p < 0.001$)
% Young adults	14.83	14.40	5.75	2.94	41.14	0.34 ($p < 0.001$)
2016 (total population = 338,208)						
% Students	10.91	10.99	7.97	3.23	83.90	0.62 ($p < 0.001$)
% University graduates	34.15	32.63	17.27	0.00	82.69	0.70 ($p < 0.001$)
% Young adults	14.82	14.87	5.70	2.16	41.57	0.42 ($p < 0.001$)
2021 (total population = 378,321)						
% Students	10.55	9.55	6.18	2.47	66.06	0.61 ($p < 0.001$)
% University graduates	40.16	37.56	16.79	5.26	82.93	0.67 ($p < 0.001$)
% Young adults	16.60	16.43	6.59	1.30	48.07	0.49 ($p < 0.001$)

3.3.2 Spatiotemporal modelling

Bayesian hierarchical models were used to analyze the spatiotemporal patterns of students, university graduates, and young adults from 2011 to 2021 at the DA level. Two models were extended from a base model: one to identify shared spatial patterns between indicators, and the other to assess the influence of public transit. Let $Y_{i,j,k}$ denote the standardized z-score of indicator

k (where $k = 1$ for the share of students, $k = 2$ for the share of university graduates, and $k = 3$ for the share of young adults) in DA i ($i = 1,2,\ldots,472$) in year j ($j = 1,2,3$ representing 2011, 2016, and 2021, respectively), the base model is specified in Equation 3-1. $Y_{i,j,k}$ was modelled as a normal distribution, commonly applied to continuous variables, with an identity link function connecting the expected value $\theta_{i,j,k}$ to $\mu_{i,j,k}$. $\mu_{i,j,k}$ was further expressed as the sum of an intercept term (α_k), a spatial effect ($\upsilon_{i,k}$), a temporal effect ($\nu_{j,k}$), and a space-time interaction term ($\delta_{i,j,k}$).

$$Data\ model: Y_{i,j,k} \sim N(\theta_{i,j,k}, \tau_k^{-1})$$
$$Process\ model: \theta_{i,j,k} = \mu_{i,j,k} = \alpha_k + \upsilon_{i,k} + \nu_{j,k} + \delta_{i,j,k} \quad (3\text{-}1)$$

Vague or weakly informative priors were assigned to the model parameters. α_k was assigned a normal distribution with mean 0 and variance 1,000. $\upsilon_{i,k}$ was given a Besag-York-Mollié (BYM) prior, which combines a structured component capturing spatial autocorrelation using an intrinsic conditional autoregressive (ICAR) prior, and a Gaussian component representing spatially uncorrelated errors (Besag et al., 1991). $\nu_{j,k}$ was modelled using a first-order random walk (RW1) prior to capture temporal dependence. $\delta_{i,j,k}$ was assigned a normal distribution to account for residual spatiotemporal variation beyond the main spatial and temporal effects. Each log-precision term was given a hyperprior of $loggamma(0.5,0.00005)$. Other hyperpriors were tested to ensure the findings were not sensitive to the choice of hyperpriors. This base model follows a common Bayesian hierarchical spatiotemporal structure (Blangiardo & Cameletti, 2015; Haining & Li, 2020). It allows flexible adaptation to various research contexts, and the autoregressive component effectively captures spatial autocorrelation, reducing bias from census-defined neighbourhood boundaries, making it well-suited for studying neighbourhood change (Hawkins et al., 2022; Johnson et al., 2022).

To examine spatial overlap between indicators, a shared component model (Equation 3-2) was used. Shared spatial components $\psi_{1,i}$ and $\psi_{2,i}$ represent spatial patterns common to students and university graduates, and students and young adults, respectively. λ_1 and λ_2 are scaling

parameters associated with the shared components. The shared components were given ICAR priors to account for spatial autocorrelation, while the scale parameters were given priors of $gamma(10,10)$. The scaling parameters are analogous to factor loadings in principal component analysis, reflecting each variable's contribution to the shared components, but with components grounded in theoretical or policy relevance (Quick & Luan, 2021). A shared component between young adults and university graduates was not included, despite their theoretical association, due to a relatively weak correlation (Pearson's r = 0.07, p = 0.008). In contrast, stronger correlations were observed between students and young adults (r = 0.51, p < 0.0001) and students and university graduates (r = 0.21, p < 0.0001). Additional testing of models with a shared component between young adults and university graduates or among all three groups also did not yield meaningful results. No covariates were included in this model because the purpose was to map the spatiotemporal patterns of the three groups rather than identifying explanatory factors.

$$\mu_{i,j,1} = \alpha_1 + \upsilon_{i,1} + \nu_{j,1} + \delta_{i,j,1} + \lambda_1\psi_{1,i} + \lambda_2\psi_{2,i}$$
$$\mu_{i,j,2} = \alpha_2 + \upsilon_{i,2} + \nu_{j,2} + \delta_{i,j,2} + \frac{1}{\lambda_1}\psi_{1,i}$$
$$\mu_{i,j,3} = \alpha_3 + \upsilon_{i,3} + \nu_{j,3} + \delta_{i,j,3} + \frac{1}{\lambda_2}\psi_{2,i} \quad \text{(3-2)}$$

Finally, a model with two binary covariates, as specified in Equation 3-3, was used to assess associations between the three groups and public transit factors. $X_{1,i,j}$ represents transit proximity to post-secondary campuses and was set to 1 if the population-weighted centroid of DA i in year j was within 10 minutes by transit or walking to a stop providing direct access to campus, based on GTFS data. The 10-minute threshold reflects typical student commute times of 5 to 15 minutes (Dhillon et al., 2021). Alternative covariate settings differentiating between university and college campuses were also tested and yielded similar results. $X_{2,i}$ represents the CTC and was set to 1 if DA i intersects the CTC. The regression coefficients ($\beta_{m,j,k}$) were modelled as the sum of a fixed term ($\gamma_{m,k}$), assigned a normal prior with mean 0 and variance 1,000, and a temporally varying

term ($\omega_{m,j,k}$), assigned an RW1 prior. This structure allows the covariate effects to vary over time, accounting for contextual shifts, including the introduction of the LRT and the onset of the COVID-19 pandemic.

$$\mu_{i,j,k} = \alpha_k + \upsilon_{i,k} + \nu_{j,k} + \delta_{i,j,k} + \beta_{1,j,k}X_{1,i,j} + \beta_{2,j,k}X_{2,i}$$
$$\beta_{m,j,k} = \gamma_{m,k} + \omega_{m,j,k}, for\ m = 1, 2 \quad (3\text{-}3)$$

3.4 Results

3.4.1 Spatial patterns

Figure 3-2 and Figure 3-3 show the shared spatial patterns between students and university graduates, and between students and young adults, respectively, based on the shared component model (Equation 3-2). The scaling parameters, λ_1 and λ_2, were estimated to be 1.02 (95% credible interval: 0.47-1.96) and 1.01 (95% credible interval: 0.5-1.76), respectively, suggesting that each variable contributed nearly equally to the corresponding shared component. Both the posterior means, indicating how much values deviated from the study area average, and the posterior probabilities of positive values, identifying hotspots where values were significantly above the study area average, were mapped. Posterior probability thresholds of 0.95, 0.9, and 0.8 were applied to define and rank hot spots (Law et al., 2020; Richardson et al., 2004). The maps reveal shared spaces between students and university graduates concentrated around post-secondary campuses in Waterloo, extending both westward and toward Uptown Waterloo. The students-young adults shared component also highlights Waterloo campuses, with additional small areas near the Kitchener campus and more prominent concentrations along the LRT corridor, especially around Downtown Kitchener.

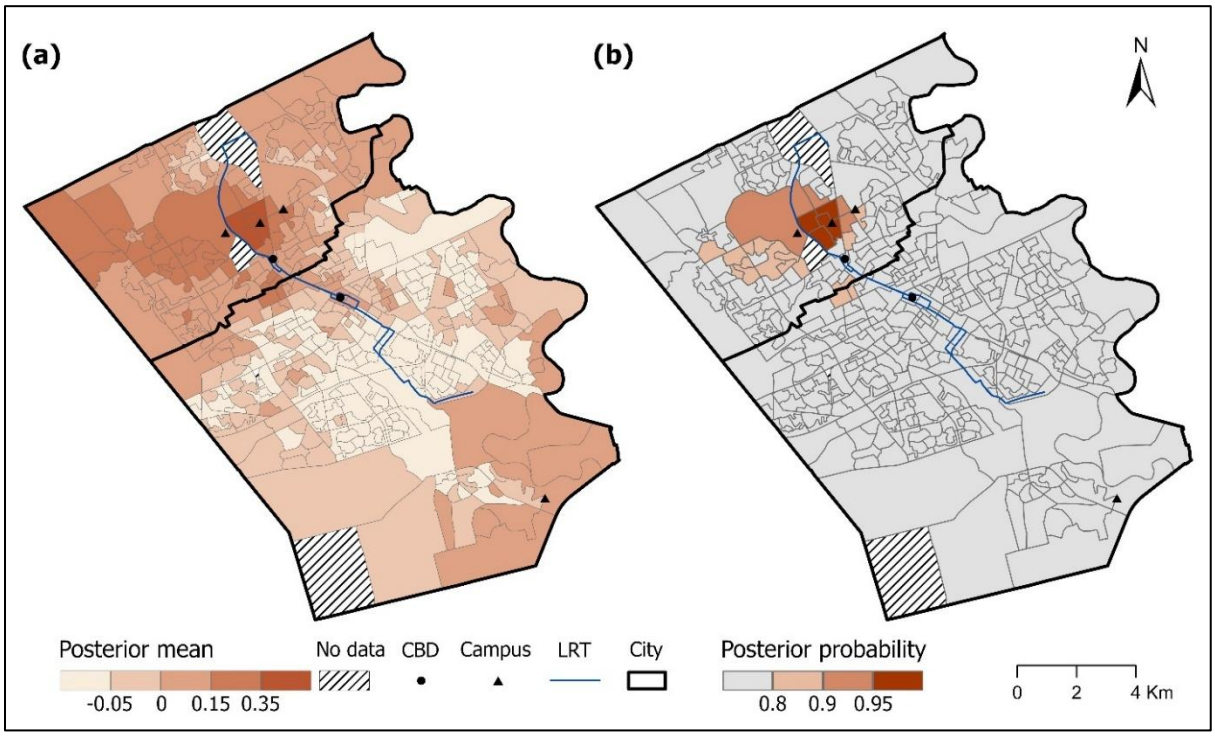


Figure 3-2: Shared spatial patterns between students and university graduates: Posterior means (a) and posterior probabilities of positive values (b) of $\lambda_1 \psi_{1,i}$ (representing the student spatial patterns explained by the shared component; the corresponding patterns for university graduates, represented by $\frac{1}{\lambda_1}\psi_{1,i}$, are highly similar as λ_1 is close to 1).

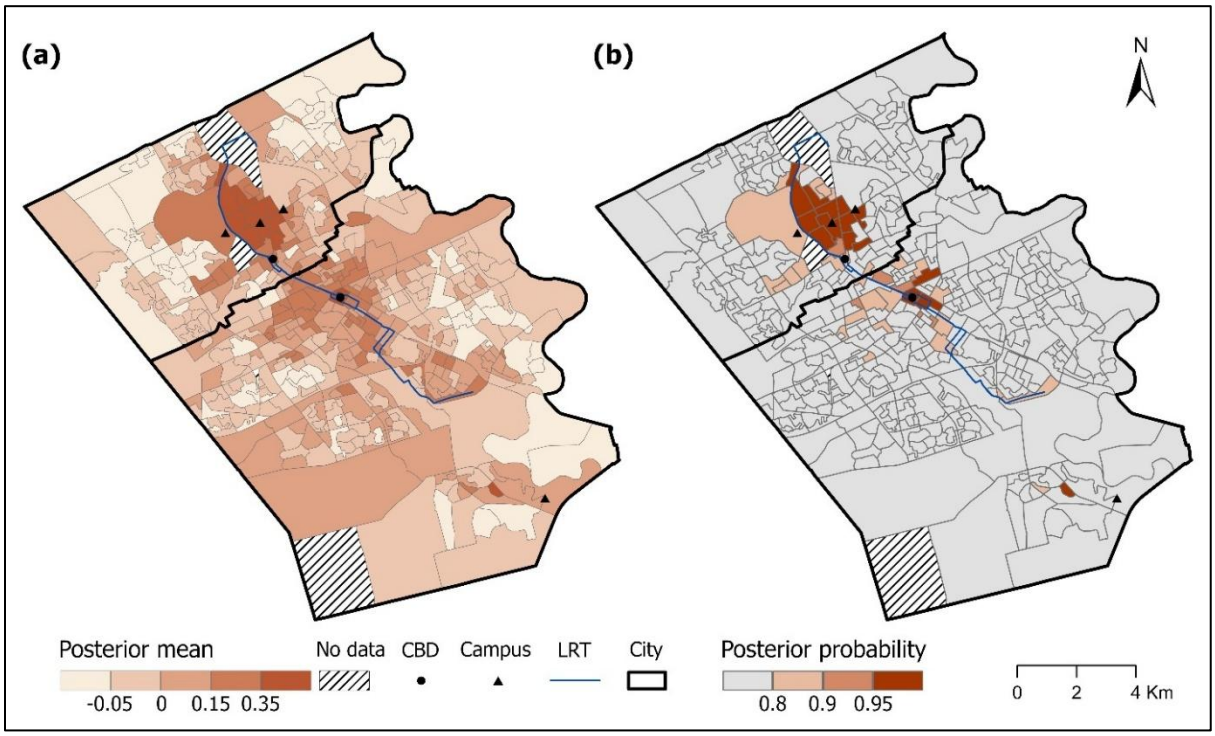


Figure 3-3: Shared spatial patterns between students and young adults: Posterior means (a) and posterior probabilities of positive values (b) of $\lambda_2\psi_{2,i}$ (representing the student spatial patterns explained by the shared component; the corresponding patterns for young adults, represented by $\frac{1}{\lambda_2}\psi_{2,i}$, are highly similar as λ_2 is close to 1).

Figure 3-4 further illustrates the overall spatial patterns of students, university graduates, and young adults, combining the effects of the shared components and group-specific spatial structures ($\upsilon_{i,k}$). Students were primarily concentrated around post-secondary campuses, with additional distribution observed along the LRT corridor. University graduates showed a pronounced city divide, with high concentrations throughout most of Waterloo. In contrast, high concentrations of university graduates in Kitchener were almost limited to downtown areas and the southeastern periphery. Young adults exhibited a centralized pattern, with strong concentrations along the LRT corridor.

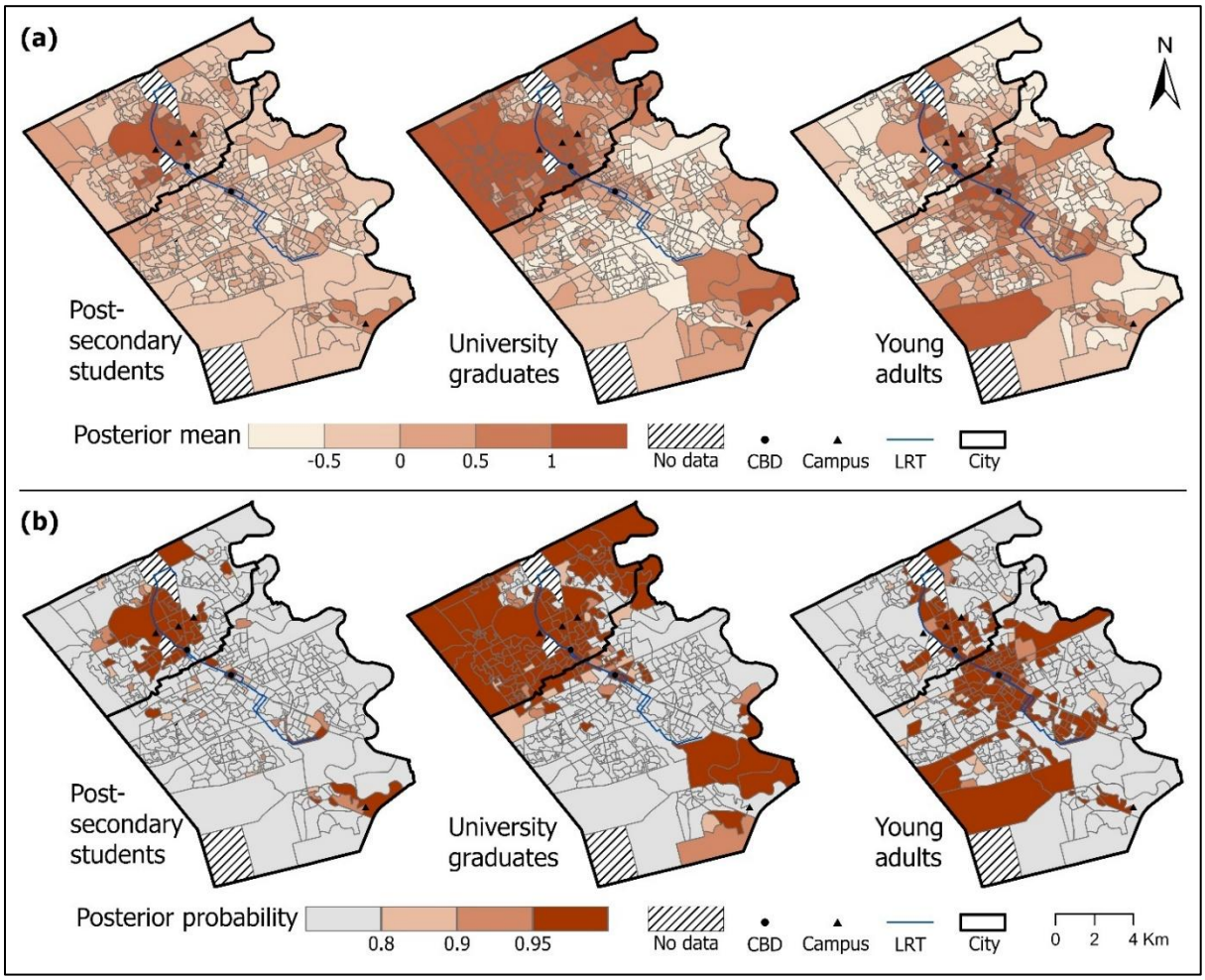


Figure 3-4: Spatial patterns of students ($v_{i,1} + \lambda_1\psi_{1,i} + \lambda_2\psi_{2,i}$), university graduates ($v_{i,2} + \frac{1}{\lambda_1}\psi_{1,i}$), and young adults ($v_{i,3} + \frac{1}{\lambda_2}\psi_{2,i}$): Posterior means (a) and posterior probabilities of positive values (b).

Since the empirical definition of students (18-24 years old) does not overlap with university graduates or young adults (both requiring individuals to be at least 25 years old), the shared components represent the spatial co-location of distinct population groups rather than individuals belonging to multiple categories. Nevertheless, graduate students (approximately 6,000 full-time graduate students in total), depending on their age, may be classified into either students or young adults, and some may also be included within university graduates. This reflects one dimension of the interconnected nature of the relevant urban processes, while also complicating the

interpretation of shared spatial patterns. As full-time graduate students likely exhibit residential patterns similar to undergraduate students, the shared components may partly reflect concentrations of graduate students. However, the group-specific spatial patterns of young adults and university graduates also revealed strong concentrations within the shared neighbourhoods, suggesting that the observed spatial patterns were unlikely to be explained solely by graduate students, who represented only a small proportion of these populations.

3.4.2 Temporal and spatiotemporal patterns

While the spatial pattern maps show the geographic distribution of students, university graduates, and young adults over the entire study period, it is also important to consider how these patterns evolved over time, particularly during this transformative period. Figure 3-5 presents the overall temporal trends for the three groups based on the shared component model. University graduates and young adults increased steadily, with a sharper rise between 2016 and 2021. In contrast, the share of students declined, particularly in 2021. Notably, the decline between 2011 and 2016 may not reflect an absolute decrease in the student population but rather a slower growth rate relative to the total population.

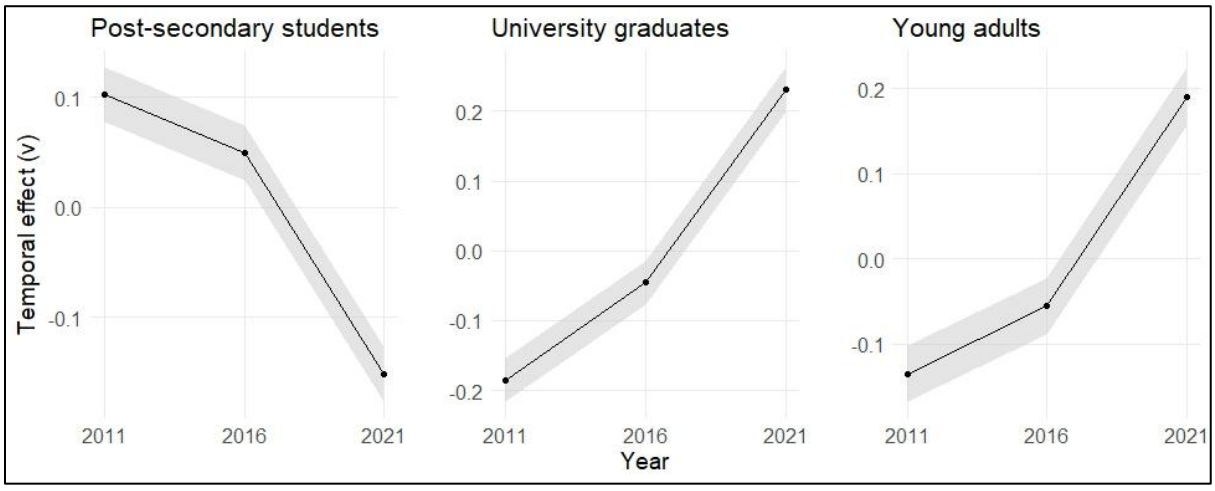


Figure 3-5: Overall temporal trends of students, university graduates, and young adults ($\nu_{j,k}$ with 95% credible intervals shaded).

Temporal variations were not spatially homogeneous and were dependent on local neighbourhood contexts. Figure 3-6 further shows the spatiotemporal patterns, mapping the posterior probabilities of positive space-time interaction term values ($\delta_{i,j,k}$). High posterior probabilities (> 0.8) identify spatiotemporal hotspots, where indicator values exceeded expectations based on overall spatial and temporal patterns. Conversely, low posterior probabilities (< 0.2) indicate cold spots, where indicator values were lower than expected. Students generally followed the overall spatial and temporal trends, with the only notable spatiotemporal hotspots appearing in 2016 in an area known as Northdale. This aligns with the Northdale Plan, introduced in 2012, which promoted intensification and resulted in a high concentration of high-rise PBSAs (Revington, 2022). University graduates and young adults exhibited more widespread and variable spatiotemporal patterns. The most prominent patterns emerged in 2021, when both groups showed hotspots near post-secondary campuses, especially for young adults. Young adults also had notable spatiotemporal hot spots along the LRT corridor during the same year.

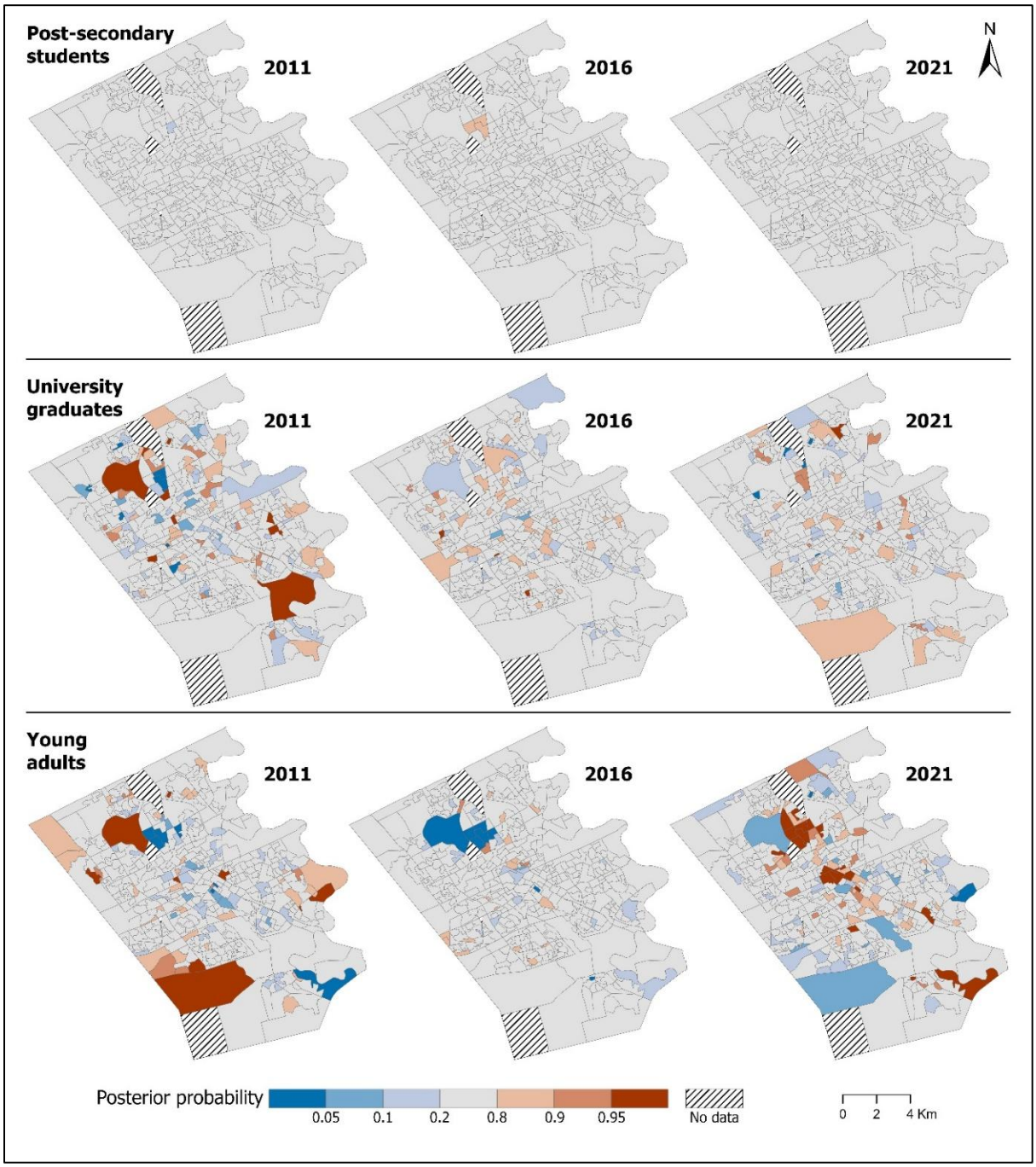


Figure 3-6: Spatiotemporal patterns of students, university graduates, and young adults: Posterior probabilities of positive values for $\delta_{i,j,k}$.

3.4.3 Covariate analysis results

Regression coefficients obtained from the model with covariates (Equation 3-3) were used to examine the associations between two binary indicators (transit proximity to campus and CTC status) and students, university graduates, and young adults. Figure 3-7 shows maps of the two covariates, while Figure 3-8 presents the temporally varying regression coefficients ($\beta_{m,j,k}$) and their fixed components ($\gamma_{m,k}$).

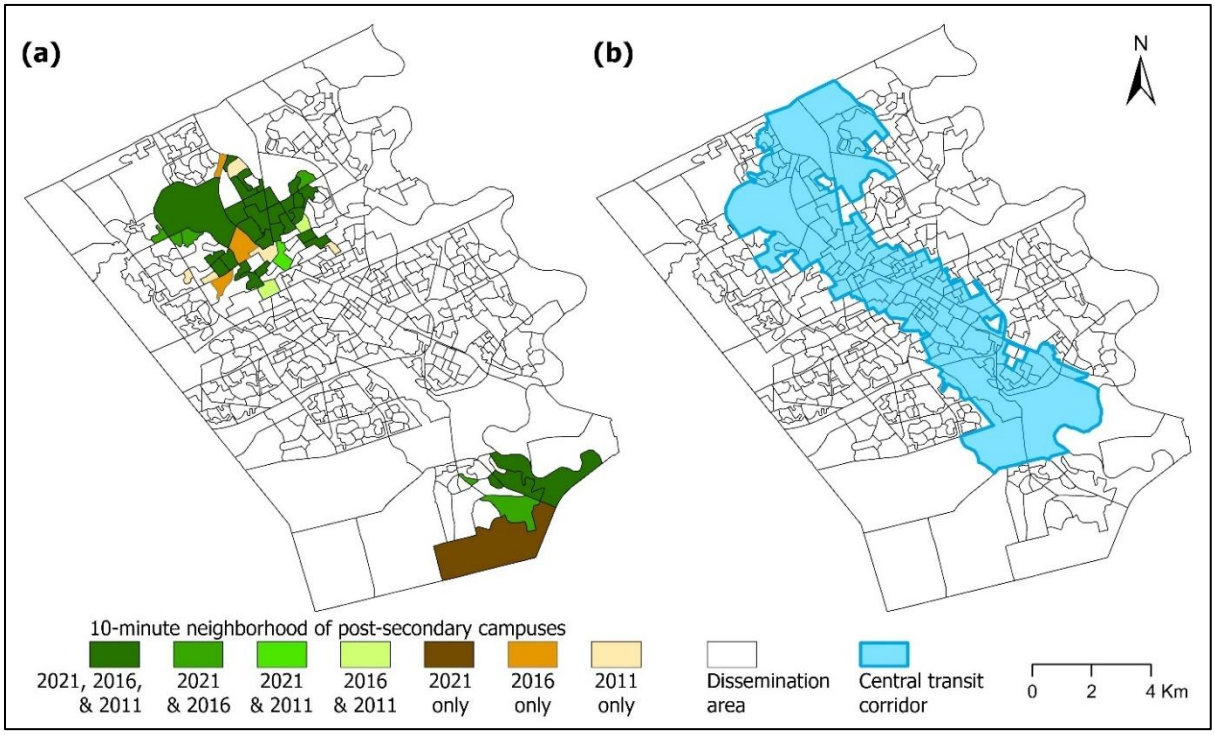


Figure 3-7: Maps of transit proximity to campus (10-minute campus-accessible neighbourhoods by transit or walking) by year (a) and the CTC (b).

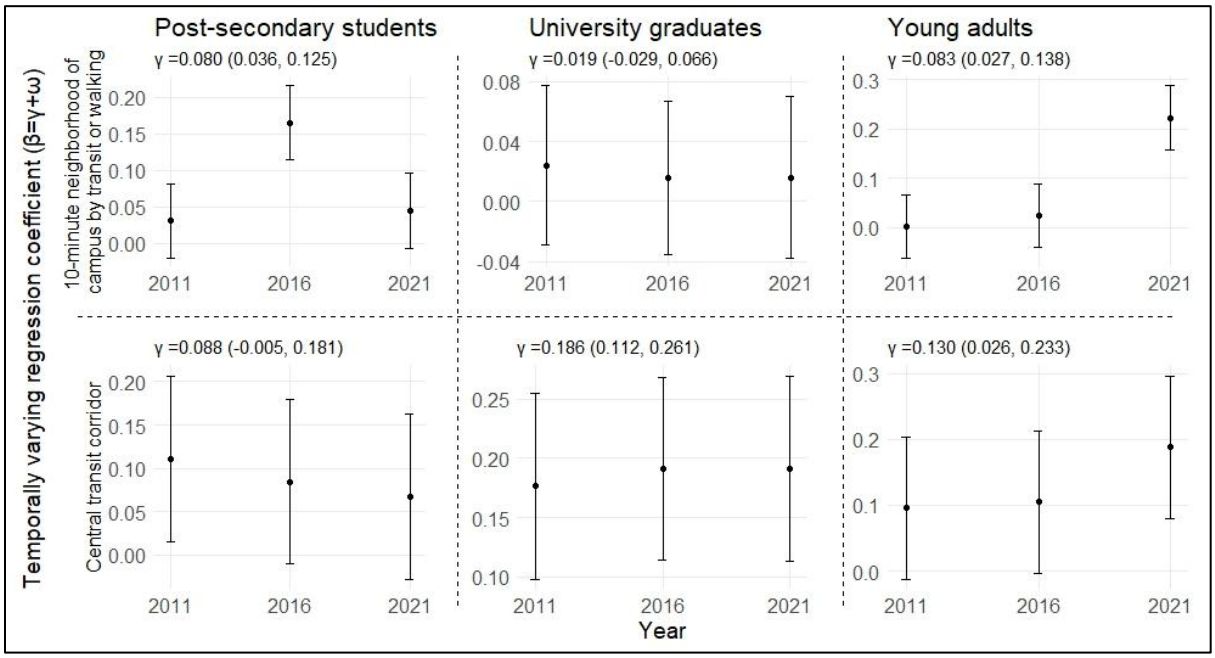


Figure 3-8: Associations between binary indicators (transit proximity to campus and CTC status) and students, university graduates, and young adults: temporally varying coefficients ($\boldsymbol{\beta_{m,j,k}}$ with 95% credible interval bars) and their fixed components ($\boldsymbol{\gamma_{m,k}}$ with 95% credible intervals in brackets).

The fixed components represent the average association across the study period and indicate that transit proximity to campus was positively associated with students and young adults at 95% credible intervals. The CTC was positively associated with university graduates and young adults and showed a marginally positive association with students at borderline significance. Temporally, the positive association between transit proximity to campus and students strengthened in 2016 but declined by 2021. The association between the CTC and students weakened over time, while it rose slightly for university graduates in 2016 and then stabilized. The associations between young adults and both transit proximity to campus and the CTC increased notably in 2021.

3.5 Discussion

3.5.1 Students sharing neighbourhoods with potential gentrifiers and young adults

Neighbourhoods shared by students and university graduates were primarily found around campuses in Waterloo (Figure 3-2), while shared areas between students and young adults extended across all campuses, both CBDs, and along the CTC (Figure 3-3). This discrepancy, along with the differing spatial patterns of university graduates and young adults (Figure 3-4), particularly the limited presence of university graduates in the majority of Kitchener, may reflect the city's historically working-class character and relatively lower living standards. While Kitchener has played an essential role in youthification by attracting young adults, possibly from diverse backgrounds, the share of university graduates has remained comparatively low. Nonetheless, redevelopment plans and signs of gentrification in Downtown Kitchener have long been documented (Davies, 2016), as further evidenced by the high concentration of university graduates, in those downtown neighbourhoods (Figure 3-4). While university graduates are not equivalent to gentrifiers, their concentration can signal potential gentrification as higher educational attainment is commonly associated with potential gentrifiers (Revington et al., 2023). University graduates also form a key component of Ley's sociocultural index[2] of gentrification used in past research (Moos, Revington, et al., 2019). Nevertheless, without population movement data, these spatial patterns represent only the observed concentration of highly educated populations and the sociocultural status of neighbourhoods, rather than direct evidence of active gentrification. Further examination is needed to determine whether and when university graduates moved into these neighbourhoods and whether their arrival was associated with gentrification.

Shared neighbourhoods located near campuses or CBDs, or within the CTC offer convenient access to campuses, shopping, dining, cultural, and recreational amenities, along with housing options that appeal to all three groups. Table 3-2 summarizes the shares of the three

[2] Ley's sociocultural index of gentrification, calculated as the average of the share of university graduates and the share of those employed in professional occupations, was also considered and showed patterns similar to those based on university graduates alone. However, it was not used in this study for two reasons: (1) university graduates, as a distinct group that is definitionally separate from the other two group, are more directly interpretable, and (2) occupation data have more missing values, particularly in DAs near campuses.

population groups and the dwelling characteristics within these neighbourhoods in 2021, along with their changes since 2011, in comparison to study area averages. These neighbourhoods are defined as DAs with significant joint spatial patterns (posterior probabilities > 0.8) in Figure 3-2 and Figure 3-3. Although no shared component among all three groups was included, the two sets of shared neighbourhoods showed some overlap. These overlapping areas, interpreted as shared by all three groups, are also included in Table 3-2.

Table 3-2: Shares of students, university graduates, and young adults, and dwelling characteristics within shared neighbourhoods in 2021, along with changes since 2011, in comparison to study area averages.

Shared neighbourhoods / Characteristics	Students and university graduates	Students and young adults	Students, university graduates, and young adults	Study area averages
Number of DAs	25	49	12	472
% Students	35.2 (+11.5)	24.0 (+3.3)	45.5 (+6.8)	10.6 (-0.3)
% University graduates	69.8 (+4.1)	49.3 (+10.4)	67.6 (+10.3)	40.2 (+9.2)
% Young adults	23.0 (+10.7)	28.2 (+5.0)	28.4 (+9.2)	16.6 (+1.9)
% Apartments	66.2 (+23.5)	74.2 (+3.3)	86.1 (+11.5)	31.4 (+1.4)
% Apartments in tall buildings (5 or more stories)	52.0 (+30.4)	48.3 (+14.4)	67.9 (+30.2)	17.5 (+4.3)
% Condominiums	46.3 (+30.3)	35.5 (+21.1)	59.7 (+37.6)	16.3 (+5.3)
% With 2 or fewer bedrooms	50.9 (+14.8)	70.0 (+0.2)	65.2 (+4.6)	37.4 (+2.7)
Average number of rooms	5.4 (-1.2)	4.4 (-0.4)	4.3 (-0.6)	6.1 (-0.4)
% Rented	66.8 (+25.2)	79.2 (+6.0)	86.8 (+12.5)	39.8 (+7.4)
$ Rent per room*	319.9 (+98.3)	309.7 (+93.3)	323.2 (+99.4)	224.3 (+64.5)
% Residents moved in the past 5 years	69.9 (+26.0)	72.5 (+7.8)	88.4 (+19.2)	44.6 (+2.8)

* Calculated as average rent (2021 dollars) divided by the average number of rooms, using DAs with available data only.

Compared to the entire study area, shared neighbourhoods not only had high proportions of students, university graduates, and young adults, but also experienced substantially faster growth in students and young adults during the study period. While the share of university graduates generally did not increase more rapidly within shared neighbourhoods, these neighbourhoods already had relatively high concentrations of university graduates at the beginning of the study period and maintained those concentrations over time. Such patterns suggest that these neighbourhoods were dominated by the three population groups and were becoming increasingly exclusive to them over time.

The attractiveness of these neighbourhoods may be partially explained by their dwelling characteristics. Compared to study area averages, shared neighbourhoods had higher proportions of renters and high-density housing, particularly tall apartment buildings and condominiums. These areas, especially those shared between students and young adults, were also characterized by small units with very few bedrooms. Neighbourhoods shared among all three groups had the highest proportions of apartments, tall buildings, and condominiums, reflecting a shared preference for high density and high-quality urban living. In addition, the development of such apartments, particularly condominiums, expanded rapidly during the study period, continuing to alter housing composition toward the needs of students, university graduates, and young adults. For students, the development of PBSAs and condominiums is a key feature of studentification, especially in the context of higher education internationalization, as international students are often thought to prefer high-quality apartments (Holton & Mouat, 2021; Kinton et al., 2018). "Condofication" is also recognized as an important form of inner-city gentrification that attracts highly educated and high-income residents (Lehrer & Wieditz, 2009). For young adults, small condominium units serve as an important housing form that facilitates youthification (Moos, 2016).

At the same time, these housing characteristics, combined with much higher rent per room than the study area average, pose barriers for other groups such as working-class families. While this research did not directly measure population movement, the substantially higher proportions of renters and residents who had moved within the past five years in shared neighbourhoods suggest high residential mobility. In the context of rapidly changing housing composition and rising housing costs, these conditions may signal potential displacement risk and increasingly

exclusionary housing environments. Exclusionary displacement, where changing housing composition makes neighbourhoods increasingly inaccessible to working-class residents, has been associated with condominium development and the loss of affordable rental housing in Canadian cities (Walks et al., 2021). Whether and how displacement occurred within these shared neighbourhoods warrants further investigation.

3.5.2 Influences of the COVID-19 pandemic and TOD

While students, university graduates, and young adults may reside within the same neighbourhoods, their concentrations do not necessarily follow the same trajectories over time. The spatiotemporal hotspots of young adults in 2021 (Figure 3-6) partially overlap with their shared spaces with students near campuses (Figure 3-3), suggesting increasing youthification in these neighbourhoods. This trend may intuitively be linked to the COVID-19 pandemic, when a shift to online learning likely led to student out-migration or reduced student influx, creating space for other groups. Notably, all 2021 spatiotemporal hot spots for young adults experienced absolute increases in young adult population since 2016, with most also seeing total population growth, indicating that the rise in proportion was not driven solely by a shrinking student or total population.

These shifts are also reflected in the covariate analysis results (Figure 3-8), which must be considered alongside another key contextual change: the opening of LRT in 2019. The extent of 10-minute campus-accessible neighbourhoods (Figure 3-7) did not expand substantially after the LRT's introduction, likely due to the existing density of bus stops and express routes serving campuses. These neighbourhoods were significantly associated with students and young adults, but not with university graduates. The temporally varying regression coefficient results show a sharp increase in the concentration of young adults in campus-proximate areas in 2021. In contrast, student concentrations rose notably from 2011 to 2016, likely due to high-density developments, but declined by 2021. This shift suggests that campus-proximate neighbourhoods became less studentified and more youthified during the pandemic. Such shifts may reflect both short-term disruptions associated with online learning and broader longer-term neighbourhood restructuring processes linked to intensification, changing housing composition, and mixed-use redevelopment.

The Northdale Plan, for example, promotes mixed-use development with a long-term goal to have one-third of residents to be non-students (Revington, 2022).

Regardless of the main causes of the shifts, they demonstrate the interconnection between studentification and youthification. As studentification slowed during the pandemic period, these neighbourhoods did not simply transition toward more socially mixed communities, but instead experienced increasing youthification. This pattern may reflect similarities in housing preferences between students and young adults, as both groups are commonly attracted to high-density housing, smaller units, transit accessibility, and urban amenities. As discussed previously, the increasingly exclusionary nature of housing in these neighbourhoods may have made them especially attractive to students and young adults while posing barriers for other residents. Such patterns may contradict planning intentions for socially mixed communities, as demographic change within these neighbourhoods appeared to occur largely among students, university graduates, and young adults rather than through broader diversification across different social groups

Although the LRT did not significantly reduce travel times to campus, it may still attract students, as commuters often prefer rail over buses when travel times are comparable due to perceived benefits like greater convenience, lower stress, and improved comfort (Scherer, 2010; Scherer & Zurich, 2012). Student commuters may conceivably accept slightly longer travel times when using the LRT, particularly given its direct service to university campuses. However, the covariate analysis results reveal a weakening relationship between students and the CTC over time. This may be explained by declining housing affordability in the CTC, especially after 2016 during LRT construction (Region of Waterloo, 2023). Evidence of early gentrification along the LRT route was documented even before its opening (Doucet, 2021; Ellis-Young & Doucet, 2024). The covariate analysis results show a consistently positive association between the CTC and university graduates, who may act as potential gentrifiers, with this association strengthening slightly in 2016. The CTC was also associated with young adults, whose concentration increased sharply in 2021, likely reflecting their preference for transit access, urban amenities, and employment opportunities along the LRT line.

Nonetheless, the extent to which the observed patterns along the CTC were influenced by the LRT opening remains unclear without further data, as both the LRT opening and the onset of

the pandemic occurred between 2016 and 2021. Post-pandemic trajectories within the CTC may follow multiple possible scenarios. Student concentrations may rebound as in-person learning fully resumes, and increasing return-to-office practices and improved transit accessibility may attract older professionals to the CTC, potentially reversing the spike in youthification. Alternatively, the increasing concentration of young adults observed in 2021 may reflect a long-term restructuring of the CTC toward increasingly youthified neighbourhoods. Regardless of the specific trajectory, the CTC is likely to continue posing barriers to disadvantaged and marginalized residents. Previous research has highlighted increasing intensification, luxury condominium development targeting young professionals, land value uplift, and changing commercial landscapes within the CTC, trends that may further reduce housing affordability and inclusiveness within TOD neighbourhoods (Huang et al., 2021, 2024; Webber, 2022).

3.5.3 Limitations and future research

This study has several limitations related to data and methodology. First, using the census-based student-aged population as a proxy for actual students introduced inaccuracies. Some individuals might be incorrectly included as students, while some actual students might be enumerated at their parental homes, leading to both overcounts and undercounts. Nonetheless, considering that Canada has a high post-secondary participation rate and that the spatial distribution of this age group broadly aligns with general local understanding of where students tend to live in the region, the variable provides a reasonable approximation of student geography. Without access to detailed student residential data, measuring studentification remains an empirical challenge. Future research could incorporate student housing surveys or supply-side data (e.g., student-oriented housing development plans) to validate studentification indicators.

Second, while the spatiotemporal dynamics of university graduates may signal potential gentrification patterns, such as the increasing concentration of university graduates within the CTC, where housing unaffordability and gentrification concerns have been documented, this study did not explicitly reveal gentrification patterns. Previous studies have used the share of university graduates, either alone or combined with professional occupations, as a sociocultural indicator of gentrification (Moos, Revington, et al., 2019; Revington et al., 2023). Nonetheless, an increasing

concentration of university graduates does not necessarily indicate gentrification without knowledge of the initial socioeconomic status of neighbourhoods and evidence of displacement. Such assessment is constrained by data limitations, including missing rent and income data in campus-proximate areas, possibly due to low reporting rates among student residents, and the lack of displacement data. Further investigation using alternative data sources or methods is therefore needed to determine whether, and to what extent, gentrification has actually occurred.

Third, while the shared component model identified overlapping spatial patterns, its use of a single scaling parameter assumes uniform contributions of participating variables across space. This aligns with common factor analysis approaches like principal component analysis but may mask spatial variation in relationships (e.g., stronger students–university graduates associations near campuses). Future work could explore methods that account for spatial heterogeneity. In addition, further research could examine a broader set of explanatory variables across different urban contexts, since only two covariates specific to the study area were included.

Finally, although the study period captures a transformative decade marked by both development and disruption, many long-term effects remain unknown. Post-pandemic data will be essential to assess the influences of the pandemic and TOD in the study area in future research. Neighbourhood change is a prolonged process, and extending the timeframe to earlier periods could offer additional insights. However, challenges such as highly inconsistent census geographic boundaries and variable definitions (e.g., the 18–24 age group not being available in earlier censuses) present obstacles that must be addressed.

3.6 Conclusion

This study employed a Bayesian modelling approach to examine the spatiotemporal patterns of students, university graduates, and young adults in a mid-sized knowledge economy region. It advances previous research by moving beyond bivariate correlation analyses to jointly analyze the spatiotemporal dynamics of three population groups. Shared neighbourhoods between students, university graduates, and young adults were primarily located near post-secondary campuses, CBDs, and along the CTC, and were characterized by high-density and high-cost rental housing.

Notably, the pandemic period saw increasing concentrations of young adults and university graduates in campus-proximate neighbourhoods, with youthification showing particularly sharp growth. Increasing youthification within the CTC during the 2016–2021 period, which encompassed both the LRT opening and the COVID-19 pandemic, was also observed. However, this was not accompanied by a parallel increase in student concentrations, a trend that warrants further investigation using post-pandemic data.

These findings suggest that studentification, youthification, and university graduate concentration operate as interconnected neighbourhood processes. When studentification slowed in areas shared with young adults and university graduates, these groups, especially young adults, continued to drive demographic change, leading to further youthification. While the COVID-19 pandemic was an exceptional disruption, other structural and institutional factors, such as enrolment trends, immigration policies affecting international students, and municipal efforts to diversify neighbourhood demographics, can also reshape studentification trajectories. The dwelling characteristics and relatively high housing costs in these areas may limit access for other population groups, such as low-income families. Whether this outcome was driven by temporary pandemic disruptions or intentional planning actions, its trajectory may conflict with goals for equitable and inclusive urban development. Likewise, the consistently positive association between the CTC and university graduates, together with the increasing youthification observed during the LRT opening and pandemic period, may not match the typical objectives of TOD for promoting accessible, inclusive, and affordable communities.

While these findings are drawn from Kitchener–Waterloo, they point to challenges faced by many university towns and knowledge economy regions. Such cities often benefit from the economic and sociocultural vibrancy associated with the influx of students, university graduates, and young adults, but they must also examine whether these processes contribute to the loss of affordable housing and potential displacement risk and address such challenges when they emerge. These challenges call for planning policies that expand affordable housing options and ensure that higher education growth, public transit development, and urban intensification do not limit housing access for other population groups in campus-proximate neighbourhoods and city centres. Future research should continue applying spatiotemporal analyses of different sociodemographic groups

across diverse urban contexts. Such efforts are essential for understanding the dynamics and interconnections among urban processes, informing equitable planning decisions, and supporting the development of socially inclusive neighbourhoods.

Chapter 4
Neighbourhood safety in a university town: The associations between studentification and crime and disorder

Summary

University and college towns represent distinctive physical and social environments that generate unique spatiotemporal patterns of crime and disorder. While on-campus offences have been widely examined, crime and disorder associated with studentification remain underexplored. Using Kitchener-Waterloo as a case study, a Bayesian hierarchical modelling approach was applied to analyze the associations between studentification and acquisitive crime, expressive crime, and disorder, and to assess how these associations vary across the academic calendar by distinguishing between academic terms and breaks as well as between business days and non-business days. Three studentification indicators (campus proximity measured by public transit time, student-oriented housing, and student-aged population) are used to enhance the robustness of the findings and to provide varied perspectives. The results reveal time-varying effects, with significant associations observed during academic terms but not during term breaks when students are largely absent. Within academic terms, expressive crime is linked to studentification primarily on non-business days, disorder is consistently associated with studentification and shows a stronger association on non-business days, and acquisitive crime is related to student-oriented housing throughout the term. These results highlight the need for targeted interventions in studentified neighbourhoods during academic terms to promote community safety and wellbeing, such as improved bylaw enforcement, strengthened building security, and enhanced coordination with police services.

4.1 Introduction

Crime and disorder are unevenly distributed across space and time. Environmental criminology links crime variability to physical and social environmental features that motivate or restrain criminal activity (Wortley & Mazerolle, 2008). In university and college towns, campus areas exhibit distinctive built environments, demographic compositions, and routine activities, often leading to crime patterns different from other urban zones. Since the late 1980s, campus crime, particularly in the United States, has received growing scholarly and policy attention as a significant social issue (Fisher & Sloan, 2022; Sloan & Fisher, 2010). However, the influence of post-secondary institutions extends well beyond their geographic boundaries, often transforming nearby neighbourhoods through studentification, in which increasing concentrations of post-secondary students (hereafter students) reshape housing markets, commercial activities, and physical and sociocultural environments (D. P. Smith, 2005; D. P. Smith et al., 2014). Given their proximity to campuses and the characteristics associated with studentification, such neighbourhoods may develop unique patterns of crime and disorder that warrant detailed investigation and targeted intervention.

Compared to on-campus offences, crime and disorder occurring in off-campus studentified neighbourhoods remain underexplored, despite their significance for the safety and wellbeing of both students and non-student residents. In the limited quantitative research on off-campus crime, surrounding neighbourhoods influenced by post-secondary institutions are often defined solely by spatial containment or adjacency (e.g., Cundiff, 2021; LaRue & Andresen, 2015). However, the influence of universities and colleges, particularly studentification, is spatially more complex, as not all campus-adjacent areas are studentified and studentification can extend well beyond immediate campus borders and may be associated with housing supply and transit networks. Furthermore, students follow academic calendars that have term breaks, which may differ markedly from the schedules of other residents, potentially generating distinct temporal patterns of crime and disorder that are characteristic of university and college towns.

This study seeks to further the understanding of crime and disorder patterns in relation to post-secondary institutions and students. Kitchener-Waterloo, a mid-sized urban area in Canada

that hosts three major post-secondary institutions, is used as a case study. A Bayesian hierarchical modelling approach is applied to analyze acquisitive crime (offences committed for material gain, such as theft), expressive crime (offences motivated by emotion or conflict, such as assault), and disorder (offences reflecting public order disturbances, such as public intoxication). The study has two main objectives: first, to determine whether crime and disorder are spatially associated with studentification by testing multiple indicators of studentified neighbourhoods; and second, to assess how such associations are temporally influenced by the academic calendar.

4.2 Background

4.2.1 Disorder and disorganization in studentified neighbourhoods

Studentification, referring to the influx and concentration of transient student populations that can displace or create tensions with long-term residents, has its roots in the concept of gentrification (D. P. Smith, 2005). Gentrification is commonly understood as the transformation of previously low-income neighbourhoods or vacant lands into areas occupied by middle-class in-movers (Lees et al., 2008). Although it is sometimes associated with potential benefits (e.g., increased fiscal revenues), existing literature frequently emphasizes its adverse impacts on original residents, including shifts in local services, rising housing costs, and direct or indirect displacement of disadvantaged groups (Atkinson & Bridge, 2004; Zuk et al., 2018). While studentification shares similarities with gentrification in transforming neighbourhoods, it is no longer driven solely by middle-class students due to increasingly diverse student backgrounds, and its forms have also evolved over time (Nakazawa, 2017). Early studentification typically involved converting single-family housing into low-quality houses in multiple occupation (HMOs) for students near expanding higher education institutions, while more recent forms have been characterized by the rise of purpose-built student accommodation (PBSA), including high-quality apartment buildings (Hubbard, 2009; Kinton et al., 2018; D. P. Smith & Hubbard, 2014). Studentification often leads to disruption to residential neighbourhoods due to student lifestyles, which can include late-night noise, social gathering, drinking, littering, property neglect, and other forms of disorderly conduct (Allinson, 2006; Munro & Livingston, 2012; Sage et al., 2012a). One purpose of PBSA is to

address neighbourhood concerns by redistributing and regulating student residential locations, yet it can also heighten socio-spatial segregation and create student enclaves with persistent nuisance and disorder (Sage et al., 2013).

Student-perpetrated disorder, particularly arising from partying and drinking, has been a reported concern by both post-secondary institutions and wider communities (Weiss, 2013). According to broken windows theory, high levels of visible disorder, such as public drinking and vandalism, may increase fear of crime, weaken social control, and encourage further disorder and crime, potentially escalating into more serious offences (Wilson & Kelling, 1982). Drawing on this framework, crime control strategies such as disorder-focused policing have been implemented in many regions as proactive efforts to maintain order and reduce crime (Braga et al., 2015). Nevertheless, addressing "broken windows" in studentified neighbourhoods is often viewed as futile due to a constantly changing transient population and inadequate policing in response to pervasive disorder (Woldoff & Weiss, 2018).

Another aspect to link studentification to crime and disorder is through social disorganization theory. This perspective argues that crime is more prevalent in neighbourhoods with structural characteristics that undermine informal crime control, such as low socioeconomic status (e.g., poverty and limited education attainment), residential instability, and racial heterogeneity (Bursik & Grasmick, 1999; Elliot et al., 1996; Sampson & Groves, 1989). Sampson et al. (1997) identify collective efficacy as the intervening factor between these neighbourhood conditions and crime, reflecting the degree of social cohesion and the shared willingness of community members to exercise informal social control. Studentification is characterized by residential transience, tensions between students and non-student residents, and possible ethnic and cultural heterogeneity within student populations, depending on the institution, all of which have the potential to weaken collective efficacy and contribute to disorder and crime. Furthermore, students often show limited community engagement, lack awareness of ordinances, disregard rules and norms, and rarely intervene in peers' deviant behaviour, while non-student residents may feel unwilling or unable to act, thereby making social control particularly difficult to sustain in studentified neighbourhoods (Munro & Livingston, 2012; K. H. Powell, 2014; Woldoff & Weiss, 2018).

4.2.2 Crime opportunities in studentified neighbourhoods

Opportunities contribute to the occurrence of all forms of offences (Felson & Clarke, 1999). Opportunity theories are widely cited to explain the uneven spatial and temporal distribution of crime. Routine activity theory states that a crime occurrence requires the convergence of a motivated offender, a suitable target, and the lack of effective guardianship in space and time (Cohen & Felson, 1979). Crime pattern theory further emphasizes that crime patterns are shaped by the routine movements of both potential criminals and victims. Offenders develop awareness spaces through their daily activities and typically encounter and select attractive targets whose activity spaces overlap with their awareness spaces (Brantingham & Brantingham, 1993). These theories help explain the concentration of crime in crime generators, where large numbers of individuals share activity spaces and create crime opportunities, and crime attractors, where the perceived crime opportunities draw intentional offenders (Brantingham & Brantingham, 1995). For example, bar districts can function as both crime generators and crime attractors, where potential offenders and targets frequently interact and alcohol consumption often heightens offender aggression and target vulnerability. In university and college towns, a considerable proportion of crime incidents involving students, as offenders and/or victims, are linked to parties and the use of alcohol or other substances, whether on campus, in drinking establishments, or within studentified neighbourhoods (A. Allen & Jacques, 2013; Bennett & Holloway, 2018; Brower & Carroll, 2007; Weiss, 2013; Weiss & Dilks, 2016).

While important, partying and intoxication are surely not the sole contributor to abundant crime opportunities in studentified neighbourhoods. Crime pattern theory highlights the roles of activity nodes (e.g., workplaces, schools, and leisure locations) and paths connecting nodes, where potential offenders and targets routinely intersect (Brantingham & Brantingham, 1993, 1995). Studentified neighbourhoods, in addition to their already high residential density due to HMOs and PBSAs, are typically located near or contain major activity nodes such as university campuses, transit hubs, bars, restaurants, and other businesses targeting students. These areas attract high levels of human activity and create numerous opportunities for various types of crime. Furthermore, students are often viewed as attractive targets for crime, both on campus and off campus, due to their perceived vulnerability and possession of valuable personal items (Cundiff, 2021; Fisher et

al., 1998; Gregory, 2022; Kenyon, 1997). In studentified neighbourhoods, the number of students who routinely carry expensive items (e.g., laptops), student lifestyles (e.g., walking out late at night), students' lack of knowledge about personal and property security, poor management and inadequate security measures in student housing, and the limited reach of campus security beyond campus boundaries all contribute to the concentration of suitable targets with insufficient guardianship, thereby facilitating crime opportunities.

Crime opportunities and occurrences exhibit heterogeneity not only across space but also over time, with the spatial and temporal dimensions inherently interconnected. Activity nodes highlighted in crime pattern theory often function with temporal constraints, limiting the spatiotemporal convergence of potential offenders and suitable targets (Ratcliffe, 2006). Examples include outdoor leisure spaces such as parks, which are typically more active during summer months; workplaces and schools, which generally operate during business hours on weekdays; and bars and nightclubs, which tend to be busiest at night, especially on weekends. Crime seasonality (e.g., Andresen & Malleson, 2013; Linning, 2015), the influence of weekends or holidays on crime rates (e.g., Cai & Tan, 2025a; Yang et al., 2020), and intra-day crime patterns (Matijosaitiene et al., 2019; Uittenbogaard & Ceccato, 2012) have been widely researched. Studentified neighbourhoods are no exception to spaces where crime opportunities follow temporal patterns. While students often have more irregular schedules and their leisure activities, such as partying and drinking, tend to be more disruptive, these areas generally resemble other residential neighbourhoods, with work or school routines during weekdays and leisure concentrated on weekends and holidays. However, studentified areas exhibit distinct seasonality, that is, during academic term breaks, many students leave, leading to a sharp decline in population and activity (Kinton et al., 2016; Sage et al., 2012b). This vacancy typically reduces disorder and crime opportunities, although offences like break and enter could potentially increase due to the lack of capable guardianship.

4.2.3 Empirical evidence on the influence of studentification on crime and disorder

Although empirical research explicitly examining the influence of studentification on crime and disorder remains limited, campus-proximate or student-dominated neighbourhoods have been considered in some studies conducted in university and college towns. In London, Ontario,

Malczewski and Poetz (2005) found that neighbourhoods adjacent to campuses experienced elevated residential burglary risks and identified a positive association between average dwelling value and burglary risk in those areas using geographically weighted regression. In Madison, Wisconsin, Brower and Carroll (2007) used mapping techniques to analyze both spatial and temporal patterns of police calls, revealing that noise complaints peaked around midnight in areas where student and long-term resident populations intersected, while assaults and batteries peaked after bar closing times along streets with a high concentration of campus bars.

In a study that directly quantified the relationship between university locations and crime, LaRue and Andresen (2015) applied spatial regression in Ottawa and found that neighbourhoods containing university campuses were positively associated with burglary and motor vehicle theft, after controlling for other neighbourhood crime predictors. Similarly, Cundiff (2021) employed multilevel negative binomial regression to analyze 54 cities with colleges in United States and found positive associations between campus-bordering neighbourhoods and crime rates of robbery, larceny, and burglary. Using the same dataset, Tapia et al. (2024) found that neighbourhoods peripheral to campuses experienced elevated crime rates, particularly for property crimes. While these quantitative studies confirmed an association between campus-adjacent neighbourhoods and crime, implying the influence of campuses and student populations, they did not formally establish a relationship between studentification and crime. It is important to note that neighbourhoods bordering campuses are not necessarily studentified, particularly when larger units of analysis, such as census tracts, are used. Moreover, studentification can extend beyond campus-adjacent areas, especially in cities with well-developed public transit systems.

Some qualitative research has contributed additional insights into the link between studentification and crime or disorder. Woldoff and Weiss (2018) identified perceptions of neighbourhood decline and disorder attributed to studentification in Morgantown, West Virginia, noting that non-student residents had to normalize student-perpetrated disorder to avoid further conflicts due to ineffective social control associated with high student residential turnover and limited responsiveness from local authorities. Gregory (2022) found that students living in studentified neighbourhoods in Johannesburg, South Africa were vulnerable to targeted crimes

such as robbery and burglary, and highlighted the role of housing type, noting that PBSAs were perceived as safer than HMOs.

Purely spatial studies of crime are limited because spatial crime patterns do not necessarily remain consistent over time. In a temporal study of campus crime seasonality in Brantford, Ontario, Hodgkinson and Vamvakaris (2025), using regression analysis, found positive associations between academic terms and total police calls, assault, social disorder, and violent crime on the university campus, with most regression coefficients large enough to indicate substantively meaningful effects. Such seasonal fluctuations in crime and disorder, driven by the academic calendar of post-secondary institutions, may conceivably extend beyond campus boundaries into studentified neighbourhoods and should be integrated into spatial crime analyses.

4.3 Methodology

4.3.1 Statistical modelling

This study adopted a Bayesian hierarchical regression modelling approach to assess the associations between studentification and acquisitive crime, expressive crime, and disorder, and to examine how these associations vary across the academic calendar. Acquisitive crimes included theft, motor vehicle theft, fraud, break and enter, robbery, and extortion; expressive crimes included assault, threatening, criminal harassment or stalking, and sex offence; and disorder offences included indecent act, drugs, liquor offence, property damage, gaming and betting, unwanted contact, disturbance, dispute, intoxicated person, unwanted person, graffiti, and bylaw violation. The academic calendar was operationalized by distinguishing academic terms from term breaks and business days from non-business days (i.e., weekends and public holidays), resulting in four categories of days: business days during terms, non-business days during terms, business days during breaks, and non-business days during breaks. To more accurately capture human activity patterns, a day was defined as a 24-hour period starting at 6 p.m. on the previous evening. For example, Friday night, which often involves heightened student nightlife and social activities, was counted as part of Saturday and therefore classified as a non-business day.

Crime and disorder counts, rather than rates, were analyzed because no suitable population data were available to accurately represent the at-risk population, particularly considering population changes across day categories. The residential population count was incorporated as a covariate to serve as a control variable, consistent with common practice in the literature (e.g., Gruenewald et al., 2023; LaRue & Andresen, 2015; Quick et al., 2019). Previous research has suggested the use of ambient population measures that estimate the number of individuals present in an area during specific times to approximate the population at risk (Malleson & Andresen, 2016). However, no high spatial resolution dataset for the study area was available that could also capture temporal variations associated with the academic calendar.

For each of the three types of offences considered, let $Y_{i,j}$ denotes the occurrence count in neighbourhood i ($i = 1, 2, \dots, n$, where n is the total number of neighbourhoods in the study area) during time period j ($j = 1, 2, 3, 4$ corresponding to the four day categories). The statistical model is specified in Equation 4-1 below.

$$Data\ model: Y_{i,j} \sim Poisson(E_j \mu_{i,j})$$
$$Process\ model: \log(\mu_{i,j}) = \alpha_j + S_{i,j} + U_{i,j} + \lambda_j Z_i + \sum_{k=1}^{K} \beta_k X_{k,i} \quad (4\text{-}1)$$

$Y_{i,j}$ was modelled in a Poisson distribution, commonly applied to count data, where the expected count (E_j) was derived under the assumption that occurrences were evenly distributed across space and time (i.e., the total number of offences divided by the total number of days in the study period, multiplied by the number of days in time period j, divided by n). The natural log of the relative risk ($\mu_{i,j}$) was expressed as the sum of an intercept (α_j), structured (S_{ij}) and unstructured (U_{ij}) spatial random effects to capture spatial autocorrelation and overdispersion, K control variables ($X_{k,i}$) with regression coefficients (β_k), and a studentification indicator (Z_i) with its regression coefficient (λ_j). Control variable effects were restricted to be constant across day categories, while all other effects were category-specific. Vague Gaussian priors were assigned to intercepts and

regression coefficients. Structured spatial effects followed intrinsic conditional autoregressive priors to reflect positive spatial autocorrelation (i.e., neighbouring areas tend to exhibit similar counts; Besag et al., 1991). Unstructured spatial effects for the four categories of days were modelled jointly using a multivariate normal distribution to account for correlated random errors across categories. Adapted from Gruenewald et al. (2023), this model accounts for common sources of spatial random errors, such as measurement errors, while allowing each day category to exhibit distinct overall levels of crime or disorder, spatial offence patterns, and the influence of studentification on crime or disorder.

4.3.2 Study area, data, and variables

The study area is Kitchener-Waterloo, a mid-sized urban area in the Region of Waterloo, Ontario, Canada, located approximately 100 kilometres west of Toronto. Although administratively distinct, Kitchener and Waterloo are often viewed as "twin cities" and collectively referred to as "Kitchener–Waterloo" due to their geographic proximity. The study area encompasses approximately 201 km² of land area and had a census residential population of about 338,000 in 2016. Kitchener-Waterloo is one of the fastest-growing areas in Canada and a leading innovation hub, hosting numerous technology firms and supporting a vibrant knowledge economy. Although not generally characterized as a high-crime area, Kitchener-Waterloo experienced notable increases in crime prior to the COVID-19 pandemic. The crime severity index, which measures both the volume and seriousness of crime, rose significantly and exceeded that of comparable regions by a considerable margin (KPMG, 2023).

Kitchener-Waterloo is also home to three major post-secondary institutions: the University of Waterloo and Wilfrid Laurier University, both of which operate their main campuses in Waterloo, and Conestoga College, a polytechnic institution with a campus in Waterloo, located near the university campuses, and another in Doon, a southern suburban community in Kitchener. There are also small satellite campuses in the central business district (CBD) of Kitchener, namely Downtown Kitchener, but they are not considered in this study due to their limited scale and specialized scope. Students enrolled at the three institutions accounted for more than 59,500 residents in the Region of Waterloo in 2019, the vast majority of whom resided within Kitchener-

Waterloo, largely in off-campus housing (Region of Waterloo, 2020). Such concentration of students makes the study area an ideal case for examining the influence of studentification.

A study area map is provided in Figure 4-1. The dissemination area (DA) was used as the neighbourhood spatial unit of analysis to capture detailed socioeconomic and demographic variations that might be masked when using census tracts or other larger spatial units (Prouse et al., 2014). Three of the 467 DAs within the study area were excluded from the analysis due to insufficient data. This study used crime data between 2015 and 2019, obtained from the Waterloo Region Police Service, and census data from 2016, available from Statistics Canada. These datasets were selected in lieu of more recent years of crime data to avoid the impacts of the COVID-19 pandemic that affected both overall crime counts and the spatial distribution of crime due to changes in human activity patterns (Andresen & Hodgkinson, 2023; Hodgkinson & Andresen, 2020). Similarly, the 2021 census was not used, as it reflects pandemic-era conditions that are not representative of the study period. For example, many DAs recorded lower shares of student-aged population in 2021 compared to 2016, likely due to temporary student relocation rather than a gradual decline in student population, as the shift to online teaching led many students to move away from university towns and return to their homes (Prada-Trigo et al., 2022, 2024). Although pandemic-related effects are important and warrant further investigation, they are beyond the scope of the current study.

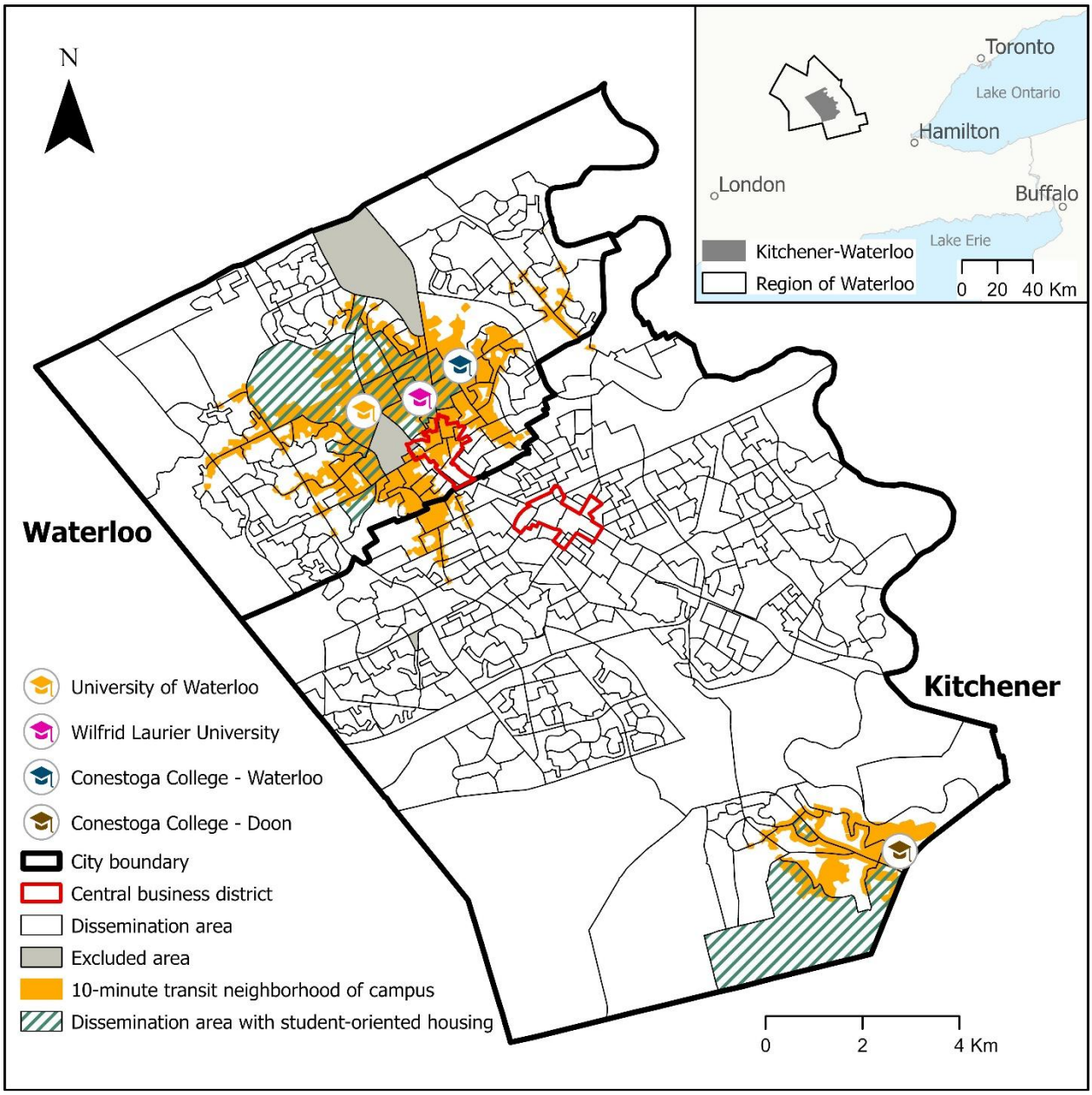


Figure 4-1: Study area context map showing DAs, campus locations, transit-accessible neighbourhoods of campuses, and student-oriented housing in Kitchener-Waterloo.

Main campus locations, where academic activities take place and most on-campus residences are situated, are shown in Figure 4-1. Three indicators of studentification around these

campus areas were considered and modelled separately in this study. The first was campus proximity, defined as areas within a 10-minute walk or transit ride to stops serving the campuses, reflecting typical student commute times of 5 to 15 minutes based on local student surveys (Dhillon et al., 2021). As shaded on the map, these areas were delineated using 2016 General Transit Feed Specification (GTFS) data from OpenMobilityData (transitfeeds.com). This indicator was operationalized as a binary variable, with a value of 1 assigned to DAs where the population-weighted centroid (available from the census) fell within the 10-minute transit neighbourhoods and 0 otherwise.

The second indicator was student-oriented housing, including PBSAs (the most common form), apartment- or house-style student residences embedded within residential neighbourhoods, and any other rental apartment buildings explicitly marketed to students. To compile these data, building permit records were filtered to identify developments described as student rentals, student apartments, or student residences (residences located within core campus areas were excluded). Since only a small proportion of student rental apartments could be identified using building permits, online searches were conducted on rental company websites and rental listing platforms to identify buildings advertised as student rentals. Field investigations were then undertaken to resolve uncertainties by verifying whether buildings were occupied by students or displayed visible signs of student rentals. Although student housing intensity could theoretically be measured using unit or bed counts, no official source systematically identified such information, and compiling this information at the DA level would require extensive searching across multiple sources and substantial subjective judgment beyond the scope of this study. As shown on the map, this indicator was therefore operationalized as a binary variable, with DAs assigned a value of 1 if student-oriented housing was present. Although data on exact bed counts were unavailable, available data sources indicated that all such DAs contained large-scale student housing developments exceeding 100 beds. As a result, a binary variable was considered both practical and meaningful at the DA level. The third indicator of studentification was the percentage of the student-aged (18–24) population in each DA, derived from census data and used as a proxy for the share of the student population (Foote, 2017; Revington et al., 2023). The spatial distribution of this variable is presented in Figure 4-2, together with maps of crime and disorder.

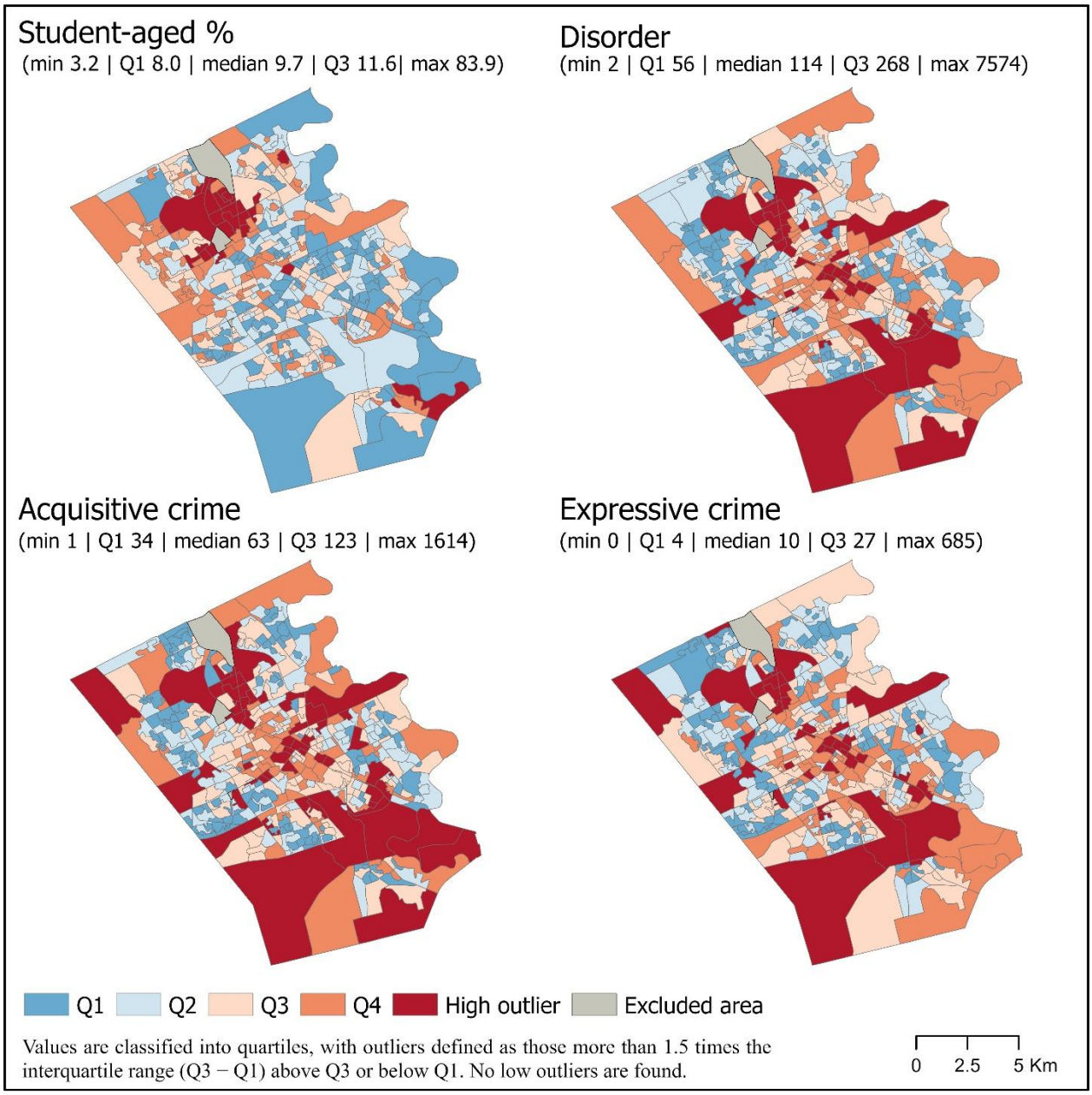


Figure 4-2: Spatial distribution of student-aged population, acquisitive crime, expressive crime, and disorder in Kitchener-Waterloo, displayed as box maps (the cartographic counterpart of boxplots).

Police-reported occurrences between 2015 and 2019 were grouped into acquisitive crime, expressive crime, and disorder. Five-year aggregated offence counts were used to mitigate year-to-year volatility in small areas. An initial visual inspection of Figure 4-1 and Figure 4-2 suggests some degree of overlap between areas of studentification and areas with elevated crime and disorder. To assess the influence of studentification, this study aimed to focus on off-campus crime only. However, because the crime data were offset to the nearest street intersections for privacy, distinguishing on-campus from off-campus incidents was not feasible. To address this limitation, all models were also tested with the four DAs containing campuses excluded, and the main findings remained unchanged.

To examine temporal variation in the associations with studentification, occurrences were disaggregated into four categories of days. While the three institutions follow broadly similar but not fully consistent academic calendars, this study adopted the calendar of the University of Waterloo, as it accounted for most students. This classification resulted in 1,124 business days during terms, 479 non-business days during terms, 130 business days during breaks, and 93 non-business days during breaks. Detailed academic schedules, counts of each specific crime and disorder type, and spatial autocorrelation test results (justifying the inclusion of a spatially structured effect term in the model) are provided in Appendix C.

Additional datasets were obtained to derive control variables for crime and disorder. CBD, park and bus stop locations from Region of Waterloo Open Data were used to reflect effects of built environment features. The 2016 Ontario Marginalisation Index (On-Marg), published by Public Health Ontario, was used to control for neighbourhood socioeconomic characteristics. Including four indicators (residential instability, material deprivation, dependency, and ethnic concentration) derived from census data using principal component factor analysis, On-Marg captures socioeconomic disadvantages, reduces the risk of multicollinearity compared to using individual census variables, and is well suited for crime analysis in the Ontario context (Matheson, 2018; Wang et al., 2019). Descriptions and summary statistics for all variables are presented in Table 4-1.

Table 4-1: Descriptions and summary statistics for regression variables ($N = 464$)

Dependent variables: Crime and disorder				
Offence count, standardized to 365 days for comparison: Mean (SD)				
	Business days during terms	*Non-business days during terms*	*Business days during breaks*	*Non-business days during breaks*
Acquisitive crime	28.73 (46.11)	21.14 (34.28)	29.86 (46.05)	20.33 (32.57)
Expressive crime	5.29 (10.30)	4.51 (10.44)	4.50 (9.09)	3.90 (8.20)
Disorder	48.16 (101.69)	69.73 (152.94)	49.35 (96.88)	59.74 (119.22)
Covariates: Studentification indicators (Z_i), modelled separately				
Variable: Description				**Mean (SD)**
Campus proximity: DAs within 10-minute transit neighbourhoods of campuses				0.09 (Binary)
Student-oriented housing: Presence of student-oriented housing within DAs				0.03 (Binary)
Student-aged %: Percentage of census population aged 18-24				11.01 (8.03)
Covariates: Control variables ($X_{k,i}$), included in every model specification				
Variable: Description				**Mean (SD)**
Population size: Census population (hundred)				7.27 (6.66)
Residential instability (On-Marg indicator): Concentrations of individuals with high family or housing instability (renters, singles, etc.)				0.26 (1.08)
Material deprivation (On-Marg indicator): Concentrations of individuals with limited access to basic material needs (low incomes, low education attainments, etc.)				-0.14 (0.86)
Dependency (On-Marg indicator): Concentrations of individuals without employment incomes (seniors, children, etc.)				-0.26 (0.78)
Ethnic concentration (On-Marg indicator): Concentrations of recent immigrants and visible minorities				-0.02 (0.75)
Distance to CBD: Distance (km) to the nearest CBD (Uptown Waterloo or Downtown Kitchener)				2.49 (1.70)
Parks: Presence of parks (community/neighbourhood level or above) within DAs				0.42 (Binary)
Bus Stops: Stop density per km^2				15.29 (13.33)

4.4 Results

With three types of offences examined and three studentification indicators assessed separately, a total of nine model specifications were fitted. Table 4-2 presents regression coefficient estimates in the form of relative risks (i.e., exponentiated coefficients), indicating the proportional change in crime or disorder for a one-unit increase in a covariate (or, for binary variables, when the variable equals one rather than zero), holding other covariates constant. For example, the relative risk of 1.827 for student-oriented housing (binary) on disorder on business days during terms indicates

that the presence of student-oriented housing is associated with an 82.7% increase in disorder counts. For the percentage of student-aged population (continuous), the relative risk of 1.017 indicates that each one-percentage-point increase is associated with a 1.7% increase in disorder counts. A relative risk is considered significant if consistently greater or lower than 1 at the 95% credible interval (CI). As previously described, regression coefficients for studentification indicators were allowed to vary by day category, while those for control variables were constrained to be consistent across day categories.

Table 4-2: Regression coefficient estimates (posterior means and 95% CIs of relative risks)

Covariate	Acquisitive crime	Expressive crime	Disorder
Campus proximity as the studentification indicator (time-varying effects)			
λ_1 (term - business)	1.214 (0.902, 1.634)	1.068 (0.738, 1.545)	1.254 (0.928, 1.695)
λ_2 (term - non-business)	1.288 (0.941, 1.762)	1.302 (0.892, 1.907)	1.472 (1.096, 1.975)*
λ_3 (break - business)	1.093 (0.805, 1.483)	0.785 (0.503, 1.225)	1.082 (0.796, 1.471)
λ_4 (break – non-business)	1.103 (0.784, 1.550)	1.050 (0.674, 1.636)	1.230 (0.909, 1.663)
Control variables (consistent effects over time)			
Population size	1.070 (1.055, 1.084)*	1.063 (1.046, 1.080)*	1.067 (1.053, 1.081)*
Residential instability	1.330 (1.191, 1.485)*	1.417 (1.240, 1.619)*	1.553 (1.394, 1.729)*
Material deprivation	1.056 (0.937, 1.190)	1.202 (1.043, 1.387)*	1.093 (0.972, 1.228)
Dependency	0.954 (0.852, 1.069)	0.904 (0.788, 1.037)	0.864 (0.773, 0.965)*
Ethnic concentration	0.996 (0.868, 1.143)	0.982 (0.831, 1.160)	0.961 (0.840, 1.100)
Distance to CBD	0.853 (0.804, 0.904)*	0.877 (0.816, 0.942)*	0.885 (0.834, 0.939)*
Parks	1.228 (1.038, 1.454)*	1.255 (1.023, 1.541)*	1.305 (1.107, 1.539)*
Bus stops	1.010 (1.003, 1.017)*	1.012 (1.004, 1.020)*	1.011 (1.004, 1.017)*
Student-oriented housing as the studentification indicator (time-varying effects)			
λ_1 (term - business)	1.732 (1.043, 2.878)*	1.410 (0.763, 2.603)	1.827 (1.088, 3.070)*
λ_2 (term - non-business)	1.728 (1.016, 2.941)*	1.887 (1.009, 3.533)*	2.281 (1.380, 3.772)*
λ_3 (break - business)	1.332 (0.797, 2.226)	0.922 (0.463, 1.835)	1.301 (0.770, 2.197)
λ_4 (break – non-business)	1.435 (0.820, 2.509)	1.252 (0.632, 2.484)	1.293 (0.775, 2.156)
…Coefficient estimates for control variables are included in Appendix C.			
Student-aged % as the studentification indicator (time-varying effects)			
λ_1 (term - business)	1.008 (0.995, 1.021)	1.009 (0.994, 1.025)	1.017 (1.003, 1.030)*
λ_2 (term - non-business)	1.009 (0.995, 1.022)	1.016 (1.000, 1.032)*	1.024 (1.011, 1.037)*
λ_3 (break - business)	1.002 (0.989, 1.015)	0.999 (0.983, 1.015)	1.010 (0.997, 1.024)
λ_4 (break – non-business)	1.005 (0.991, 1.019)	1.006 (0.989, 1.022)	1.010 (0.997, 1.023)
… Coefficient estimates for control variables are included in the Appendix C.			

Note: All covariates were mean-centred. * Represents significance at the 95% CI.

Control variable results are reported only for models with campus proximity as the studentification indicator, as results from other specifications are very similar in value and unchanged in significance, and are therefore omitted to avoid redundancy. While not the central focus of this study, these results show positive associations of population size, residential instability, proximity to CBDs, parks, and bus stops with all three offence types, consistent with expectations and criminology theories. Residential instability contributes to social disorganization by disrupting neighbourhood networks and weakening crime control, while CBDs, parks, and bus stops are locations of high human activity that can act as crime generators and attractors. Material deprivation, as another structural condition linked to social disorganization, is associated with expressive crime. Dependency is negatively associated with disorder, likely reflecting demographic composition (more children and seniors) and greater community stability and guardianship provided by parents and older adults.

Focusing on the studentification indicators, Figure 4-3 presents their regression results as posterior means of relative risks with 95% CIs, enabling clearer identification of significant associations and comparisons across time periods and offence types. Campus proximity is significant only for disorder on non-business days during academic terms. Considering the suburban and peripheral location of the Doon campus of Conestoga College, and the potentially different commuting patterns compared to the clustered campuses in the City of Waterloo, a specification with separate campus proximity variables (one for Doon and another for the Waterloo campuses) was tested, but this did not alter the results in terms of significance. Such specifications were not tested for the other two studentification variables as they were directly defined at the DA level, reflecting localized student housing presence and student clustering regardless of campus affiliation. Student-oriented housing shows significant effects on non-business days during terms for all offence types, and on business days during terms for acquisitive crime and disorder. Student-aged population is significant for disorder during terms, on both business and non-business days, and for expressive crime during terms, only on non-business days. Models that constrained studentification effects to be consistent across day categories were tested and compared with the current models using the deviance information criterion (DIC; Spiegelhalter et al., 2002). In all cases the current models yielded lower DIC values, with most showing moderate to strong

improvements, suggesting the appropriateness of modelling the effects of studentification as time-varying. DIC results, along with full regression results, are provided in Appendix C.

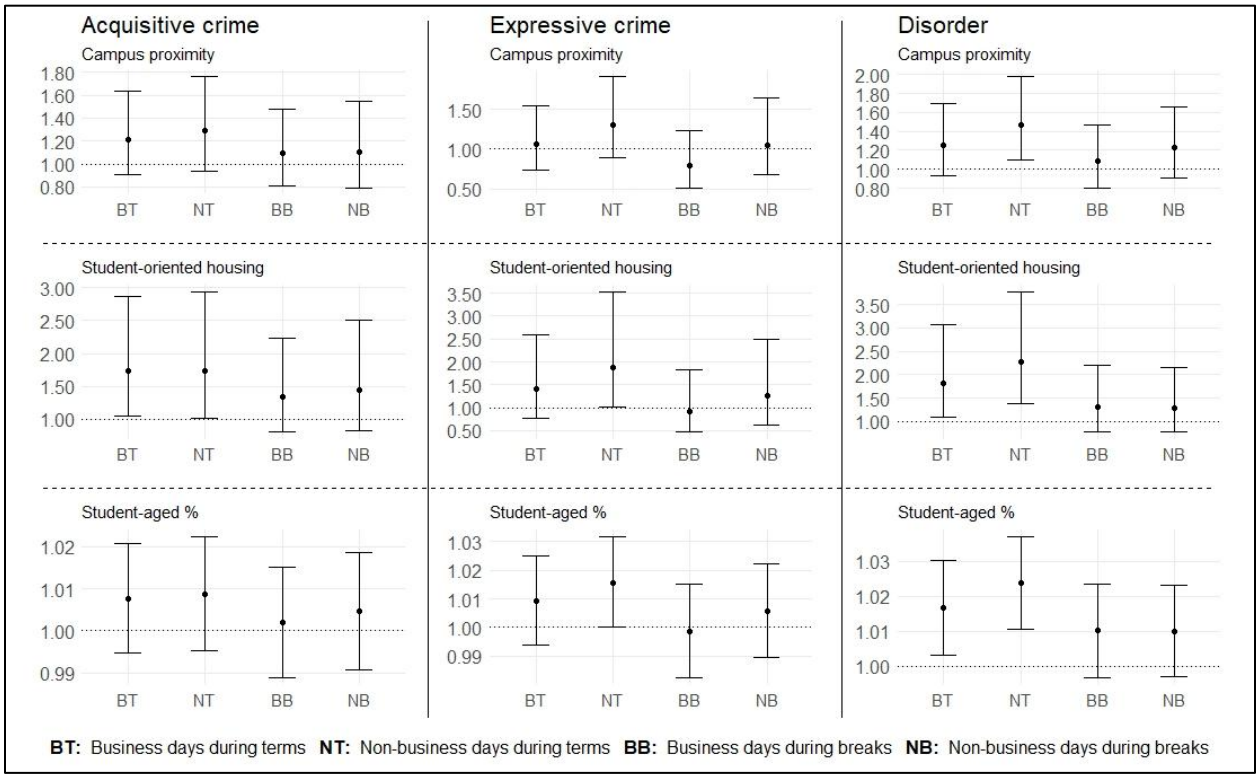


Figure 4-3: Regression coefficient estimates for the studentification indicators (posterior means and 95% CIs of relative risks).

4.5 Discussion

4.5.1 The time-varying associations between studentification and crime and disorder

The regression coefficients shown in Figure 4-3 reveal important temporal variation in crime and disorder risks associated with studentification across the academic calendar. Coefficients are generally higher during academic terms than during breaks, and no significant associations are found during term breaks regardless of business or non-business days, suggesting that studentification is not linked to heightened crime or disorder during term breaks. This finding is

expected since most students leave the Kitchener-Waterloo area, resulting in lower neighbourhood activity and fewer opportunities for crime.

Focusing on academic terms, disorder exhibits the strongest association with studentification among the three offence types, particularly on non-business days, where significant associations are observed for all three indicators. This is consistent with expectations and prior qualitative research highlighting community concerns over disorderly behaviours in studentified neighbourhoods, particularly those linked to distinctive student lifestyles and party culture, including alcohol-related offences, littering, and noise disturbances (Sage et al., 2012a; Woldoff and Weiss, 2018). Although weaker, significant associations also appear for student-oriented housing and student-aged population on business days, suggesting that disorder problems in studentified areas are not confined to weekends and holidays but tend to persist throughout the academic term.

Expressive crime shows significant associations with studentification only on non-business days during academic terms, linked to both the student-aged population and student-oriented housing. The stronger associations observed for expressive crime and disorder on non-business days during academic terms, compared with business days, reflect their socially and emotionally driven nature, with elevated risks likely tied to social activities such as partying and alcohol consumption that are more prevalent on weekends and holidays in studentified neighbourhoods. Acquisitive crime, with its more instrumental nature, shows more consistent associations between business days and non-business days during academic terms, but significant associations are only found with the student-oriented housing indicator. Previous campus crime research has highlighted that the concentration of students in shared living and community spaces, their possession of valuable goods, and limited security awareness can create abundant opportunities for offences such as theft (Fisher et al., 1998; Reyns et al., 2022). This may also apply to areas with student-oriented housing such as PBSAs, where similar spatial distributions and lifestyle patterns can contribute to elevated risks of acquisitive crime.

4.5.2 Studentification indicators and their implications for crime and disorder control

While quantitative studies involving neighbourhood-level studentification remain scarce, the measurement of studentification has already emerged as a significant challenge from a data perspective. Employing multiple indicators to capture different dimensions of possible studentification allows for a more comprehensive assessment of the influence of studentification on crime and disorder and enables an examination of the robustness of the findings. This study employed three studentification indicators (campus proximity, student-oriented housing, and student-aged population), each providing useful insights while also involving certain constraints that are worth discussing.

Among the three indicators, campus proximity is the weakest predictor across all offence types, likely because it is the most prone to overcounting areas as studentified. This measure extends earlier indicators of campus influence in crime literature that were typically based on spatial containment or adjacency. The choice of 10-minute neighbourhoods by transit or walking was tailored to the local context, drawing on local reports of student commute times and supported by the region's dense bus network that full-time students can access at no additional cost. Inevitably, this approach includes some DAs within 10 minutes of campus that are not studentified. It may also capture campus-related effects in some non-studentified areas, such as those with high commercial density near campuses. Nevertheless, its significant association observed with disorder, together with the significant associations found for the other two indicators, strengthens the evidence that studentification is linked to disorder during academic terms, particularly on weekends and holidays. This highlights the need for targeted disorder control strategies in campus-proximate neighbourhoods, such as strengthened bylaw enforcement and community–university partnerships.

The second binary indicator (student-oriented housing) highlights areas of the highest levels of studentification, particularly the effects of PBSAs, but it may undercount studentification where clusters of HMOs exist elsewhere. It should also be noted that the locations of HMOs are difficult to identify comprehensively. With its highly financialized housing market, the City of Waterloo alone accounts for 42% of private PBSA supply in Canada, totalling more than 17,500

beds. (Revington & August, 2020). While high concentrations of students can create spaces of persistent student-related disorder, PBSAs are commonly perceived as a safer student housing option in terms of crime due to enhanced security systems (e.g., controlled entry and surveillance cameras) and the sense of safety derived from living among fellow students (Gregory, 2022; Revington, 2024; Sage et al., 2013). Nevertheless, high levels of student activity in the neighbourhoods may still generate abundant opportunities for students' exposure to crime as both potential offenders and vulnerable targets. Moreover, the typically mid- or high-rise, high-density form of PBSAs in Kitchener-Waterloo generates substantial daily foot traffic. This can complicate access control beyond what is advertised and potentially increase crime risks. The associations with all three offence types emphasize the need for enhanced crime and disorder control measures in student-oriented housing, such as improved building design, student tenant orientation programs, and coordination with local police services, particularly in this study area where the PBSA market is rapidly expanding.

This finding draws attention to the role of major private student housing providers in promoting safe living environments, particularly given that a considerable share of PBSA supply is provided by several large companies in the study area (Revington & August, 2020). Crime prevention approaches aimed at reducing crime opportunities, such as situational crime prevention and crime prevention through environmental design, emphasize the importance of housing design and management that enhances territoriality, surveillance, and target hardening (Armitage, 2013; Cozens et al., 2005). While a formal assessment of building design is beyond the scope of this study, field observations conducted during verification of student housing locations revealed that most student rental apartment buildings incorporated key fob entry systems and surveillance cameras. Nevertheless, prior research has shown that the mere presence of security features does not ensure effective crime prevention when weaknesses exist in access control and territorial reinforcement (Hodgkinson et al., 2018). Such weaknesses in student housing may include poor visitor management and vulnerability to tailgating. Delays in addressing maintenance needs, particularly major repairs such as malfunctioning locks, are also common in student rentals and may contribute to safety concerns (Dhillon et al., 2021). These issues call for greater accountability from housing providers and property managers serving student residents.

Ideally, studentification could be measured directly as the share of the student population in a neighbourhood, but this is infeasible without access to individual student residential addresses, which are unavailable due to privacy and confidentiality concerns. The third indicator (student-aged population) therefore provides a simple census-based approximation of the student population. The 18–24 age group reflects the typical age of college and university students, particularly given the relatively high post-secondary participation rate in Canada. Although imperfect, since some non-students fall within this age range and some students are enumerated at parental homes, it remains the best available proxy based on census data and has been applied in previous studentification studies (Foote, 2017; Revington et al., 2023). Complementing the first two indicators, this measure captures students living farther away from campus and outside student-oriented housing, offering additional insights into how the intensity of student presence influences crime and disorder. Its results add robustness to the observed associations between studentification and expressive crime and disorder.

4.5.3 Limitations and future research

This study has several limitations that are worth noting and could be addressed in future research where suitable datasets become available. First, the quantification of crime and disorder is imperfect. Police-reported data underrepresents actual incidents due to low reporting rates (Moreau et al., 2020). This could have particularly significant influence in studentified neighbourhoods, considering some students may be less likely to report offences due to limited awareness of reporting procedures, concerns about police involvement, or perceptions that certain behaviours are part of normal student life. Future research could adopt alternative approaches, such as surveys of the student population, to obtain individual-level data that complement the quantitative analyses and help assess the robustness of the findings.

Second, DAs were used as proxies for neighbourhoods, but studentified neighbourhoods and spatial clusters of crime may not align with DA boundaries. As highlighted by the modifiable areal unit problem (MAUP), different spatial aggregation units may yield different statistical results (Fotheringham & Wong, 1991; Openshaw, 1984). Prior research has shown that sociodemographic patterns, crime patterns, and their associations can vary across spatial scales,

and that census geographic units may not accurately reflect perceived or "true" neighbourhood boundary units (Cai & Tan, 2025b). Similarly, the temporal configuration could be further refined; for example, separating long weekends from regular weekends or distinguishing exam periods from class periods might better capture variations in student activity and related crime and disorder patterns. Additionally, different approaches exist for aggregating crime and disorder, and grouping offences into broad categories may obscure important differences, since individual offence types often have distinct opportunity structures and spatial patterns (Andresen & Linning, 2012). However, disaggregating spatial units, temporal units, and offence types simultaneously risks creating a severe small number problem, where sparse incident counts undermine statistical reliability (Oberwittler & Wikström, 2009). Balancing these trade-offs, this study prioritized the smallest available spatial unit to capture fine-grained variation in student clustering and local sociodemographic conditions. Future work could systematically compare alternative spatial, temporal, and offence aggregations to address the MAUP and its temporal counterpart, as well as the offence aggregation problem. In addition to neighbourhood-level patterns, building-level analyses could be conducted, where data are available, to examine how student accommodation types, housing design features, and management practices are associated with offence patterns.

Third, the influence of students on crime and disorder may not be confined to studentified neighbourhoods. It may extend to places students frequently visit, such as bar and entertainment districts. This study tested allowing CBDs (both as a single variable or as separate variables for Uptown Waterloo and Downtown Kitchener), where bars, pubs, and other nightlife locations concentrate, to vary across day categories but did not yield meaningful results. This may reflect imprecise capture of nightlife locations that are most frequented by students. Past research in this study area has included binary indicators of commercial land use and eating and drinking establishments (Quick et al., 2019). However, these measures would largely overlap with the binary studentification variable in this study, since studentified neighbourhoods typically have shops or restaurants, and including both in the model would result in multicollinearity issues. Future research could incorporate more detailed measures of business density or foot traffic data to better capture commercial activity, which were not available for this study. Identifying student activity spaces directly would also be valuable, for example through student surveys, to better

assess the relationship between student presence and crime beyond students' residential neighbourhoods, as well as their temporal behaviours.

Finally, while the study area reflects many traits of a typical university town, such as concentrated student populations and a local economy and sociocultural life strongly shaped by post-secondary institutions, it also has distinctive features. These include its mid-sized urban setting, strong knowledge economy, and a highly developed PBSA market that may not characterize other university towns. As such, results should be generalized with caution, and further studies in varied contexts are needed to strengthen understanding of how studentification shapes crime and disorder across different types of university and college towns.

4.6 Conclusion

University and college towns represent a distinctive urban form, where post-secondary institutions and students bring vibrancy to the local economy and sociocultural fabric, but may also generate tensions with long-term residents, contribute to neighbourhood disorder and disorganization, and create opportunities for crime. Using a Bayesian modelling approach, this study examined the time-varying associations between studentification and crime and disorder in Kitchener–Waterloo, revealing significant relationships during academic terms. Expressive crime is associated with studentification mainly on non-business days during academic terms when social activities are more frequent. Disorder is associated with studentification throughout the term and the association is stronger on non-business days. Acquisitive crime during academic terms is linked to student-oriented housing, where the highest concentrations of students reside. These results broadly align with criminology theories that imply social disorganization and increased crime opportunities in studentified neighbourhoods, as well as with prior qualitative research highlighting community concerns over student-related disorder and students' fear of crime. They also provide new empirical insights into how the relationships between studentification and crime and disorder vary across the academic calendar, differ by offence type, and depend on distinct indicators of studentification that capture different dimensions and locations of student presence.

The findings of this study point to the need for targeted crime and disorder control during academic terms in studentified neighbourhoods, particularly in areas with student-oriented housing, such as PBSAs, which are strongly associated with all offence types examined and are also relatively easy to identify as a practical entry point for policy intervention. Relevant measures may include enforcing high security standards for PBSAs, facilitating timely maintenance of buildings and surrounding environments to address visible physical disorder and security breaches, implementing community initiatives to support students' awareness of personal safety and local regulations, and increasing patrols alongside rapid bylaw and police responses aligned with the academic calendar. In regions with large student populations and expansive student housing markets, coordinated efforts by post-secondary institutions, local authorities, and communities are essential to foster secure and supportive academic environments for students while ensuring safe and peaceful living conditions for both students and long-term residents.

Chapter 5
Linking perceived wellbeing to official statistics

Summary

Quantitative studies, including the manuscripts in this dissertation, commonly rely on spatially aggregated official statistics to analyze neighbourhood processes, but their ability to capture residents' lived experiences and subjective perceptions is questionable. This supplementary study examines the extent to which neighbourhood-level indicators derived from official statistics reflect residents' perceptions of wellbeing in Kitchener–Waterloo. Drawing on survey data from the Canadian Index of Wellbeing, the analysis focuses on two key outcomes, perceived housing affordability and neighbourhood safety, and links them to census-based dwelling value and rent, and police-reported crime and disorder, respectively. Correlation analyses reveal that perceived housing unaffordability is positively associated with rent but not dwelling value, while perceived neighbourhood unsafety shows a positive association with both measured disorder and major street crime rates. Maps of these variables show that, even where significant correlations exist, spatial patterns only partially align and may differ across years, possibly due to shifts in contextual factors. Multilevel modelling further demonstrates that individual sociodemographic characteristics, such as age, disability status, and institutional trust, play a significant role in shaping perceptions. These findings highlight the limitations of relying solely on official statistics and underscore the importance of integrating perception-based data to better understand neighbourhood dynamics and inform more people-centred planning and policy in future research.

5.1 Official statistics and residents' perceptions of neighbourhood conditions

Quantitative studies of neighbourhood characteristics often rely on spatially aggregated data, typically provided by government agencies or other public organizations. The three manuscripts included in this dissertation are no exception, relying on census data for sociodemographic variables and police-reported occurrence data for crime and disorder. These official statistics, which are usually systematically measured and reported, provide a standardized and comparable way for researchers and policymakers to assess spatial patterns and temporal dynamics of neighbourhood conditions. However, this reliance on quantitatively measuring neighbourhood conditions raises questions about how well such metrics capture residents' lived experiences or how neighbourhoods are actually perceived.

Perceived neighbourhood quality typically arises from direct encounters with local conditions rather than from knowledge of official statistics or profile characteristics. Residents may interpret the same neighbourhood differently based on individual attributes, including age, gender, socioeconomic status, family structure, cognitive processes, mental health, and prior experiences in other neighbourhoods, and some perceptions may diverge substantially from what official statistical indicators suggest (Roosa et al., 2003, 2009). These perceptions influence everyday decision-making and shape residents' daily routine, use of public space, and social interactions, while also affecting stress levels and overall wellbeing (Rees-Punia et al., 2018; Wen et al., 2006; L. Zhang et al., 2021). However, most quantitative studies assume that indicators based on official statistics adequately capture neighbourhood effects on individual outcomes, even though the relevant causal pathways often operate through residents' perceptions, which may not accurately reflect measured neighbourhood contexts (Troost et al., 2025).

Focusing on the neighbourhood-level processes analyzed in this dissertation, including gentrification, youthification, studentification, and studentification-related crime and disorder, their social implications ultimately impact individual residents' wellbeing and ability to remain in places they wish to live. This highlights the importance of whether officially measured indicators based on census data accurately reflect residents' perceptions and actual experiences in their

neighbourhoods of residence. For example, perceived housing unaffordability may not align with housing value indicators, with the former directly influencing residents' sense of belonging and relocation decisions during gentrification processes (Gibbons, 2021). Similarly, fear of crime does not necessarily correspond to recorded crime, and whether real or perceived, a lack of safety can have negative effects on individual wellbeing, such as discouraging physical activity and mobility (Rees-Punia et al., 2018).

As supplementary research to the three manuscripts included in this dissertation, this study aims to evaluate the relevance of their findings to local residents' wellbeing. Perceptions can be measured using both quantitative and qualitative approaches. This study uses existing quantitative community survey data to examine perceived wellbeing, while recognizing qualitative approaches, such as interviews, as an important direction for future neighbourhood change research. By mapping wellbeing variables and analyzing the relationships between neighbourhood-level indicators derived from official statistics and community survey results in Kitchener-Waterloo, this study seeks to assess whether indicators based on official statistics explain residents' perceptions and to explore the potential of wellbeing surveys and other perception-based data as complementary data sources in future research. Due to limitations in the availability of comparable wellbeing variables and constraints related to spatial aggregation units, not all neighbourhood outcomes examined in the manuscripts can be analyzed. The statistical analysis therefore focuses on two main outcomes only: housing affordability and neighbourhood safety. The former is an important neighbourhood change outcome examined in *Chapter 2* and *Chapter 3* and is closely related to potential displacement pressures, while the latter is the main focus of *Chapter 4* and directly influences residents' lived experiences and wellbeing.

5.2 Residents' wellbeing in Kitchener-Waterloo

This study draws on wellbeing survey data collected in 2018 and 2022 by the Canadian Index of Wellbeing (CIW) in partnership with Wellbeing Waterloo Region. The CIW defines wellbeing as:

> The presence of the highest possible quality of life in its full breadth of expression, focused on but not necessarily exclusive to: good living standards, robust health, a

> sustainable environment, vital communities, an educated populace, balanced time use, high levels of democratic participation, and access to and participation in leisure and culture. (2012, Section "What is Wellbeing")

Survey respondents can be spatially attributed to either Forward Sortation Areas (the first three digits of the postal code) or neighbourhoods, with the latter used as the spatial unit of analysis because they are spatially contiguous and more relevant to policymaking and planning. It is important to note that the CIW uses neighbourhoods defined by the Region of Waterloo, which are much larger than dissemination areas (DAs), the neighbourhood unit of analysis used in previous chapters of this dissertation. Figure 5-1 illustrates the names and boundaries of the 22 neighbourhoods in Kitchener–Waterloo. All neighbourhoods referred to in this chapter follow these definitions. Figure 5-2 reports the number of total respondents who submitted usable questionnaires in each neighbourhood (excluding respondents without neighbourhood information), with census population counts shown for reference. In each mapping and statistical analysis conducted in this study, a small proportion of respondents were further excluded due to missing or invalid responses for the specific variables of interest.

The data include responses to questions across eight CIW domains (community vitality, democratic engagement, education, environment, healthy populations, leisure and culture, living standards, and time use), along with demographic information collected from survey respondents, as well as a series of derived composite measures (Smale & Gao, 2019). To provide an overall sense of residents' wellbeing, Figure 5-3 shows neighbourhood-level averages of overall wellbeing, a final composite measure that combines all eight domains and ranges from 1.00 to 7.00, for 2018 and 2022. Survey weights provided in the data to adjust for age and sex were used to calculate neighbourhood-level CIW variables in this figure and in all subsequent maps.

Maps of material deprivation index scores from the Ontario Marginalisation Index (ON-Marg) of the closest census years are provided in Figure 5-3 for comparison. The index, which were also used in *Chapter 4* for crime and disorder modelling, was derived from census-based indicators closely related to residents' inability to access basic material needs, such low educational attainment, unemployment, and low income (Matheson, 2018). The index scores and all census-

derived variables used in subsequent maps were aggregated from DAs to neighbourhoods. Values are standardized to facilitate comparison across variables.

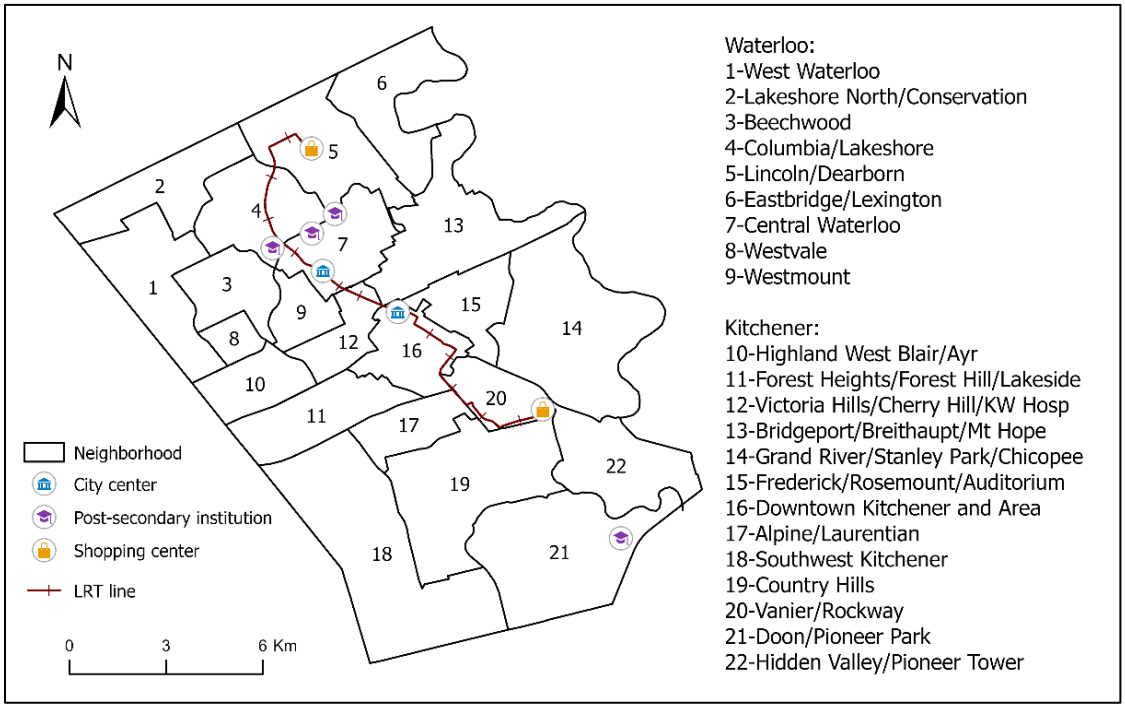


Figure 5-1: Neighbourhoods in Kitchener-Waterloo.

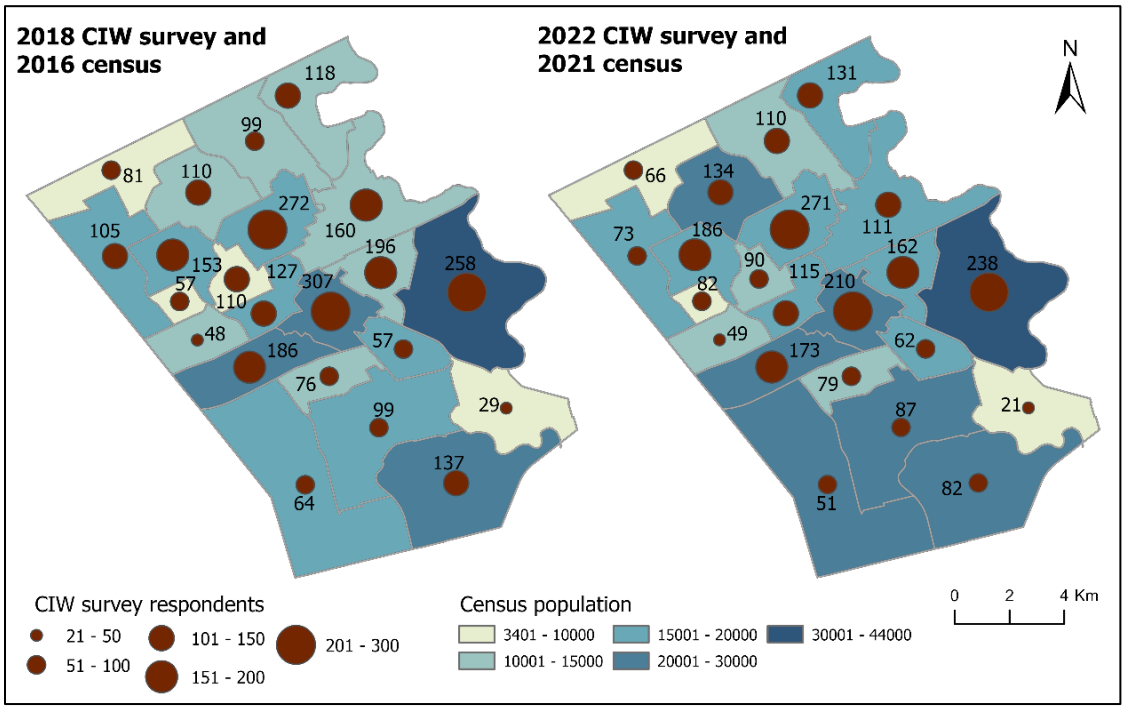


Figure 5-2: Numbers of CIW survey respondents, labelled and shown as graduated symbols, over neighbourhoods shaded by census population.

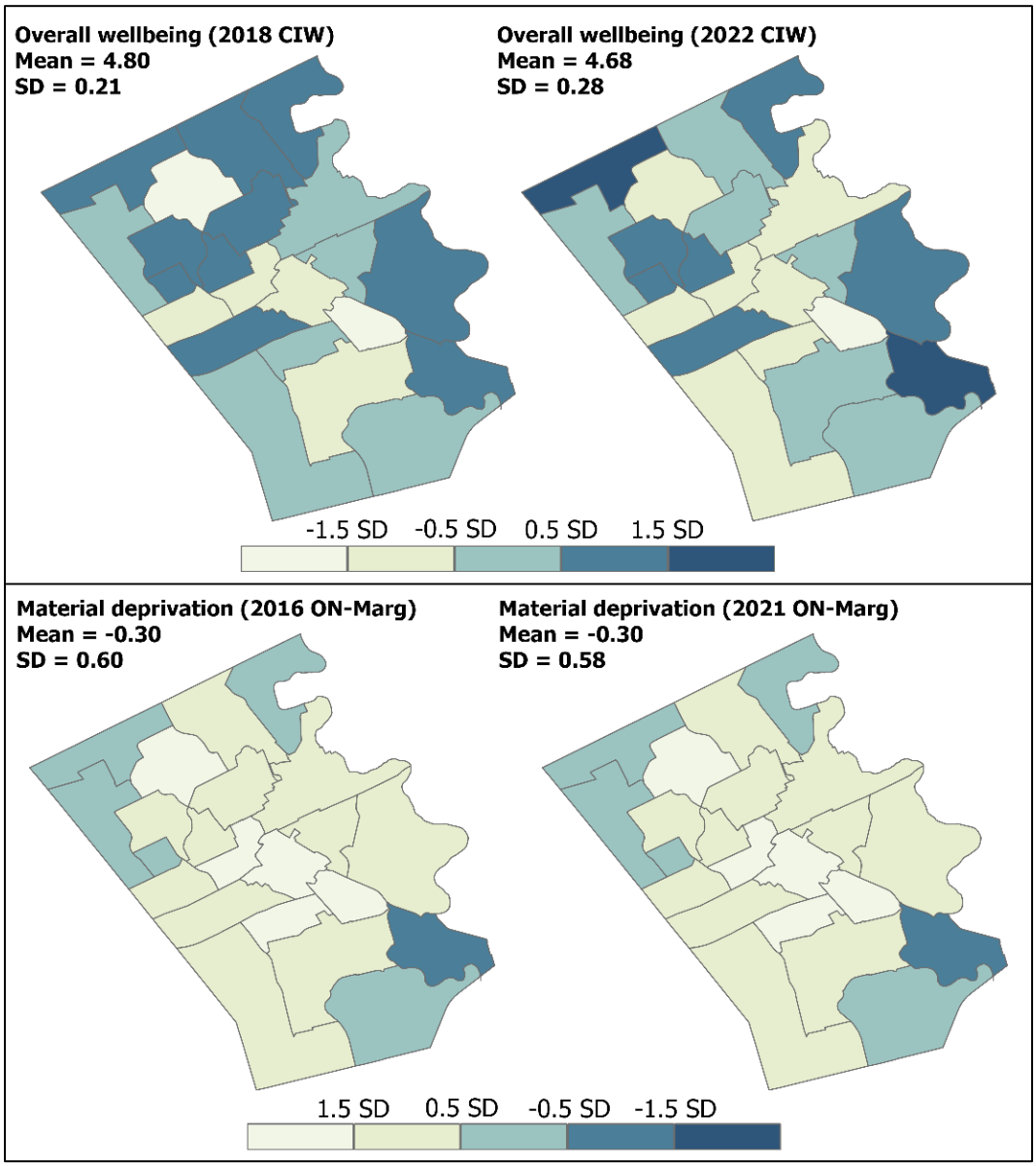


Figure 5-3: Weighted average of residents' overall wellbeing by neighbourhood (2018 and 2022 CIW) compared with census-derived material deprivation index scores (2016 and 2021 ON-Marg; an inverse symbol order is used to facilitate comparison to wellbeing).

Moderate to high levels of wellbeing were observed across much of Waterloo, except in Columbia/Lakeshore, the neighbourhood that encompasses the main campus of the University of Waterloo. In Kitchener, higher levels of wellbeing were primarily found in peripheral neighbourhoods, particularly in the eastern areas, while central neighbourhoods, including those

along the LRT corridor and around Downtown Kitchener, exhibited lower levels of wellbeing. Areas of higher material deprivation broadly corresponded to areas of lower wellbeing to some extent, including Columbia/Lakeshore and several central neighbourhoods in Kitchener. Nevertheless, the patterns did not entirely align, likely due to the complex and multidimensional nature of wellbeing.

A correlation analysis revealed a strong negative association between perceived overall wellbeing in 2018 and neighbourhood-level material deprivation in 2016 (Pearson's $r = -0.72$, p-value = 0.0001). Although slightly weaker, the relationship remained significantly negative between wellbeing in 2022 and material deprivation in 2021 (Pearson's $r = -0.65$, p-value = 0.001). The 2022 wellbeing scores also exhibited greater spatial differentiation, while material deprivation remained relatively stable over time. This divergence again suggests that neighbourhood-level material resources capture only one dimension of wellbeing. In addition, broader temporal context, including the impacts of the COVID-19 pandemic on perceptions, may have influenced responses. The relatively small survey sample compared with census data may also have contributed to additional variability in perceived wellbeing.

5.3 Perceived housing affordability and neighbourhood safety

Two CIW perception-based variables closely related to this dissertation and directly comparable to neighbourhood indicators derived from official statistics were further analyzed: satisfaction with housing affordability, a key component of the living standards domain of wellbeing, and perceived neighbourhood safety, an important component of the community vitality domain of wellbeing. Satisfaction with housing affordability, only available in the 2022 CIW, was measured using a five-point scale: 1 (very dissatisfied), 2 (dissatisfied), 3 (neither satisfied nor dissatisfied), 4 (satisfied), and 5 (very satisfied). In this study, responses of 1 and 2 were classified as indicating perceived housing unaffordability and were subsequently linked to neighbourhood-level indicators derived from the 2021 Census, including dwelling value per room (average dwelling value divided by average number of rooms per dwelling) and rent per room (average monthly shelter cost for rented dwellings divided by average number of rooms per dwelling). In *Chapter 2*, dwelling value was

included as a measurable outcome of neighbourhood upgrading and gentrification, while rent was not examined due to insufficient data at the DA scale. Rent was included in this study to provide an additional perspective on housing affordability. Figure 5-4 presents a map of neighbourhood-level weighted percentages of respondents perceiving housing as unaffordable, along with maps of dwelling value per room and rent per room. Pearson correlation test results between the two census-based variables and perceived housing unaffordability are also included.

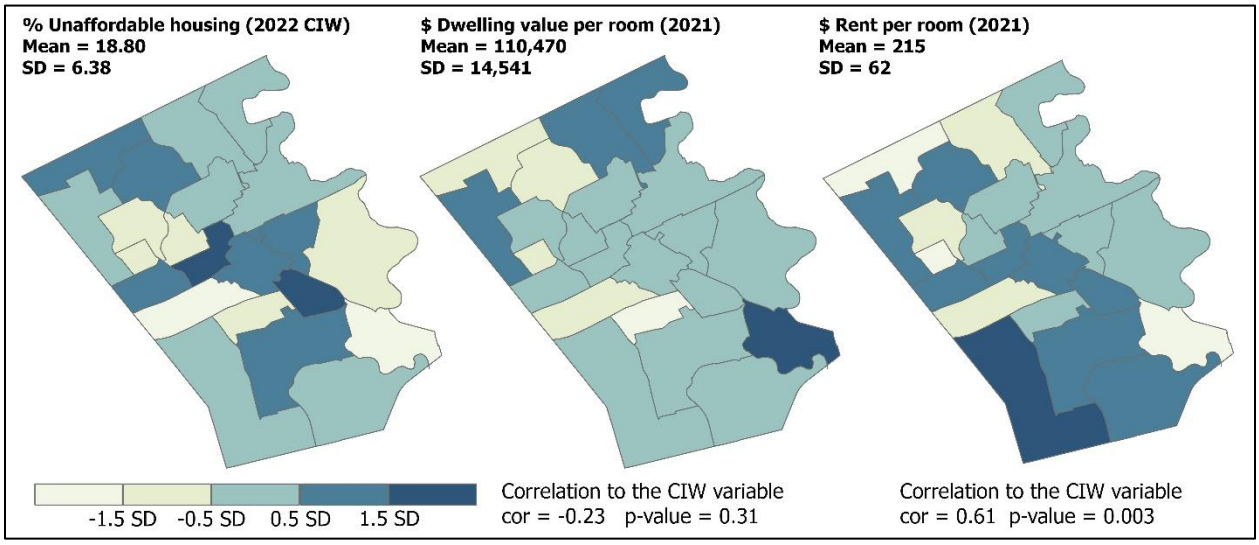


Figure 5-4: Weighted percentage of respondents perceiving housing as unaffordable, average dwelling value per room, and average rent per room by neighbourhood (2022 CIW and 2021 census).

Overall, residents in the central zone of the study area and some neighbourhoods of northern Waterloo were more likely to report housing unaffordability. This spatial distribution broadly aligned with patterns of rent per room, with correlation tests indicating a significant positive association. In contrast, dwelling value per room showed a less consistent spatial relationship with perceived unaffordability, and the corresponding correlation coefficient was not statistically significant. The stronger association with rent likely arises because rent more accurately captures direct lived housing costs in the neighbourhood, while dwelling value reflects broader market conditions that may not have translated into perceived affordability.

Figure 5-5 and Figure 5-6 present the weighted percentages of residents who perceived their neighbourhood as unsafe in 2018 and 2022, respectively, along with neighbourhood-level

police-reported disorder and crime rates for the corresponding years. The unsafe neighbourhood variable was derived from responses to the question on perceived safety when walking alone after dark in the neighbourhood. Response options included 1 (very unsafe), 2 (somewhat unsafe), 3 (reasonably safe), 4 (very safe), and 5 (I never walk alone there after dark). In this study, responses of 1 and 2 were classified as unsafe, while responses of 5 were treated as invalid and excluded from the analysis. Disorder (offences reflecting public order disturbances), examined in relation to studentification in *Chapter 4*, may contribute to broken windows effects, whereby visible disorder signals reduced social control, encouraging further offences and increasing fear of crime (Wilson & Kelling, 1982). The same as in *Chapter 4*, indecent act, drugs, liquor offence, property damage, gaming and betting, unwanted contact, disturbance, dispute, intoxicated person, unwanted person, graffiti, and bylaw violation were included in disorder offences. For crime, this study adopted an aggregation scheme aligned with the context of walking after dark: major street crime (robbery and assault), which is particularly relevant for perceptions of safety in public spaces.

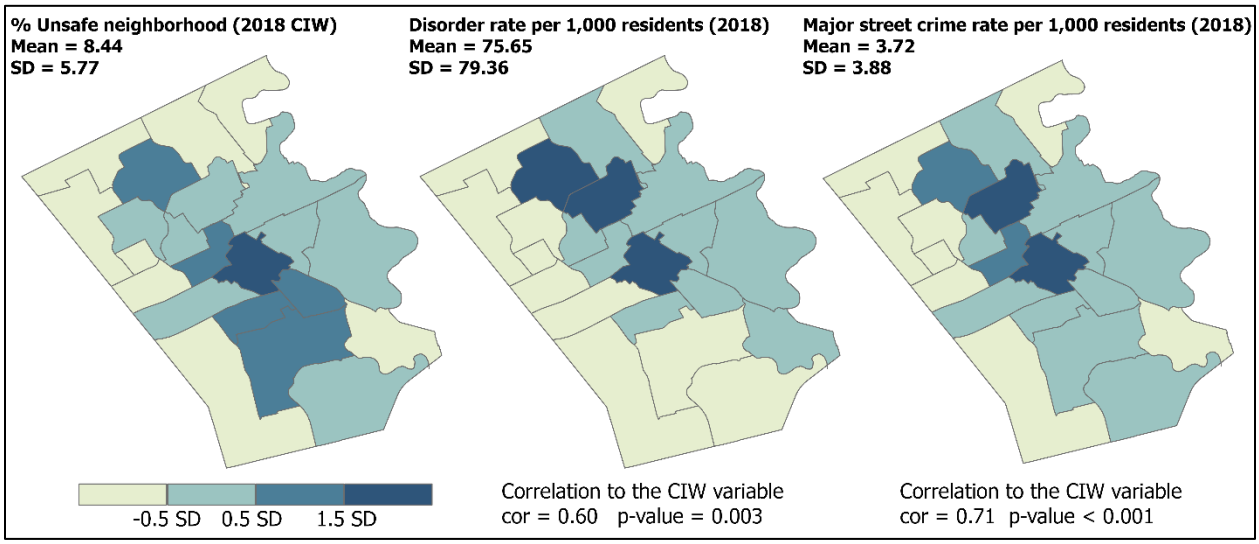


Figure 5-5: Weighted percentage of respondents perceiving their neighbourhood as unsafe to walk in after dark, disorder rate, and major street crime rate by neighbourhood (2018 CIW and police-reported incidents).

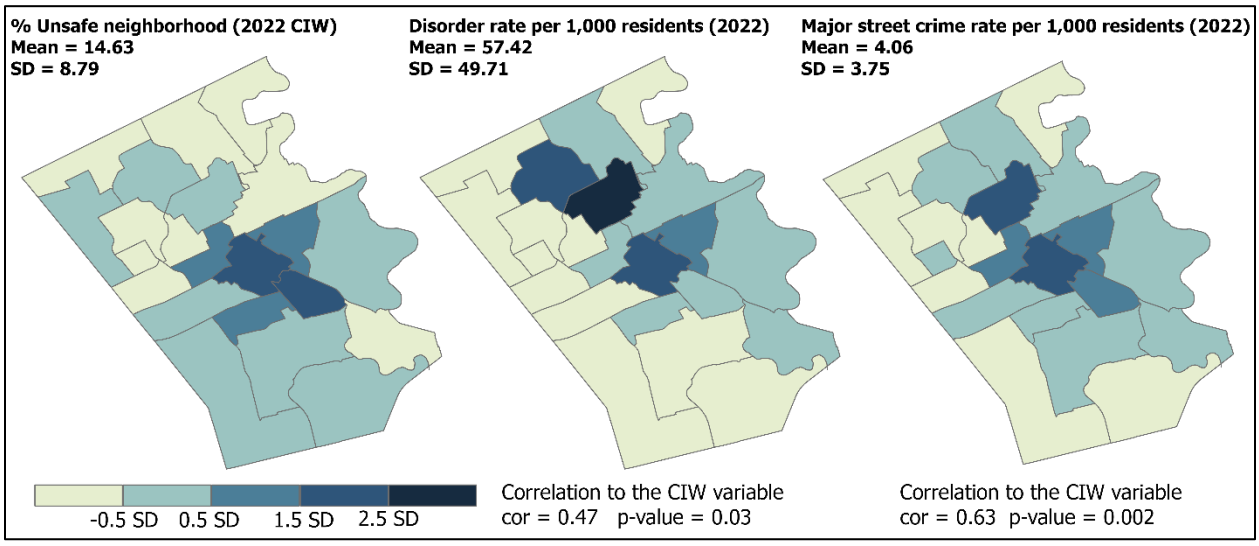


Figure 5-6: Weighted percentage of respondents perceiving their neighbourhood as unsafe to walk in after dark, disorder rate, and major street crime rate by neighbourhood (2022 CIW and police-reported incidents).

Compared with the patterns observed for housing unaffordability, there was a clearer spatial association between perceived neighbourhood unsafety and measured disorder and crime rates, particularly in 2018. Central zones and university areas were highlighted as both high-offence and high-perceived-unsafety locations, which is expected due to elevated human activity and greater opportunities for disorder and crime in those areas. Correlation analyses also indicated a significant positive relationship between perceived unsafety and measured offence rates. In 2022, a larger proportion of respondents reported feeling unsafe, and the spatial alignment between perceived unsafety and measured disorder and crime became less consistent, despite correlations remaining statistically significant. This divergence might be partially due to the influence of the COVID-19 pandemic, especially during the first half of the year, when public activity was still restricted and most post-secondary students were still absent. This might have altered both offence patterns and the demographic composition of residents in the study area, including those who responded to the survey.

5.4 Statistical modelling of residents' perceptions

Considering the influence of individual characteristics on perceptions, multilevel modelling analyses were conducted to examine the relationships between individual-level perceived housing unaffordability and neighbourhood-level dwelling value and rent, as well as between individual-level perceived neighbourhood unsafety and neighbourhood-level disorder and crime. Residents' individual characteristics, including sex, age, marital status, education attainment, employment status, and disability status, were included as control variables. Residents' confidence in local government and in the police were also included for perceived housing unaffordability and perceived neighbourhood unsafety, respectively, as previous research has shown that institutional trust is associated with biased estimations of social reality (Troost et al., 2025). Table 5-1 provides descriptions and summary statistics for all variables used in this study. The multilevel model is specified in Equation 5-1 below.

$$Data\ model:\ Y_{i,j} \sim Bernoulli(p_{ij})$$
$$Process\ model: logit\left(p_{ij}\right) = \alpha + \sum \beta_k X_{k,i} + (\gamma Z_j + U_j) + bT_i \quad \textbf{(5-1)}$$

$Y_{i,j}$ denotes the perception variable being analyzed, where i indexes individual respondents and j indexes the neighbourhood in which the respondent resides. As a binary variable, $Y_{i,j}$ was modelled using a Bernoulli distribution, with p_{ij} representing the probability that $Y_{i,j}$ is 1 (representing perceived unaffordable housing or unsafe neighbourhood). The logit of p_{ij} was modelled as the sum of an intercept term (α), the effects of individual-level covariates ($X_{k,i}$) with associated regression coefficients (β_k), a neighbourhood-level covariate (Z_j) with its associated regression coefficient (γ), an neighbourhood-level random effect (U_j), and a temporal effect (bT_i), with T_i coded as -0.5 and 0.5 for responses collected in 2018 and 2022, respectively, and b representing the overall linear trend between the two survey years. The temporal effect was not included for unaffordable housing, as this variable was only available for the 2022 survey year. Vague Gaussian priors were given to regression coefficients and random variables. Table 5-2

presents the regression results in the form of posterior mean and 95% credible interval (CI). Regression coefficients are considered statistically significant if their 95% CIs do not include zero.

Table 5-1: Variable descriptions and summary statistics.

Variable: Descriptions	Year	Mean (SD)
Individual-level variables obtained/derived from the CIW data		
Unaffordable housing: Binary variable derived from housing satisfaction with being affordable.	2022	0.15
Unsafe neighbourhood: Binary variable derived from perceived safety when walking alone after dark in the neighbourhood.	2018	0.11
	2022	0.17
Female: Binary indicator for respondents whose sex at birth is female.	2018	0.68
	2022	0.63
Youth and young adults: Binary indicator for respondents aged 16–34 (respondents had to be at least 16 years old).	2018	0.19
	2022	0.16
Seniors: Binary indicator for respondents aged 65 and over.	2018	0.22
	2022	0.31
Partnered: Binary indicator for respondents who are married or living in common-law.	2018	0.65
	2022	0.66
Post-secondary education: Binary indicator for respondents with post-secondary certificate, diploma, or degree.	2018	0.80
	2022	0.79
Employed full-time: Binary indicator for respondents who are employed full time.	2018	0.46
	2022	0.38
Disability: Binary indicator for respondents living with a disability or chronic illness that limits activity.	2018	0.23
	2022	0.30
Confidence in the police: Responses range from 1 (no confidence at all) to 7 (a great deal of confidence).	2018	5.06 (1.50)
	2022	4.80 (1.78)
Confidence in the local government: Responses range from 1 (no confidence at all) to 7 (a great deal of confidence).	2022	4.17 (1.64)
Neighbourhood-level variables derived from the census data (aggregated from DAs to neighbourhoods)		
Dwelling value per room (unit: $1,000).	2021	11.05 (1.45)
Rent per room (unit: $100).	2021	2.15 (0.62)
Neighbourhood-level variables derived from the Waterloo Region Police occurrence data		
Disorder: Occurrences of disorder per 1,000 census residents.	2018	75.65 (79.36)
	2022	57.42 (49.71)
Major street crime: Occurrences of robbery and assault, per 1,000 census residents.	2018	3.72 (3.88)
	2022	4.06 (3.75)

Note: Standard deviations are not reported for binary variables.

Table 5-2: Regression coefficients with 95% credible intervals.

Variables	Unaffordable housing		Unsafe neighbourhood	
Intercept (α)	-2.214 (-2.380, -2.048)*	-2.230 (-2.396, -2.063)*	-2.214 (-2.424, -2.015)*	-2.229 (-2.432, -2.036)*
Overall temporal trend (b)			0.452 (0.260, 0.644)*	0.413 (0.227, 0.598)*
Neighbourhood-level covariates				
Dwelling value per room	0.084 (-0.049, 0.216)			
Rent per room		0.262 (0.002, 0.523)*		
Disorder			0.003 (0.001, 0.005)*	
Major Street Crime				0.089 (0.046, 0.140)*
Individual-level covariates				
Female	0.258 (-0.028, 0.543)	0.260 (-0.026, 0.546)	1.075 (0.849, 1.301)*	1.074 (0.848, 1.301)*
Youth and young adults	0.759 (0.453, 1.064)*	0.729 (0.423, 1.035)*	0.082 (-0.156, 0.320)	0.080 (-0.158, 0.318)
Seniors	-1.201 (-1.640, -0.762)*	-1.176 (-1.617, -0.736)*	0.105 (-0.141, 0.351)	0.104 (-0.142, 0.351)
Partnered	-0.619 (-0.892, -0.345)*	-0.605 (-0.879, -0.331)*	-0.131 (-0.324, 0.063)	-0.126 (-0.320, 0.068)
Post-secondary education	0.067 (-0.309, 0.442)	0.094 (-0.280, 0.468)	-0.486 (-0.721, -0.252)*	-0.490 (-0.725, -0.255)*
Employed full-time	0.228 (-0.062, 0.518)	0.231 (-0.059, 0.521)	-0.187 (-0.398, 0.023)	-0.194 (-0.404, 0.017)
Disability	0.639 (0.362, 0.917)*	0.625 (0.347, 0.903)*	0.463 (0.264, 0.662)*	0.456 (0.257, 0.656)*
Confidence in the local government	-0.365 (-0.447, -0.283)*	-0.364 (-0.445, -0.282)*		
Confidence in the Police			-0.200 (-0.254, -0.145)*	-0.198 (-0.252, -0.143)*

Note: All covariates were mean-centred. * Represents significance at the 95% CI.

Among individual characteristics, females were more likely to perceive their neighbourhoods as unsafe and individuals with post-secondary education were more likely to report feeling safe, consistent with previous theoretical and empirical research (Henson & Reyns, 2015; Scarborough et al., 2010). Youth and young adults were more likely to report housing as

unaffordable, while seniors and residents with partners were less likely to do so, possibly reflecting greater housing stability and financial security. Respondents with disabilities were more likely to perceive both housing unaffordability and neighbourhood unsafety, which may relate to heightened vulnerability and barriers to accessing resources. Lower institutional confidence was associated with less favourable perceptions of housing affordability and neighbourhood safety.

After controlling for individual characteristics, the associations between perceptions and neighbourhood-level indicators remained unchanged in terms of statistical significance compared to neighbourhood-level bivariate correlation results. Perceived neighbourhood unsafety was positively associated with both disorder and major street crime rates. A positive association with perceived housing unaffordability was observed for rent per room but not dwelling value per room. As rent appeared to be a stronger predictor, examining the relationships separately for renters and homeowners could provide additional insights. However, this was not feasible because renters comprised only a small proportion of respondents, resulting in insufficient sample sizes for modelling at the neighbourhood scale.

5.5 Implications and conclusion

This supplementary study examined the relationship between neighbourhood indicators derived from official statistics and residents' perceptions. The mapping and statistical analysis results suggest that while official indicators capture important structural conditions, they only partially explain how residents perceive their living environments and overall wellbeing, with individual characteristics, as well as broader social and temporal contexts, playing important roles in shaping perceptions. These findings have implications for interpreting the results of the previous chapters and for guiding future research that incorporates subjective perception-based data alongside official statistics.

First, the positive association between perceived neighbourhood unsafety when walking alone after dark and measured crime and disorder rates highlights the relevance of studentification-related crime and disorder identified in *Chapter 4* for residents' wellbeing and everyday experiences. However, the significant influence of individual characteristics, such as gender and

education attainment, suggests that further research is needed to fully understand the residents' perceptions in studentified neighbourhoods, which are characterized by distinctive demographic compositions. For example, post-secondary students may experience and interpret neighbourhood conditions differently from other residents, with distinct perceptions of safety and overall wellbeing shaped by life stage, mobility, and social routines.

Second, perceived housing affordability was linked to rent but not dwelling value, possibly due to the impacts of dwelling value being less directly translated into everyday lived experiences depending on housing tenure and ownership status. In particular, a large proportion of survey respondents were homeowners, many of whom may have owned their homes outright or had stable mortgage payments, meaning increases in neighbourhood dwelling values may not have translated into immediate affordability concerns. This implies that neighbourhood change measured by dwelling value, including LRT-related change identified in *Chapter 2*, may not always be directly perceived by local residents in terms of immediate housing affordability, yet it remains an implicit factor to lived experience by signalling longer-term investment dynamics that reshape neighbourhoods over time. Additional factors may have also contributed to this lack of direct association. The neighbourhood units used in this study may be too large to capture localized housing dynamics, since each neighbourhood can contain multiple submarkets, and aggregation at this scale may mask relationships between housing costs and perceived unaffordability that could emerge at finer spatial resolutions, such as DAs. It is also important to note that although both rent and dwelling value are commonly treated as relatively objective indicators, they are self-reported in census data. While rent is typically known due to regular payments, dwelling value is based on owners' self-assessments, which may be less precise and may lag behind market changes (Immergluck & Hollis, 2024).

Third, due to the scope and format of the CIW survey, this study was not able to fully capture how some neighbourhood processes analyzed in this dissertation are perceived by residents, such as studentification and youthification. In particular, studentification often occurs at very localized spatial scales, clustering within small areas that are not well represented by larger neighbourhood units. Even if the survey results could be aggregated into smaller spatial units, limited sample sizes would restrict the ability to conduct reliable or meaningful analyses. This

highlights an important direction for future research, suggesting the need for targeted survey or interview approaches to complement quantitative analyses. Focusing on specific groups, such as renters who are more sensitive to housing unaffordability and more susceptible to displacement than homeowners, could help deepen understanding of how unaffordability is perceived and how it influences housing decisions. Attention to particular populations in identified spatial contexts, for example students and long-term residents in studentified neighbourhoods, could also provide valuable insights into how studentification and related patterns of crime and disorder are experienced and interpreted in everyday life.

Finally, this supplementary study highlights the value of integrating perception-based data with conventional indicators derived from official statistics. While official statistics remain essential for quantifying and measuring neighbourhood conditions, such as sociodemographic compositions, housing costs, and crime rates, research findings must also reflect how neighbourhoods are perceived by residents. Future research would benefit from combining statistical analyses of high-resolution spatial data with quantitative insights gained from targeted surveys and qualitative approaches, such as interviews. Together, these mixed methods can offer a more comprehensive understanding of neighbourhood dynamics by connecting measured conditions and lived experience, potentially supporting more people-centred planning and policy.

Chapter 6 Conclusion

6.1 Summary of findings

This dissertation comprises three standalone manuscripts that examine different aspects of neighbourhood processes in Kitchener–Waterloo, along with a supplementary study that explores the association between perceived wellbeing and official statistics. Each manuscript addressed a distinct research question corresponding to the research objectives listed in *Section 1.3*, while collectively contributing to a deeper understanding of the spatiotemporal dynamics of neighbourhood sociodemographic change and their relationships with broader neighbourhood conditions.

The first manuscript (*Chapter 2*) contributed to the debate on public transit development and gentrification, and offered a novel perspective on a research question that has been widely examined but remains unresolved in the literature:

> ***Is new urban rapid transit development associated with neighbourhood upgrading and gentrification?***

The relationship between neighbourhood upgrading and urban rapid transit development is dependent on the specific locations and time periods considered. In the case study of LRT in Kitchener–Waterloo, a spatiotemporal regression model that allows the coefficient for distance to LRT to vary across space and time was applied. LRT-related neighbourhood upgrading, including increases in income and dwelling value, was observed in certain neighbourhoods around CBD stations and terminal locations, with some of these changes indicating potential gentrification upon further investigation. Dwelling value increases were primarily identified during the planning and

construction phases, while income improvements mainly occurred during the opening stage. These findings highlight the importance of accounting for spatiotemporal variation in transit-related neighbourhood change and indicate that research assuming spatiotemporally uniform relationships may produce misleading results.

The second manuscript (*Chapter 3*) extended previous research on the spatial overlap of urban processes and sociodemographic groups in the knowledge economy context and addressed the following research question with detailed spatiotemporal insights for Kitchener-Waterloo:

> ***What are the shared and distinct spatiotemporal patterns of post-secondary students, university graduates, and young adults?***

Between 2011 and 2021 in Kitchener–Waterloo, shared neighbourhoods between students, university graduates, and young adults were primarily located near campuses, CBDs, and along the CTC, where high-density and high-cost rental housing was concentrated. At the same time, the three groups exhibited distinct spatiotemporal dynamics, particularly between 2016 and 2021, a period marked by important contextual shifts, including the onset of the COVID-19 pandemic and the opening of the LRT. During this period, as students returned home due to online teaching, increasing concentrations of young adults and university graduates were observed in campus-proximate neighbourhoods, with youthification showing particularly sharp growth. In addition, university graduates and young adults were associated with TOD, signalling youthification and potential gentrification, with youthification along the LRT corridor becoming more pronounced following the system's opening. Overall, these findings demonstrate that the three population groups both co-locate and diverge across space and time, shaped by local development and contextual conditions. Housing barriers for other population groups, such as working-class families, in neighbourhoods shared by these groups, as well as the increasing concentration of young adults and university graduates associated with TOD, raise concerns about whether current neighbourhood planning achieves the goal of inclusive communities.

While the first two manuscripts examined the spatiotemporal patterns of neighbourhood change, the third manuscript (*Chapter 4*) further explored how neighbourhood processes in the university town context relate to important societal issues. It specifically answered the following research question:

Are crime and disorder associated with studentification in a university town?

In the case study of the Kitchener-Waterloo area, there is an association between studentification and crime and disorder during academic terms, but not during term breaks when students are largely absent. Moreover, this association varies by offence type and by how studentification is measured. Using three studentification indicators (campus proximity, student-oriented housing, and student-aged population), the regression results showed a strong association between disorder and studentification during academic terms, with effects strengthening on non-business days and consistently significant across all indicators. Expressive crime was found to be associated with student-oriented housing and the student-aged population on non-business days during terms, while acquisitive crime was associated only with student-oriented housing throughout the term. These patterns reflect both the differing nature of offences and the distinct dimensions of studentification captured by each indicator. Expressive crime and disorder are more emotionally driven and often linked to social activities, making them more prevalent on non-business days in studentified areas. Student-oriented housing, such as PBSAs, concentrates large student populations and, when coupled with poor management, creates more opportunities for offences, making it a significant predictor of all three offence types. Overall, these findings highlight the need for targeted interventions in studentified neighbourhoods during academic terms to support community safety and wellbeing.

With all research findings in the manuscripts based on statistical modelling of official data, including census data and police-reported crime data, the supplementary study (Chapter 5) addressed the following important question:

Do official statistics reflect residents' perceptions of wellbeing in neighbourhoods?

Indicators based on official statistics capture important structural conditions but may only partially reflect residents' perceptions and lived experience. In Kitchener–Waterloo, perceived housing unaffordability was associated with census-based rent but not with dwelling value, while perceived neighbourhood unsafety is associated with both police-reported disorder and major street crime rates. However, even where these relationships were statistically significant, the spatial patterns between the measured variables and perceived wellbeing are only partially aligned. Multilevel modelling further showed that individual sociodemographic characteristics significantly shape

perceptions. Overall, these findings suggest that relying solely on official statistics may overlook important subjective dimensions of wellbeing, highlighting the need to integrate perception-based data to better understand neighbourhood dynamics and support more people-centred planning and policymaking.

As neighbourhoods are constantly evolving, neighbourhood processes such as gentrification, studentification, and youthification are not by definition societal problems. However, without appropriate planning and policy measures, these processes may create displacement pressures, reduce housing opportunities for certain population groups, contribute to increasingly exclusionary neighbourhood environments, and generate neighbourhood disorder and safety concerns. Without interventions that promote housing affordability, community inclusiveness, and neighbourhood safety, these changes may ultimately reinforce social and spatial inequalities by affecting residents' access to neighbourhood resources, lived experiences and wellbeing, and their opportunities to choose, access, and remain in the neighbourhoods where they wish to live.

6.2 Research contributions

This dissertation has theoretical, methodological and practical contributions. First, this research advances theoretical understandings of neighbourhood processes, public transit development, and environmental criminology from a spatiotemporal perspective. The first manuscript conceptualizes the spatiotemporal variability in the relationship between transit development and neighbourhood change, an aspect that previous research has either not captured or only partially addressed. This perspective helps explain why the theoretical relationship between urban rapid transit development and gentrification has not been consistently supported in empirical research. The second manuscript builds on existing knowledge of the spatial overlap of students, university graduates, and young adults by identifying and explaining their spatiotemporal patterns, including divergent temporal shifts of different groups within shared neighbourhoods in response to changing contextual conditions. The third manuscript extends environmental criminology to the context of studentification by drawing on broken windows theory, social disorganization theory, and

opportunity theories to explain spatiotemporal patterns of crime and disorder in studentified neighbourhoods, an area that has received limited attention in prior research.

Second, from a methodological perspective, although no entirely new models were developed, this research extended the application of existing methods to new contexts, particularly in neighbourhood change research where spatiotemporal modelling approaches have rarely been applied. The first manuscript adapted a spatiotemporal modelling approach with spatiotemporally varying regression coefficients, previously used in public health research, to examine neighbourhood change. This approach enables the identification of where and when LRT is associated with neighbourhood change, demonstrating the value and broader applicability of advanced spatiotemporal models. The second manuscript moved beyond bivariate correlation analyses used in previous research by employing joint modelling of multiple population groups to capture detailed spatiotemporal dynamics, including where and when these groups co-locate or diverge. The third manuscript applied modelling techniques increasingly used in crime analysis to the context of studentification, illustrating their capacity to examine societal issues related to neighbourhood processes. Furthermore, although more exploratory due to data constraints, the supplementary study highlights the importance of integrating perception-based data with official statistics and points to future methodological directions for more comprehensive analyses of neighbourhood dynamics.

Finally, from a practical perspective, the findings of this dissertation provide insights relevant to policy and planning decisions in Kitchener–Waterloo and in other regions with similar characteristics worldwide. The first manuscript identifies specific neighbourhoods where potential LRT-related gentrification has occurred, offering clear guidance on where interventions may be needed to address concerns such as housing affordability. It also introduces a spatiotemporal perspective on the transit–gentrification relationship that can be applied in other urban contexts to identify when and where policy responses are required. Similarly, the second manuscript identifies neighbourhoods that accommodate students, university graduates, and young adults but may present barriers to other groups, particularly disadvantaged populations, due to housing characteristics, highlighting areas where actions are needed to support more inclusive communities. These insights are also relevant to other university towns and knowledge economy regions

experiencing similar demographic and housing dynamics. The third manuscript highlights the need for targeted approaches to crime and disorder control in university towns, such as aligning bylaw enforcement and police patrols with academic calendars, improving the regulation and management of student-oriented housing, and strengthening community–university partnerships.

6.3 Limitations and uncertainties

Although limitations are discussed within the individual manuscripts and further complemented in the supplementary study, several challenges encountered in this research are worth discussing. Given that the central focus of this research is neighbourhood change, these challenges can be broadly categorized into those related to the definition of a neighbourhood and those related to the measurement of change.

6.3.1 The issue of defining a neighbourhood

All spatial statistical analyses in this dissertation were based on data available at, or aggregated to, neighbourhood units, defined as DAs in the manuscripts. As such, the research is subject to the modifiable areal unit problem (MAUP), which recognizes that data is usually arbitrarily aggregated into geographic units and different data aggregation units may result in different statistical output (Fotheringham & Wong, 1991; Openshaw, 1984). Finer spatial resolution helps capture localized sociodemographic variation that may be obscured in larger units (Prouse et al., 2014). This is particularly relevant to this research. Distance to LRT is measured more accurately at finer units. Studentification tends to be highly clustered in small areas, especially where high-density PBSAs are the dominant form. Crime research also favours smaller units that are more likely to reflect relatively homogeneous environmental conditions (Weisburd et al., 2009).

Nonetheless, smaller units are not always better, as they contain fewer observations (e.g., dwellings, residents, crime occurrences), which can lead to unstable and unreliable statistical estimates, known as the small numbers problem (Oberwittler & Wikström, 2009). Moreover, the appropriate spatial scale should align with the underlying process, as some processes, such as large-scale redevelopment, operate at broader spatial levels. Bayesian models with spatial random

effects can "borrow" information from the overall dataset and from neighbouring areas to partially address these issues (Law et al., 2014). However, uncertainties remain regarding whether analyses at coarser spatial scales (e.g., CTs) produce different yet meaningful results. Analyses at finer scales than DAs may also lead to different outcomes but require alternative data sources.

In addition to the issue of scale, MAUP concerns variations in analytical results arising from different boundary definitions at the same spatial resolution, known as the zoning effect. (Jelinski & Wu, 1996; Openshaw, 1984). Even when the scale of analysis aligns with the neighbourhood processes being studied, these processes may not conform to census boundaries. Research suggests constructing more meaningful neighbourhood boundaries tailored to specific analytical purposes based on some nuclear units, such as property addresses (Sperling, 2012). However, this again requires alternative data sources. Furthermore, when considering residents' lived experiences, their perceived neighbourhoods should not be overlooked. This further complicates the definition of neighbourhood, as perceived boundaries do not align with census or planning units, and may vary significantly even among residents living in close proximity (Coulton et al., 2013; Minnery et al., 2009).

6.3.2 The issue of measuring neighbourhood change

Measuring neighbourhood characteristics and change is constrained by data limitations. Census-based sociodemographic indicators and police-reported crime data were used in this dissertation selected based on research objectives and existing literature. Although these variables are imperfect, they provide reasonable proxies for neighbourhood conditions when alternative data, such as population movement data, accurate student residential locations, or actual crime incidents, are unavailable.

Even within available data, different choices of variables can lead to different results. For example, prior research has shown that different indicators and thresholds used to identify gentrification can lead to substantially different results (Preis et al., 2021). To mitigate this issue, different variable specifications were tested in each statistical modelling process. For example, this is reflected in the use of three studentification indicators in the third manuscript, while more variables were excluded after preliminary evaluation. However, it is not possible to test all

potential measures, and uncertainties therefore remain regarding how alternative quantifications may influence the results.

It is important to recognize that neighbourhood change is a continuous process. In practice, however, analyses rely on discrete temporal snapshots, leading to the modifiable temporal unit problem (MTUP). The MTUP, as the temporal counterpart of MAUP, refers to uncertainties in analytical outcomes caused by the arbitrary temporal units used for data aggregation (Cheng & Adepeju, 2014). Like most quantitative neighbourhood change research, analyses in this research relied on a relatively coarse temporal scale defined by census intervals (i.e., 5 years). This may mask rapid changes and conflate the effects of different contextual shifts. For example, the 2016–2021 period captures both the opening of the LRT and the onset of the COVID-19 pandemic, which may have had contrasting impacts on neighbourhood change but cannot be disentangled. Addressing this limitation would require moving beyond reliance on census data.

6.4 Future directions

Each manuscript outlines potential directions for future research to extend its findings. This section further highlights future directions within a broader context for studying neighbourhood processes. First, the spatiotemporal analyses conducted in Kitchener–Waterloo can be extended to other study areas globally. While Kitchener–Waterloo represents a typical university town and knowledge economy region, it also has unique characteristics, such as its twin-city structure, relatively dense transit network, and strong PBSA market. Examining whether the findings observed here hold in other contexts would therefore be valuable. Moreover, comparative studies of multiple cities can further advance understanding of urban processes. For example, Gu and Smith (2020) qualitatively compared studentification in China and the UK, highlighting both similarities and differences shaped by factors ranging from national policies to student characteristics. Similarly, comparative quantitative analyses across different regions could help determine the extent to which findings are generalizable or shaped by local context.

Second, more research questions about neighbourhood processes can be asked and answered with similar spatiotemporal analysis. Overall, spatiotemporal perspectives remain

underutilized in neighbourhood change research, despite such processes being inherently spatiotemporal. The individual and neighbourhood outcomes of neighbourhood processes also remain understudied. For example, although links between gentrification and health outcomes have been examined, they often lack a spatial perspective (Delong, 2023). Similarly, crime and other societal issues could be further examined within the neighbourhood change context using spatiotemporal approaches. For example, future research could ask whether gentrification reduces or displaces crime over time, or whether youthification is associated with increased neighbourhood disorder, similar to patterns observed in studentification.

Third, although extending the analysis to other study areas or other research questions may involve different datasets and potentially alleviate some data limitations, reliance on official data with fixed spatial and temporal units and limited available indicators is likely to remain a major constraint. Therefore, more systematic approaches are required to address data-related limitations in future research. Attempts to downscale census data have been made in prior studies, which can partially address restrictions imposed by census geographic boundaries (Chen et al., 2019; Patias et al., 2020). In addition, compared to sociodemographic characteristics and population movement, neighbourhood physical change may be more readily captured at high spatial and temporal resolution. From this perspective, neighbourhood change can be examined using alternative datasets such as remote sensing imagery and street view images (L. Lin et al., 2021; Thackway et al., 2023). Rapid advances in machine learning and GeoAI, which is the integration of artificial intelligence with geospatial data to extract patterns from large and complex spatial datasets, offer further potential to detect such changes and to integrate them with social data. Such novel methods may present further opportunities for analyses at higher spatiotemporal resolutions while reducing reliance on traditional sociodemographic indicators.

Finally, there are limits to what official statistics can capture. Neighbourhood change research, and social science more broadly, is fundamentally concerned with people and where they live, including their perceptions and physical and mental wellbeing. Greater integration of perception-based data, through large-scale surveys for quantitative analysis or interviews for qualitative insights, could complement statistical analyses based on official indicators. Measures derived from official statistics and perception-based data should not be seen as competing

approaches, but as complementary. Official statistics are more suitable for systematically capturing neighbourhood conditions, particularly at fine spatiotemporal resolution or across multiple study areas. In contrast, perception-based data help address the “so what” and “why” questions by revealing how changes are experienced by residents, especially in single case studies aimed at informing planning and policy decisions.

6.5 Conclusion

In summary, this dissertation advances the understanding of neighbourhood change by examining different urban processes from a spatiotemporal perspective in Kitchener–Waterloo. Utilizing various spatial and spatiotemporal models, the research demonstrates that neighbourhood transformations and their associations with other neighbourhood conditions are dynamic and context-dependent across space and time. The findings highlight the importance of moving beyond static and non-spatial analyses toward more robust frameworks that account for spatiotemporal variability and dependence, while also recognizing the limitations of relying solely on official statistics at aggregate scales of analysis. This research also opens up opportunities for future studies to refine methods, incorporate alternative data sources, and extend analyses to different geographical contexts. Ultimately, a deeper understanding of neighbourhood processes is critical for addressing pressing societal challenges and for guiding evidence-based planning and policy that enhance individual wellbeing and advance social equity.

References

Addie, J.-P. D., Keil, R., & Olds, K. (2015). Beyond town and gown: Universities, territoriality and the mobilization of new urban structures in Canada. *Territory, Politics, Governance*, *3*(1), 27–50. https://doi.org/10.1080/21622671.2014.924875

Allen, A., & Jacques, S. (2013). Alcohol-related crime among college students: A review of research and fruitful areas for future work. *Criminal Justice Studies*, *26*(4), 478–494. https://doi.org/10.1080/1478601X.2013.832673

Allen, J., & Taylor, Z. (2018). A new tool for neighbourhood change research: The Canadian Longitudinal Census Tract Database, 1971–2016. *Canadian Geographies / Géographies Canadiennes*, *62*(4), 575–588. https://doi.org/10.1111/cag.12467

Allinson, J. (2006). Over-educated, over-exuberant and over here? The impact of students on cities. *Planning Practice & Research*, *21*(1), 79–94. https://doi.org/10.1080/02697450600901541

Andresen, M. A., & Hodgkinson, T. (2023). In a world called catastrophe: The impact of COVID-19 on neighbourhood level crime in Vancouver, Canada. *Journal of Experimental Criminology*, *19*(2), 487–511. https://doi.org/10.1007/s11292-021-09495-6

Andresen, M. A., & Linning, S. J. (2012). The (in)appropriateness of aggregating across crime types. *Applied Geography*, *35*(1), 275–282. https://doi.org/10.1016/j.apgeog.2012.07.007

Andresen, M. A., & Malleson, N. (2013). Crime seasonality and its variations across space. *Applied Geography*, *43*, 25–35. https://doi.org/10.1016/j.apgeog.2013.06.007

Andrienko, G., Andrienko, N., Demsar, U., Dransch, D., Dykes, J., Fabrikant, S. I., Jern, M., Kraak, M.-J., Schumann, H., & Tominski, C. (2010). Space, time and visual analytics. *International Journal of Geographical Information Science*, *24*(10), 1577–1600. https://doi.org/10.1080/13658816.2010.508043

Anselin, L. (1988). *Spatial Econometrics: Methods and Models*. Springer. https://doi.org/10.1007/978-94-015-7799-1

Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical Analysis*, *27*(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Armitage, R. (2013). *Crime prevention through housing design*. Palgrave Macmillan. https://doi.org/10.1057/9781137316059

Atkinson, R., & Bridge, G. (2004). Introduction. In R. Atkinson & G. Bridge (Eds.), *Gentrification in a Global Context: The new urban colonialism* (pp. 1–17). Routledge. https://doi.org/10.4324/9780203392089

Baker, D. M., & Lee, B. (2019). How does light rail transit (LRT) impact gentrification? Evidence from fourteen US urbanized areas. *Journal of Planning Education and Research*, *39*(1), 35–49. https://doi.org/10.1177/0739456X17713619

Bardaka, E. (2024). Transit-induced gentrification and displacement: Future directions in research and practice. *Transport Reviews*, *44*(3), 567–571. https://doi.org/10.1080/01441647.2023.2282285

Bardaka, E., Delgado, M. S., & Florax, R. J. G. M. (2018). Causal identification of transit-induced gentrification and spatial spillover effects: The case of the Denver light rail. *Journal of Transport Geography*, *71*, 15–31. https://doi.org/10.1016/j.jtrangeo.2018.06.025

Barton, M. S. (2016). Gentrification and violent crime in New York City. *Crime & Delinquency*, *62*(9), 1180–1202. https://doi.org/10.1177/0011128714549652

Bathelt, H., Kogler, D. F., & Munro, A. K. (2011). Social foundations of regional innovation and the role of university spin-offs: The case of Canada's technology triangle. *Industry and Innovation*, *18*(5), 461–486. https://doi.org/10.1080/13662716.2011.583462

Bejinaru, R. (2017). Universities in the knowledge economy. *Management Dynamics in the Knowledge Economy*, *5*(2), 251–271. https://doi.org/10.25019/MDKE/5.2.05

Bennett, T., & Holloway, K. (2018). Drug and alcohol-related crime among university students. *International Journal of Offender Therapy and Comparative Criminology*, *62*(14), 4489–4509. https://doi.org/10.1177/0306624X18769601

Bereitschaft, B. (2020). Gentrification central: A change-based typology of the American urban core, 2000–2015. *Applied Geography, 118*, 102206. https://doi.org/10.1016/j.apgeog.2020.102206

Besag, J., York, J., & Mollié, A. (1991). Bayesian image restoration, with two applications in spatial statistics. *Annals of the Institute of Statistical Mathematics*, *43*(1), 1–20. https://doi.org/10.1007/BF00116466

Blangiardo, M., & Cameletti, M. (2015). *Spatial and Spatio-temporal Bayesian Models with R - INLA*. John Wiley & Sons.

Bobic, S., & Akhavan, M. (2022). Tourism gentrification in Mediterranean heritage cities. The necessity for multidisciplinary planning. *Cities*, *124*, 103616. https://doi.org/10.1016/j.cities.2022.103616

Bolstad, W. M., & Curran, J. M. (2016). *Introduction to Bayesian Statistics* (3rd ed.). John Wiley & Sons.

Bourne, L. S., & Hulchanski, J. D. (2020). Inequality and neighbourhood change: Context, concept, and process. In J. Grant, A. Walks, & H. Ramos (Eds.), *Changing neighbourhoods: Social and spatial polarization in Canadian cities*. University of British Columbia Press.

Braga, A. A., Welsh, B. C., & Schnell, C. (2015). Can policing disorder reduce crime? A systematic review and meta-analysis. *Journal of Research in Crime and Delinquency*, *52*(4), 567–588. https://doi.org/10.1177/0022427815576576

Bramwell, A., Nelles, J., & Wolfe, D. A. (2008). Knowledge, innovation and institutions: Global and local dimensions of the ICT cluster in Waterloo, Canada. *Regional Studies*, *42*(1), 101–116. https://doi.org/10.1080/00343400701543231

Bramwell, A., & Wolfe, D. A. (2008). Universities and regional economic development: The entrepreneurial University of Waterloo. *Research Policy*, *37*(8), 1175–1187. https://doi.org/10.1016/j.respol.2008.04.016

Brantingham, P., & Brantingham, P. (1993). Nodes, paths, and edges: Considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology*, *13*(1), 3–28. https://doi.org/10.1016/S0272-4944(05)80212-9

Brantingham, P., & Brantingham, P. (1995). Criminality of place: Crime generators and crime attractors. *European Journal on Criminal Policy and Research*, *3*(3), 5–26. https://doi.org/10.1007/BF02242925

Bridge, G., Butler, T., & Lees, L. (2011). *Mixed Communities: Gentrification by Stealth?* Policy Press.

Broitman, D. (2023). "Passive" ecological gentrification triggered by the Covid-19 pandemic. *Urban Planning*, *8*(1), 312–321. https://doi.org/10.17645/up.v8i1.6015

Brower, A. M., & Carroll, L. (2007). Spatial and temporal aspects of alcohol-related crime in a college town. *Journal of American College Health*, *55*(5), 267–275. https://doi.org/10.3200/JACH.55.5.267-276

Brown, A. E. (2016). Rubber tires for residents: Bus rapid transit and changing neighborhoods in Los Angeles, California. *Transportation Research Record*, *2539*(1), 1–10. https://doi.org/10.3141/2539-01

Brummet, Q., & Reed, D. (2019). *The effects of gentrification on the well-being and opportunity of original resident adults and children*. (Working Paper No. 19-30). FRB of Philadelphia. https://dx.doi.org/10.21799/frbp.wp.2019.30

Bunten, D. M., Preis, B., & Aron-Dine, S. (2024). Re-measuring gentrification. *Urban Studies*, *61*(1), 20–39. https://doi.org/10.1177/00420980231173846

Burgess, E. W. (1925). The growth of the city. In R. E. Park, E. W. Burgess, & R. D. McKenzie (Eds.), *The city*. University of Chicago Press.

Bursik, R. J., & Grasmick, H. G. (1999). *Neighborhoods and Crime: The Dimensions of Effective Community Control*. Lexington Books.

Cai, R., & Tan, S.-Y. (2025a). Are there non-business days for crime? A small-area Bayesian spatiotemporal analysis of crime patterns. *Deviant Behavior*, *46*(11), 1492–1509. https://doi.org/10.1080/01639625.2024.2387659

Cai, R., & Tan, S.-Y. (2025b). Exploring the relationship between income inequality and crime in Toronto using frequentist and Bayesian models: Examining different crime types and spatial scales. *Environment and Planning B: Urban Analytics and City Science*, *52*(8), 1814–1831. https://doi.org/10.1177/23998083241311969

Canadian Index of Wellbeing. (2012). *How are Canadians Really Doing? The 2012 CIW Report*. Canadian Index of Wellbeing and University of Waterloo.

Chapple, K. (2009). *Mapping susceptibility to gentrification: The early warning toolkit*. University of California Center for Community Innovation.

Chapple, K., Waddell, P., Chatman, D., Zuk, M., Loukaitou-Sideris, A., Ong, P., Gorska, K., Pech, C., & Gonzalez, S. R. (2017). *Developing a New Methodology for Analyzing Potential Displacement*. University of California, Los Angeles. https://escholarship.org/uc/item/6xb465cq

Chava, J., & Renne, J. L. (2022). Transit-induced gentrification or vice versa? A study of neighborhoods around light rail stations from 1970–2010. *Journal of the American Planning Association*, *88*(1), 44–54. https://doi.org/10.1080/01944363.2021.1920453

Checker, M. (2011). Wiped out by the "greenwave": Environmental gentrification and the paradoxical politics of urban sustainability. *City & Society*, *23*(2), 210–229.

Chen, Y., Zhang, R., Ge, Y., Jin, Y., & Xia, Z. (2019). Downscaling census data for gridded population mapping with geographically weighted area-to-point regression Kriging. *IEEE Access*, *7*, 149132–149141. https://doi.org/10.1109/ACCESS.2019.2945000

Cheng, T., & Adepeju, M. (2014). Modifiable temporal unit problem (MTUP) and its effect on space-time cluster detection. *PLOS ONE*, *9*(6), e100465. https://doi.org/10.1371/journal.pone.0100465

Chu, S. H. Y., Tan, S. Y., & Mortsch, L. (2021). Social resilience to flooding in Vancouver: The issue of scale. *Environmental Hazards, 20*(4), 400-415. https://doi.org/10.1080/17477891.2020.1834345

Cocola-Gant, A. (2023). Place-based displacement: Touristification and neighborhood change. *Geoforum*, *138*, 103665. https://doi.org/10.1016/j.geoforum.2022.103665

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review*, *44*(4), 588–608.

Corrigan, A. E., Curriero, F. C., & Linton, S. L. (2021). Characterizing clusters of gentrification in metro Atlanta, 2000 to 2016. *Applied Geography*, *137*, 102597. https://doi.org/10.1016/j.apgeog.2021.102597

Coulton, C. J., Jennings, M. Z., & Chan, T. (2013). How big is my neighborhood? Individual and contextual effects on perceptions of neighborhood scale. *American Journal of Community Psychology*, *51*(1), 140–150. https://doi.org/10.1007/s10464-012-9550-6

Couture, V., & Handbury, J. (2020). Urban revival in America. *Journal of Urban Economics*, *119*, 103267. https://doi.org/10.1016/j.jue.2020.103267

Couture, V., & Handbury, J. (2023). Neighborhood change, gentrification, and the urbanization of college graduates. *Journal of Economic Perspectives*, *37*(2), 29–52. https://doi.org/10.1257/jep.37.2.29

Cozens, P. M., Saville, G., & Hillier, D. (2005). Crime prevention through environmental design (CPTED): A review and modern bibliography. *Property Management*, *23*(5), 328–356. https://doi.org/10.1108/02637470510631483

Cundiff, K. (2021). Colleges and community crime: An analysis of campus proximity and neighborhood crime rates. *Crime & Delinquency*, *67*(3), 431–448. https://doi.org/10.1177/0011128720974312

Davidson, M., & Lees, L. (2010). New-build gentrification: Its histories, trajectories, and critical geographies. *Population, Space and Place*, *16*(5), 395–411. https://doi.org/10.1002/psp.584

Demšar, U., Harris, P., Brunsdon, C., Fotheringham, A. S., & McLoone, S. (2013). Principal component analysis on spatial data: an overview. *Annals of the Association of American Geographers, 103*(1), 106-128. https://doi.org/10.1080/00045608.2012.689236

Deka, D. (2017). Benchmarking gentrification near commuter rail stations in New Jersey. *Urban Studies*, *54*(13), 2955–2972. https://doi.org/10.1177/0042098016664830

Delmelle, E. C. (2015). Five decades of neighborhood classifications and their transitions: A comparison of four US cities, 1970–2010. *Applied Geography*, *57*, 1–11. https://doi.org/10.1016/j.apgeog.2014.12.002

Delmelle, E. C. (2022). GIScience and neighborhood change: Toward an understanding of processes of change. *Transaction in GIS*, *26*(2), 567–584. https://doi.org/10.1111/tgis.12871

Delmelle, E. C., Nilsson, I., & Bryant, A. (2021). Investigating transit-induced displacement using eviction data. *Housing Policy Debate*, *31*(2), 326–341. https://doi.org/10.1080/10511482.2020.1815071

Delong, S. (2023). Urban health inequality in shifting environment: Systematic review on the impact of gentrification on residents' health. *Frontiers in Public Health*, *11*. https://doi.org/10.3389/fpubh.2023.1154515

Dhillon, J., Shibli, A., Muriuki, N., Tan, T., Cammy, A., & Daniels, J. (2021). *WUSA Housing Report*. https://wusa.ca/wp-content/uploads/2022/08/WUSA-Housing-Report-May-2021-1.pdf

Ding, L., Hwang, J., & Divringi, E. (2016). Gentrification and residential mobility in Philadelphia. *Regional Science and Urban Economics*, *61*, 38–51. https://doi.org/10.1016/j.regsciurbeco.2016.09.004

Dong, H. (2017). Rail-transit-induced gentrification and the affordability paradox of TOD. *Journal of Transport Geography*, *63*, 1–10. https://doi.org/10.1016/j.jtrangeo.2017.07.001

Dooling, S. (2009). Ecological gentrification: A research agenda exploring justice in the city. *International Journal of Urban and Regional Research*, *33*(3), 621–639. https://doi.org/10.1111/j.1468-2427.2009.00860.x

Doucet, B. (2021). The 'hidden' sides of transit-induced gentrification and displacement along Waterloo Region's LRT corridor. *Geoforum*, *125*, 37–46. https://doi.org/10.1016/j.geoforum.2021.06.013

Edlund, L., Machado, C., & Sviatschi, M. (2022). Gentrification and the rising returns to skill. *Economica*, *89*(354), 258–292. https://doi.org/10.1111/ecca.12398

Ehlenz, M. M. (2019). The university and its neighborhood: A study of place-making and change. *Journal of Urban Affairs*, *41*(6), 776–794. https://doi.org/10.1080/07352166.2018.1530568

Elliot, D. S., Wilson, W. J., Huizinga, D., Sampson, R. J., Elliot, A., & Rankin, B. (1996). The Effects of neighborhood disadvantage on adolescent development. *Journal of Research in Crime and Delinquency*, *33*(4), 389–426. https://doi.org/10.1177/0022427896033004002

Ellis-Young, M., & Doucet, B. (2024). From “big small town” to “small big city”: Resident experiences of gentrification along Waterloo Region’s LRT corridor. *Journal of Planning Education and Research*, *44*(1), 416–430. https://doi.org/10.1177/0739456X21993914

Felson, M., & Clarke, R. V. (1999). *Opportunity Makes the Thief: Practical Theory for Crime Prevention*. Home Office.

Ferbrache, F., & Knowles, R. D. (2017). City boosterism and place-making with light rail transit: A critical review of light rail impacts on city image and quality. *Geoforum*, *80*, 103–113. https://doi.org/10.1016/j.geoforum.2017.01.013

Fincher, R., & Shaw, K. (2009). The unintended segregation of transnational students in central Melbourne. *Environment and Planning A*, *41*(8), 1884–1902. https://doi.org/10.1068/a41126

Finio, N. (2022). Measurement and definition of gentrification in urban studies and planning. *Journal of Planning Literature*, *37*(2), 249–264. https://doi.org/10.1177/08854122211051603

Fisher, B. S., & Sloan, J. J. (2022). *Campus Crime: Legal, Social, and Policy Perspectives* (4th ed.). Charles C Thomas Publisher.

Fisher, B. S., Sloan, J. J., Cullen, F. T., & Lu, C. (1998). Crime in the ivory tower: The level and sources of student victimization. *Criminology*, *36*(3), 671–710. https://doi.org/10.1111/j.1745-9125.1998.tb01262.x

Foote, N. S. (2017). Beyond studentification in United States college towns: Neighborhood change in the knowledge nodes, 1980–2010. *Environment and Planning A: Economy and Space*, *49*(6), 1341–1360. https://doi.org/10.1177/0308518X17698962

Foster, S., Giles-Corti, B., & Knuiman, M. (2010). Neighbourhood design and fear of crime: A social-ecological examination of the correlates of residents’ fear in new suburban housing developments. *Health & Place*, *16*(6), 1156–1165. https://doi.org/10.1016/j.healthplace.2010.07.007

Fotheringham, A. S., Crespo, R., & Yao, J. (2015). Geographical and temporal weighted regression (GTWR). *Geographical Analysis, 47*(4), 431-452. https://doi.org/10.1111/gean.12071

Fotheringham, A. S., & Wong, D. W. S. (1991). The modifiable areal unit problem in multivariate statistical analysis. *Environment and Planning A: Economy and Space*, *23*(7), 1025–1044. https://doi.org/10.1068/a231025

Freeman, L. (2005). Displacement or succession?: Residential mobility in gentrifying neighborhoods. *Urban Affairs Review*, *40*(4), 463–491. https://doi.org/10.1177/1078087404273341

Galster, G. (2001). On the nature of neighbourhood. *Urban Studies*, *38*(12), 2111–2124. https://doi.org/10.1080/00420980120087072

Gibbons, J. (2021). Measuring gentrification's association with perceived housing unaffordability: A Philadelphia case study. *Housing Policy Debate*, *31*(2), 306–325. https://doi.org/10.1080/10511482.2020.1810097

Glass, R. (1964). Aspects of change. In Centre for Urban Studies (Ed.), *London: Aspects of Change* (pp. xiii–xlii). MacGibbon & Kee.

Goetz, E. (2011). Gentrification in black and white: The racial impact of public housing demolition in American cities. *Urban Studies*, *48*(8), 1581–1604. https://doi.org/10.1177/0042098010375323

Golub, A., Guhathakurta, S., & Sollapuram, B. (2012). Spatial and Temporal Capitalization Effects of Light Rail in Phoenix: From Conception, Planning, and Construction to Operation. *Journal of Planning Education and Research*, *32*(4), 415–429. https://doi.org/10.1177/0739456X12455523

Gould, K. A., & Louis, T. L. (2012). The environmental injustice of green gentrification: The case of Brooklyn's Prospect Park. In J. N. DeSena & T. Shortell (Eds.), *The World in Brooklyn: Gentrification, immigration, and ethnic politics in a global city*. Lexington Books.

Gregory, J. (2022). An easy target: Studentification, crime and safety of students in Johannesburg. *South African Geographical Journal*, *104*(3), 366–381. https://doi.org/10.1080/03736245.2021.2004918

Grier, G., & Grier, E. (1978). *Urban Displacement: A Reconnaissance*. The Grier Partnership.

Grube-Cavers, A., & Patterson, Z. (2015). Urban rapid rail transit and gentrification in Canadian urban centres: A survival analysis approach. *Urban Studies*, *52*(1), 178–194. https://doi.org/10.1177/0042098014524287

Gruenewald, P. J., Sumetsky, N., Mair, C., Lee, J. P., & Ponicki, W. R. (2023). Micro-temporal analyses of crime related to alcohol outlets: A comparison of outcomes over weekday, weekend, daytime and nighttime hours. *Drug and Alcohol Review*, *42*(4), 902–911. https://doi.org/10.1111/dar.13644

Gu, H., & Smith, D. P. (2020). 'Living off the campus': Urban geographies of change and studentification in Beijing, China. *Urban Geography*, *41*(2), 205–224.

Haining, R. (1990). *Spatial Data Analysis in the Social and Environmental Sciences*.

Haining, R., & Li, G. (2020). *Regression Modelling with Spatial and Spatial-Temporal Data: A Bayesian Approach*. CRC Press.

Hawkins, J., Ahmed, U., Roorda, M., & Habib, K. N. (2022). Measuring the process of urban gentrification: A composite measure of the gentrification process in Toronto. *Cities*, *126*, 103708. https://doi.org/10.1016/j.cities.2022.103708

He, D., Sun, G., Li, L., & Webster, C. (2024). New metro and housing price and rent premiums: A natural experiment in China. *Urban Studies*, *61*(7), 1371–1392. https://doi.org/10.1177/00420980231208560

He, S. (2015). Consuming urban living in 'villages in the city': Studentification in Guangzhou, China. *Urban Studies*, *52*(15), 2849–2873. https://doi.org/10.1177/0042098014543703

He, S. (2019). Three waves of state-led gentrification in China. *Tijdschrift Voor Economische En Sociale Geografie*, *110*(1), 26–34. https://doi.org/10.1111/tesg.12334

Henson, B., & Reyns, B. W. (2015). The only thing we have to fear is fear Itself…and crime: The current state of the fear of crime literature and where It should go next. *Sociology Compass*, *9*(2), 91–103. https://doi.org/10.1111/soc4.12240

Hochstenbach, C. (2019). The age dimensions of urban socio-spatial change. *Population, Space and Place*, *25*(2), e2220. https://doi.org/10.1002/psp.2220

Hodgkinson, T., & Andresen, M. A. (2020). Show me a man or a woman alone and I'll show you a saint: Changes in the frequency of criminal incidents during the COVID-19 pandemic. *Journal of Criminal Justice*, *69*, 101706. https://doi.org/10.1016/j.jcrimjus.2020.101706

Hodgkinson, T., Andresen, M. A., & Saville, G. (2018). "Staying out that public housing": Examining the role of security measures in public housing design. *Crime Prevention and Community Safety*, *20*(2), 99–112. https://doi.org/10.1057/s41300-018-0040-0

Hodgkinson, T., & Vamvakaris, C. (2025). Back to school days: Crime seasonality in a campus-dominated community. *Journal of Criminal Justice*, *98*, 102388. https://doi.org/10.1016/j.jcrimjus.2025.102388

Holton, M., & Mouat, C. M. (2021). The rise (and rise) of vertical studentification: Exploring the drivers of studentification in Australia. *Urban Studies*, *58*(9), 1866–1884. https://doi.org/10.1177/0042098020925246

Huang, B., Wu, B., & Barry, M. (2010). Geographically and temporally weighted regression for modeling spatio-temporal variation in house prices. *International journal of geographical information science, 24*(3), 383-401. https://doi.org/10.1080/13658810802672469

Huang, Y., Parker, D. C., Babin, R., & Kong, F. (2024). Causal identification of transit-induced property value uplift in Canada's Waterloo Region: A spatio-temporal difference-in-differences method application. *Cities, 145*, 104676. https://doi.org/10.1016/j.cities.2023.104676

Huang, Y., Parker, D., & Minaker, L. (2021). Identifying latent demand for transit-oriented development neighbourhoods: Evidence from a mid-sized urban area in Canada. *Journal of Transport Geography, 90*, 102940. https://doi.org/10.1016/j.jtrangeo.2020.102940

Hubbard, P. (2009). Geographies of studentification and purpose-built student accommodation: Leading separate lives? *Environment and Planning A: Economy and Space*, *41*(8), 1903–1923. https://doi.org/10.1068/a4149

Hwang, J., & Lin, J. (2016). What have we learned about the causes of recent gentrification? *Cityscape*, *18*(3), 9–26.

Immergluck, D., & Balan, T. (2018). Sustainable for whom? Green urban development, environmental gentrification, and the Atlanta Beltline. *Urban Geography*, *39*(4), 546–562. https://doi.org/10.1080/02723638.2017.1360041

Immergluck, D., & Hollis, A. (2024). Different data, different measures: Comparing alternative indicators of changes in neighborhood home values. *Housing Policy Debate*, *34*(6), 793–813. https://doi.org/10.1080/10511482.2023.2254749

Infrastructure Ontario, & Metrolinx. (2022). *Transit Oriented Communities: Design Guidelines for Subway Stations Integrated within Development*. https://www.infrastructureontario.ca/48e24e/contentassets/68361bdc45aa403287f6e7d51bdf0576/toc_gudeline.pdf

Inzulza-Contardo, J. (2016). Contemporary Latin American gentrification? Young urban professionals discovering historic neighbourhoods. *Urban Geography*, *37*(8), 1195–1214. https://doi.org/10.1080/02723638.2016.1147754

Jelinski, D. E., & Wu, J. (1996). The modifiable areal unit problem and implications for landscape ecology. *Landscape Ecology*, *11*(3), 129–140. https://doi.org/10.1007/BF02447512

Johnson, G. D., Checker, M., Larson, S., & Kodali, H. (2022). A small area index of gentrification, applied to New York City. *International Journal of Geographical Information Science*, *36*(1), 137–157. https://doi.org/10.1080/13658816.2021.1931873

Jolivet, V., Reiser, C., Baumann, Y., & Gonzalès, R. (2023). Before displacement: Studentification, campus-led gentrification and rental market transformation in a multiethnic neighborhood (Parc-Extension, Montréal). *Urban Geography*, *44*(5), 983–1002. https://doi.org/10.1080/02723638.2022.2073150

Jun, H.-J. (2017). The spatial dynamics of neighborhood change: Exploring spatial dependence in neighborhood housing value change. *Housing Studies*, *32*(6), 717–741. https://doi.org/10.1080/02673037.2016.1228852

Jun, H.-J. (2022). Spillover effects in neighborhood housing value change: A spatial analysis. *Housing Studies*, *37*(8), 1303–1330. https://doi.org/10.1080/02673037.2020.1842338

Keels, M., Burdick–Will, J., & Keene, S. (2013). The effects of gentrification on neighborhood public schools. *City & Community*, *12*(3), 238–259. https://doi.org/10.1111/cico.12027

Kenyon, E. L. (1997). Seasonal sub-communities: The impact of student households on residential communities. *The British Journal of Sociology*, *48*(2), 286–301. https://doi.org/10.2307/591753

Kinton, C., Smith, D. P., & Harrison, J. (2016). De-studentification: Emptying housing and neighbourhoods of student populations. *Environment and Planning A: Economy and Space*, *48*(8), 1617–1635. https://doi.org/10.1177/0308518X16642446

Kinton, C., Smith, D. P., Harrison, J., & Culora, A. (2018). New frontiers of studentification: The commodification of student housing as a driver of urban change. *The Geographical Journal*, *184*(3), 242–254. https://doi.org/10.1111/geoj.12263

Knorr-Held, L. (2000). Bayesian modelling of inseparable space-time variation in disease risk. *Statistics in Medicine*, *19*(17–18), 2555–2567. https://doi.org/10.1002/1097-0258(20000915/30)19:17/18%253C2555::AID-SIM587%253E3.0.CO;2-%2523

KPMG. (2023). *Waterloo Regional Police Service Neighbourhood Policing Staffing & Workload Review*. https://www.wrps.on.ca/en/resources/WRPS-Final-Report-redacted.pdf

Kramer, A. (2018). The unaffordable city: Housing and transit in North American cities. *Cities*, *83*, 1–10. https://doi.org/10.1016/j.cities.2018.05.013

Lager, D., & Hoven, B. van. (2019). Exploring the experienced impact of studentification on ageing-in-place. *Urban Planning*, *4*(2), 96–105. https://doi.org/10.17645/up.v4i2.1947

LaRue, E., & Andresen, M. A. (2015). Spatial patterns of crime in Ottawa: The role of universities. *Canadian Journal of Criminology and Criminal Justice*, *57*(2), 189–214. https://doi.org/10.3138/CJCCJ.2013.E47

Law, J., Quick, M., & Chan, P. (2014). Bayesian spatio-temporal modeling for analysing local patterns of crime over time at the small-area level. *Journal of Quantitative Criminology*, *30*(1), 57–78. https://doi.org/10.1007/s10940-013-9194-1

Law, J., Quick, M., & Chan, P. W. (2015). Analyzing hotspots of crime using a Bayesian spatiotemporal modeling approach: A case study of violent crime in the Greater Toronto Area. *Geographical Analysis, 47*(1), 1-19. https://doi.org/10.1111/gean.12047

Law, J., Quick, M., & Jadavji, A. (2020). A Bayesian spatial shared component model for identifying crime-general and crime-specific hotspots. *Annals of GIS*, *26*(1), 65–79. https://doi.org/10.1080/19475683.2020.1720290

Lawson, A. B. (2018). *Bayesian Disease Mapping: Hierarchical Modeling in Spatial Epidemiology, Third Edition* (3rd ed.). Chapman and Hall/CRC. https://doi.org/10.1201/9781351271769

Lee, H. (2022). Are Millennials leaving town? Reconciling peak Millennials and youthification hypotheses. *International Journal of Urban Sciences*, *26*(1), 68–86. https://doi.org/10.1080/12265934.2020.1871061

Lee, R. J., & Newman, G. (2021). The relationship between vacant properties and neighborhood gentrification. *Land Use Policy*, *101*, 105185. https://doi.org/10.1016/j.landusepol.2020.105185

Lees, L. (2003). Super-gentrification: The Case of Brooklyn Heights, New York City. *Urban Studies*, *40*(12), 2487–2509. https://doi.org/10.1080/0042098032000136174

Lees, L., Slater, T., & Wyly, E. (2008). *Gentrification*. Routledge.

Lehrer, U., & Wieditz, T. (2009). Condominium development and gentrification: The relationship between policies, building activities and socio-economic development in Toronto. *Canadian Journal of Urban Research*, *18*(1), 140–161.

Ley, D. (1986). Alternative explanations for inner-city gentrification: A Canadian assessment. *Annals of the Association of American Geographers*, *76*(4), 521–535. https://doi.org/10.1111/j.1467-8306.1986.tb00134.x

Ley, D. (1994). Gentrification and the politics of the new middle class. *Environment and Planning D: Society and Space*, *12*(1), 53–74. https://doi.org/10.1068/d120053

Ley, D. (1996). *The new middle class and the remaking of the central city*. Oxford University Press.

Li, G., Haining, R., Richardson, S., & Best, N. (2014). Space–time variability in burglary risk: A Bayesian spatio-temporal modelling approach. *Spatial Statistics*, *9*, 180–191. https://doi.org/10.1016/j.spasta.2014.03.006

Lin, J.-J., & Chung, J.-C. (2017). Metro-induced gentrification: A 17-year experience in Taipei. *Cities*, *67*, 53–62. https://doi.org/10.1016/j.cities.2017.04.019

Lin, L., Di, L., Zhang, C., Guo, L., & Di, Y. (2021). Remote Sensing of Urban Poverty and Gentrification. *Remote Sensing*, *13*(20), 4022. https://doi.org/10.3390/rs13204022

Liu, J., Zhao, Y., Yang, Y., Xu, S., Zhang, F., Zhang, X., Shi, L., & Qiu, A. (2017). A mixed geographically and temporally weighted regression: Exploring spatial-temporal variations from global and local perspectives. *Entropy, 19*(2), 53. https://doi.org/10.3390/e19020053

Linning, S. J. (2015). Crime seasonality and the micro-spatial patterns of property crime in Vancouver, BC and Ottawa, ON. *Journal of Criminal Justice*, *43*(6), 544–555. https://doi.org/10.1016/j.jcrimjus.2015.05.007

Lupton, R., & Power, A. (2004). *What we know about neighbourhood change: A literature review* (Report No. 27). Centre for Analysis of Social Exclusion. http://sticerd.lse.ac.uk/case/

Malczewski, J., & Poetz, A. (2005). Residential burglaries and neighborhood socioeconomic context in London, Ontario: Global and local regression analysis. *The Professional Geographer*, *57*(4), 516–529. https://doi.org/10.1111/j.1467-9272.2005.00496.x

Malleson, N., & Andresen, M. A. (2016). Exploring the impact of ambient population measures on London crime hotspots. *Journal of Criminal Justice*, *46*, 52–63. https://doi.org/10.1016/j.jcrimjus.2016.03.002

Marcuse, P. (1985). Gentrification, abandonment, and displacement: Connections, causes, and policy responses in New York City. *Washington University Journal of Urban and Contemporary Law*, *28*, 195–248.

Massey, D. S., & Denton, N. A. (1988). The dimensions of residential segregation. *Social Forces*, *67*(2), 281–315. https://doi.org/10.1093/sf/67.2.281

Matheson, F. I. (2018). *2016 Ontario Marginalization Index: User Guide*. Public Health Ontario.

Matijosaitiene, I., Zhao, P., Jaume, S., & Gilkey Jr, J. W. (2019). Prediction of hourly effect of land use on crime. *ISPRS International Journal of Geo-Information*, *8*(1), 16. https://doi.org/10.3390/ijgi8010016

Melser, D. (2020). Estimating the housing capitalization effects of new infrastructure: Should we be using rents instead of prices? *Transportation Research Part A: Policy and Practice*, *138*, 402–421. https://doi.org/10.1016/j.tra.2020.04.016

Miessner, M. (2021). Studentification in Germany: How investors generate profits from student tenants in Goettingen and the impacts on urban segregation. *European Urban and Regional Studies*, *28*(2), 133–154. https://doi.org/10.1177/0969776420934850

Mikelbank, B. A. (2011). Neighborhood déjà vu: Classification in metropolitan Cleveland, 1970-2000. *Urban Geography, 32*(3), 317-333. https://doi.org/10.2747/0272-3638.32.3.317

Minnery, J., Knight, J., Byrne, J., & Spencer, J. (2009). Bounding neighbourhoods: How do residents do it? *Planning Practice & Research*, *24*(4), 471–493. https://doi.org/10.1080/02697450903327170

Moos, M. (2014). "Generationed" space: Societal restructuring and young adults' changing residential location patterns. *Canadian Geographies / Géographies Canadiennes*, *58*(1), 11–33. https://doi.org/10.1111/j.1541-0064.2013.12052.x

Moos, M. (2016). From gentrification to youthification? The increasing importance of young age in delineating high-density living. *Urban Studies*, *53*(14), 2903–2920. https://doi.org/10.1177/0042098015603292

Moos, M., Filion, P., Quick, M., & Walter-Joseph, R. (2019). Youthification across the metropolitan system: Intra-urban residential geographies of young adults in North American metropolitan areas. *Cities*, *93*, 224–237. https://doi.org/10.1016/j.cities.2019.05.017

Moos, M., Revington, N., Wilkin, T., & Andrey, J. (2019). The knowledge economy city: Gentrification, studentification and youthification, and their connections to universities. *Urban Studies*, *56*(6), 1075–1092. https://doi.org/10.1177/0042098017745235

Moreau, G., Jaffray, B., & Armstrong, A. (2020, October 29). *Police-reported crime statistics in Canada, 2019*. https://www150.statcan.gc.ca/n1/pub/85-002-x/2020001/article/00010-eng.htm

Morisson, A., & Bevilacqua, C. (2019). Balancing gentrification in the knowledge economy: The case of Chattanooga's innovation district. *Urban Research & Practice*, *12*(4), 472–492. https://doi.org/10.1080/17535069.2018.1472799

Mösgen, A., Rosol, M., & Schipper, S. (2019). State-led gentrification in previously 'un-gentrifiable' areas: Examples from Vancouver/Canada and Frankfurt/Germany. *European Urban and Regional Studies*, *26*(4), 419–433. https://doi.org/10.1177/0969776418763010

Munro, M., & Livingston, M. (2012). Student impacts on urban neighbourhoods: Policy approaches, discourses and dilemmas. *Urban Studies*, *49*(8), 1679–1694. https://doi.org/10.1177/0042098011419237

Musthafa, S. N. A. M., Leh, O. L. H., Omar, D., & Karuppannan, S. (2015). Theoretical review on environmental health in relation to neighbourhood planning and human physical activity. *Procedia - Social and Behavioral Sciences*, *201*, 325–332. https://doi.org/10.1016/j.sbspro.2015.08.182

Nakazawa, T. (2017). Expanding the scope of studentification studies. *Geography Compass*, *11*(1), e12300. https://doi.org/10.1111/gec3.12300

Oberwittler, D., & Wikström, P.-O. H. (2009). Why small is better: Advancing the study of the role of behavioral contexts in crime causation. In D. Weisburd, W. Bernasco, & G. J. N. Bruinsma (Eds.), *Putting Crime in its Place: Units of Analysis in Geographic Criminology* (pp. 35–59). Springer. https://doi.org/10.1007/978-0-387-09688-9_2

Olesen, K. (2020). Infrastructure imaginaries: The politics of light rail projects in the age of neoliberalism. *Urban Studies*, *57*(9), 1811–1826. https://doi.org/10.1177/0042098019853502

Openshaw, S. (1984). *The Modifiable Areal Unit Problem*. GeoBooks.

Padeiro, M., Louro, A., & da Costa, N. M. (2019). Transit-oriented development and gentrification: A systematic review. *Transport Reviews*, *39*(6), 733–754. https://doi.org/10.1080/01441647.2019.1649316

Patias, N., Rowe, F., & Cavazzi, S. (2020). A scalable analytical framework for spatio-temporal analysis of neighborhood change: A sequence analysis approach. In P. Kyriakidis, D. Hadjimitsis, D. Skarlatos, & A. Mansourian (Eds.), *Geospatial Technologies for Local*

and Regional Development (pp. 223–241). Springer International Publishing. https://doi.org/10.1007/978-3-030-14745-7_13

Phillips, M. (2010). Counterurbanisation and rural gentrification: An exploration of the terms. *Population, Space and Place*, *16*(6), 539–558.

Powell, K. H. (2014). In the shadow of the ivory tower: An ethnographic study of neighborhood relations. *Qualitative Social Work*, *13*(1), 108–126. https://doi.org/10.1177/1473325013509299

Powell, W. W., & Snellman, K. (2004). The knowledge economy. *Annual Review of Sociology*, *30*, 199–220. https://doi.org/10.1146/annurev.soc.29.010202.100037

Prada-Trigo, J., Aravena-Solís, N., & Barra-Vieira, P. (2022). Temporary destudentification caused by COVID-19: Motivations and effects on social relations in a Chilean university city. *Population, Space and Place*, *28*(4), e2529. https://doi.org/10.1002/psp.2529

Prada-Trigo, J., Revington, N., & Sánchez-Ondoño, I. (2024). Differences and similarities in student residential mobility during the COVID-19 pandemic in Temuco and Montréal. *Housing Studies*. https://doi.org/10.1080/02673037.2024.2409314

Preis, B., Janakiraman, A., Bob, A., & Steil, J. (2021). Mapping gentrification and displacement pressure: An exploration of four distinct methodologies. *Urban Studies*, *58*(2), 405–424. https://doi.org/10.1177/0042098020903011

Prouse, V., Ramos, H., Grant, J. L., & Radice, M. (2014). How and when Scale Matters: The Modifiable Areal Unit Problem and Income Inequality in Halifax. *Canadian Journal of Urban Research*, *23*(1), 61–82.

Quastel, N., Moos, M., & Lynch, N. (2012). Sustainability-as-density and the return of the social: The case of Vancouver, British Columbia. *Urban Geography*, *33*(7), 1055–1084. https://doi.org/10.2747/0272-3638.33.7.1055

Quick, M., Law, J., & Li, G. (2019). Time-varying relationships between land use and crime: A spatio-temporal analysis of small-area seasonal property crime trends. *Environment and Planning B: Urban Analytics and City Science*, *46*(6), 1018–1035. https://doi.org/10.1177/2399808317744779

Quick, M., Law, J., & Luan, H. (2017). The influence of on-premise and off-premise alcohol outlets on reported violent crime in the region of Waterloo, Ontario: Applying Bayesian spatial modeling to inform land use planning and policy. *Applied Spatial Analysis and Policy, 10*(3), 435-454. https://doi.org/10.1007/s12061-016-9191-5

Quick, M., Li, G., & Brunton-Smith, I. (2018). Crime-general and crime-specific spatial patterns: A multivariate spatial analysis of four crime types at the small-area scale. *Journal of Criminal Justice, 58*, 22-32. https://doi.org/10.1016/j.jcrimjus.2018.06.003

Quick, M., & Luan, H. (2021). The spatial structure of socioeconomic disadvantage: A Bayesian multivariate spatial factor analysis. *International Journal of Geographical Information Science*, *35*(1), 63–83. https://doi.org/10.1080/13658816.2020.1759807

Rankin, K. N., & McLean, H. (2015). Governing the commercial streets of the city: New terrains of disinvestment and gentrification in Toronto's inner suburbs. *Antipode*, *47*(1), 216–239. https://doi.org/10.1111/anti.12096

Ratcliffe, J. H. (2006). A temporal constraint theory to explain opportunity-based spatial offending patterns. *Journal of Research in Crime and Delinquency*, *43*(3), 261–291. https://doi.org/10.1177/0022427806286566

Rees-Punia, E., Hathaway, E. D., & Gay, J. L. (2018). Crime, perceived safety, and physical activity: A meta-analysis. *Preventive Medicine*, *111*, 307–313. https://doi.org/10.1016/j.ypmed.2017.11.017

Region of Waterloo. (2020). *Year-End 2019 Population and Household Estimates for Waterloo Region*. https://www.regionofwaterloo.ca/en/regional-government/resources/Census/DOCS_ADMIN-3260012-v3-PDL-CPL-20-11__Year-End_2019_Population_and_Household_Estimates_for_Waterloo_Region.pdf

Region of Waterloo. (2023). *Monitoring Change in the CTC 2022 Report*. https://www.regionofwaterloo.ca/en/regional-government/resources/LandUse_BuildingActivity/Monitoring-Change-in-the-Central-Transit-Corridor-2022_.pdf

Region of Waterloo (n.d.). Education and Talent. Retrieved on December 1, 2023, from https://www.regionofwaterloo.ca/en/doing-business/education-and-talent.aspx

Revington, N. (2015). Gentrification, transit, and land use: Moving beyond neoclassical theory. *Geography Compass*, *9*(3), 152–163. https://doi.org/10.1111/gec3.12203

Revington, N. (2022). Post-studentification? Promises and pitfalls of a near-campus urban intensification strategy. *Urban Studies*, *59*(7), 1424–1442. https://doi.org/10.1177/00420980211021358

Revington, N. (2024). Studentification as gendered urban process: Student geographies of housing in Waterloo, Canada. *Social & Cultural Geography*, *25*(1), 9–28. https://doi.org/10.1080/14649365.2022.2115536

Revington, N., & August, M. (2020). Making a market for itself: The emergent financialization of student housing in Canada. *Environment and Planning A: Economy and Space*, *52*(5), 856–877. https://doi.org/10.1177/0308518X19884577

Revington, N., & Benhocine, C. (2023). Financializing through crisis? Student housing and studentification during the Covid-19 pandemic and beyond. *Tijdschrift Voor Economische En Sociale Geografie*, *114*(5), 415–430. https://doi.org/10.1111/tesg.12549

Revington, N., Moos, M., Henry, J., & Haider, R. (2020). The urban dormitory: Planning, studentification, and the construction of an off-campus student housing market. *International Planning Studies*, *25*(2), 189–205. https://doi.org/10.1080/13563475.2018.1552565

Revington, N., Zwick, A., Hartt, M., & Schlosser, J. (2023). Universities and urban social structure: Gentrification, studentification, and youthification in five United States legacy cities. *Urban Geography*, *44*(1), 83–104. https://doi.org/10.1080/02723638.2021.1985306

Reyns, B. W., Sween, M., & Randa, R. (2022). College as a risk factor for victimization: Results from the national crime victimization survey. *Victims & Offenders*, *17*(1), 101–118. https://doi.org/10.1080/15564886.2021.1898506

Rice, J. L., Cohen, D. A., Long, J., & Jurjevich, J. R. (2020). Contradictions of the climate-friendly city: New perspectives on eco-gentrification and housing justice. *International Journal of Urban and Regional Research*, *44*(1), 145–165. https://doi.org/10.1111/1468-2427.12740

Richardson, S., Thomson, A., Best, N., & Elliott, P. (2004). Interpreting posterior relative risk estimates in disease-mapping studies. *Environmental Health Perspectives*, *112*(9), 1016–1025. https://doi.org/10.1289/ehp.6740

Rigolon, A., & Németh, J. (2020). Green gentrification or 'just green enough': Do park location, size and function affect whether a place gentrifies or not? *Urban Studies*, *57*(2), 402–420. https://doi.org/10.1177/0042098019849380

Rohe, W. M. (2009). From Local to Global: One Hundred Years of Neighborhood planning. *Journal of the American Planning Association*, *75*(2), 209–230. https://doi.org/10.1080/01944360902751077

Roosa, M. W., Jones, S., Tein, J.-Y., & Cree, W. (2003). Prevention science and neighborhood influences on low-Income children's development: Theoretical and methodological issues. *American Journal of Community Psychology*, *31*(1–2), 55–72. https://doi.org/10.1023/A:1023070519597

Roosa, M. W., White, R. M. B., Zeiders, K. H., & Tein, J.-Y. (2009). An examination of the role of perceptions in neighborhood research. *Journal of Community Psychology*, *37*(3), 327–341. https://doi.org/10.1002/jcop.20298

Rue, H., Martino, S., & Chopin, N. (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *71*(2), 319–392. https://doi.org/10.1111/j.1467-9868.2008.00700.x

Rue, H., Riebler, A., Sørbye, S. H., Illian, J. B., Simpson, D. P., & Lindgren, F. K. (2017). Bayesian computing with INLA: A review. *Annual Review of Statistics and Its Application*, *4*, 395–421. https://doi.org/10.1146/annurev-statistics-060116-054045

Sage, J., Smith, D., & Hubbard, P. (2012a). The diverse geographies of studentification: Living alongside people not like us. *Housing Studies*, *27*(8), 1057–1078. https://doi.org/10.1080/02673037.2012.728570

Sage, J., Smith, D., & Hubbard, P. (2012b). The rapidity of studentification and population change: There goes the (student)hood. *Population, Space and Place*, *18*(5), 597–613. https://doi.org/10.1002/psp.690

Sage, J., Smith, D., & Hubbard, P. (2013). New-build Studentification: A Panacea for Balanced Communities? *Urban Studies*, *50*(13), 2623–2641. https://doi.org/10.1177/0042098013477694

Sampson, R. J., & Groves, W. B. (1989). Community structure and crime: Testing social-disorganization theory. *American Journal of Sociology*, *94*(4), 774–802. https://doi.org/10.1086/229068

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science of The Total Environment*, *277*(5328), 918–924. https://doi.org/10.1126/science.277.5328.918

Sandel, M., Faugno, E., Mingo, A., Cannon, J., Byrd, K., Garcia, D. A., Collier, S., McClure, E., & Jarrett, R. B. (2016). Neighborhood-level interventions to improve childhood opportunity and lift children out of poverty. *Academic Pediatrics, 16*(3), S128–S135. https://doi.org/10.1016/j.acap.2016.01.013

Scarborough, B. K., Like-Haislip, T. Z., Novak, K. J., Lucas, W. L., & Alarid, L. F. (2010). Assessing the relationship between individual characteristics, neighborhood context, and fear of crime. *Journal of Criminal Justice*, *38*(4), 819–826. https://doi.org/10.1016/j.jcrimjus.2010.05.010

Scherer, M. (2010). Is light rail more attractive to users than bus transit?: Arguments based on cognition and rational choice. *Transportation Research Record*, *2144*(1), 11–19. https://doi.org/10.3141/2144-02

Scherer, M., & Zurich, E. (2012). Bus or rail: An approach to explain the psychological rail factor. *Journal of Public Transportation*, *15*(1), 75–93. https://doi.org/10.5038/2375-0901.15.1.5

Schnake-Mahl, A. S., Jahn, J. L., Subramanian, S. V., Waters, M. C., & Arcaya, M. (2020). Gentrification, neighborhood change, and population health: A systematic review. *Journal of Urban Health*, *97*(1), 1–25. https://doi.org/10.1007/s11524-019-00400-1

Shaw, K. (2008). Gentrification: What it is, why it is, and what can be done about it. *Geography Compass*, *2*(5), 1697–1728. https://doi.org/10.1111/j.1749-8198.2008.00156.x

Simmie, J. (2003). Innovation and urban regions as national and international nodes for the transfer and sharing of knowledge. *Regional Studies*, *37*(6–7), 607–620. https://doi.org/10.1080/0034340032000108714

Singh, Y. J., Lukman, A., Flacke, J., Zuidgeest, M., & Van Maarseveen, M. F. A. M. (2017). Measuring TOD around transit nodes—Towards TOD policy. *Transport Policy*, *56*, 96–111. https://doi.org/10.1016/j.tranpol.2017.03.013

Slater, T. (2006). The Eviction of critical perspectives from gentrification research. *International Journal of Urban and Regional Research*, *30*(4), 737–757. https://doi.org/10.1111/j.1468-2427.2006.00689.x

Sloan, J. J., & Fisher, B. S. (2010). *The Dark Side of the Ivory Tower: Campus Crime as a Social Problem*. Cambridge University Press.

Smale, B., & Gao, M. (2019). *Wellbeing in Waterloo Region: A Summary of Results from the CIW Community Wellbeing Survey*. Canadian Index of Wellbeing and the University of Waterloo.

Smith, D. P. (2005). 'Studentification': The gentrification factory? In R. Atkinson & G. Bridge (Eds.), *Gentrification in a Global Context* (pp. 72–89). Routledge.

Smith, D. P., & Holt, L. (2007). Studentification and 'apprentice' gentrifiers within Britain's provincial towns and cities: Extending the meaning of gentrification. *Environment and Planning A: Economy and Space*, *39*(1), 142–161. https://doi.org/10.1068/a38476

Smith, D. P., & Hubbard, P. (2014). The segregation of educated youth and dynamic geographies of studentification. *Area*, *46*(1), 92–100. https://doi.org/10.1111/area.12054

Smith, D. P., Sage, J., & Balsdon, S. (2014). The geographies of studentification: 'Here, there and everywhere'? *Geography*, *99*(3), 116–127. https://doi.org/10.1080/00167487.2014.12094405

Smith, N. (1979). Toward a theory of gentrification: A back to the city movement by capital, not people. *Journal of the American Planning Association*, *45*(4), 538–548. https://doi.org/10.1080/01944367908977002

Smith, N. (1987). Gentrification and the rent gap. *Annals of the Association of American Geographers*, *77*(3), 462–465. https://doi.org/10.1111/j.1467-8306.1987.tb00171.x

Song, C., Shi, X., Bo, Y., Wang, J., Wang, Y., & Huang, D. (2019). Exploring spatiotemporal nonstationary effects of climate factors on hand, foot, and mouth disease using Bayesian Spatiotemporally Varying Coefficients (STVC) model in Sichuan, China. *Science of The Total Environment*, *648*, 550–560. https://doi.org/10.1016/j.scitotenv.2018.08.114

Song, C., Shi, X., & Wang, J. (2020). Spatiotemporally Varying Coefficients (STVC) model: a Bayesian local regression to detect spatial and temporal nonstationarity in variables relationships. *Annals of GIS, 26*(3), 277-291. https://doi.org/10.1080/19475683.2020.1782469

Song, I., & Luan, H. (2022). The spatially and temporally varying association between mental illness and substance use mortality and unemployment: A Bayesian analysis in the contiguous United States, 2001–2014. *Applied Geography*, *140*, 102664. https://doi.org/10.1016/j.apgeog.2022.102664

Sperling, J. (2012). The tyranny of census geography: Small-area data and neighborhood statistics. *Cityscape*, *14*(2), 219–223.

Spiegelhalter, D. J., Best, N. G., Carlin, B. P., & Van Der Linde, A. (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *64*(4), 583–639. https://doi.org/10.1111/1467-9868.00353

Statistics Canada. (2022a). *Dictionary, Census of Population, 2021 – Census tract (CT)*. https://www12.statcan.gc.ca/census-recensement/2021/ref/dict/az/Definition-eng.cfm?ID=geo013

Statistics Canada. (2022b). *Dictionary, Census of Population, 2021 – Dissemination area (DA)*. https://www12.statcan.gc.ca/census-recensement/2021/ref/dict/az/Definition-eng.cfm?ID=geo021

Stehlin, J. (2016). The post-industrial "shop floor": Emerging forms of gentrification in San Francisco's innovation economy. *Antipode*, *48*(2), 474–493. https://doi.org/10.1111/anti.12199

Stewart, J., & Kennelly, P. J. (2010). Illuminated choropleth maps. *Annals of the Association of American Geographers*, *100*(3), 513–534. https://doi.org/10.1080/00045608.2010.485449

Tapia, M., Ochoa, E., & Cundiff, K. (2024). Social disorganization theory and the college campus periphery. *Social Science Quarterly*, *105*(7), 2054–2066. https://doi.org/10.1111/ssqu.13466

Temkin, K., & Rohe, W. (1996). Neighborhood change and urban policy. *Journal of Planning Education and Research*, *15*(3), 159–170. https://doi.org/10.1177/0739456X9601500301

Temple, P. (2012). University organisation and knowledge production. In P. Temple (Ed.), *Universities in the Knowledge Economy: Higher Education Organisation and Global Change* (pp. 11–18). Routledge.

Thackway, W., Ng, M., Lee, C.-L., & Pettit, C. (2023). Implementing a deep-learning model using Google street view to combine social and physical indicators of gentrification. *Computers, Environment and Urban Systems*, *102*, 101970. https://doi.org/10.1016/j.compenvurbsys.2023.101970

Town and Gown Committee. (2023). 2023 student accommodations report. Retrieved on December 1, 2023, from https://www.waterloo.ca/en/government/resources/Documents/Cityadministration/Student-accommodations-report-2023.pdf

Tran, L. D., Rice, T. H., Ong, P. M., Banerjee, S., Liou, J., & Ponce, N. A. (2020). Impact of gentrification on adult mental health. *Health Services Research*, *55*(3), 432–444. https://doi.org/10.1111/1475-6773.13264

Troost, A. A., Manley, D. J., & van Ham, M. (2025). Do you see it how I see it? Differences in neighborhood perceptions explained by individuals' socioeconomic characteristics and trust attitudes. *Urban Geography*, *46*(10), 2281–2301. https://doi.org/10.1080/02723638.2025.2501456

Uittenbogaard, A., & Ceccato, V. (2012). Space-time clusters of crime in Stockholm, Sweden. *Review of European Studies*, *4*(5), 148–156. https://doi.org/10.5539/res.v4n5p148

Van Ham, M., Manley, D., Bailey, N., Simpson, L., & Maclennan, D. (2012). Understanding neighbourhood dynamics: New insights for neighbourhood effects research. In M. van Ham, D. Manley, N. Bailey, L. Simpson, & D. Maclennan (Eds.), *Understanding*

neighbourhood dynamics: New insights for neighbourhood effects research (pp. 1–21). Springer.

Venter, C., Jennings, G., Hidalgo, D., & Valderrama Pineda, A. F. (2018). The equity impacts of bus rapid transit: A review of the evidence and implications for sustainable transport. *International Journal of Sustainable Transportation*, *12*(2), 140–152. https://doi.org/10.1080/15568318.2017.1340528

Vinodrai, T. (2017). Planning for "cool": Millennials and the innovation economy of cities. In M. Moos, D. Pfeiffer, & T. Vinodrai (Eds.), *The Millennial City* (pp. 27–37). Routledge.

Walks, A., Hawes, E., & Simone, D. (2021). Gentrification in large Canadian cities: Tenure, age, and exclusionary displacement 1991-2011. *Urban Geography, 42*(5), 603–633. https://doi.org/10.1080/02723638.2020.1832376

Walks, R. A., & Maaranen, R. (2008). *The Timing, Patterning, & Forms of Gentrification & Neighbourhood Upgrading in Montreal, Toronto, & Vancouver, 1961 to 2001*. Cities Centre, University of Toronto.

Wang, L., Lee, G., & Williams, I. (2019). The spatial and social patterning of property and violent crime in Toronto neighbourhoods: A spatial-quantitative approach. *ISPRS International Journal of Geo-Information*, *8*(1), 51. https://doi.org/10.3390/ijgi8010051

Watanabe, S. (2009). *Algebraic Geometry and Statistical Learning Theory*. Cambridge University Press.

Webber, K. (2022). *Exploring the relationship between transit-induced intensification and retail gentrification in a mid-sized Canadian city* [Master's Thesis, University of Waterloo]. Retrieved http://hdl.handle.net/10012/18760

Weisburd, D., Bruinsma, G. J. N., & Bernasco, W. (2009). Units of analysis in geographic criminology: Historical development, critical issues, and open questions. In D. Weisburd, W. Bernasco, & G. J. N. Bruinsma (Eds.), *Putting Crime in its Place: Units of Analysis in Geographic Criminology* (pp. 3–31). Springer. https://doi.org/10.1007/978-0-387-09688-9_1

Weiss, K. G. (2013). *Party School: Crime, Campus, and Community*. Northeastern University Press.

Weiss, K. G., & Dilks, L. M. (2016). Intoxication and crime risk: Contextualizing the effects of "party" routines on recurrent physical and sexual attacks among college students. *Criminal Justice Review*, *41*(2), 173–189. https://doi.org/10.1177/0734016816634784

Wen, M., Hawkley, L. C., & Cacioppo, J. T. (2006). Objective and perceived neighborhood environment, individual SES and psychosocial factors, and self-rated health: An analysis of older adults in Cook County, Illinois. *Social Science & Medicine*, *63*(10), 2575–2590. https://doi.org/10.1016/j.socscimed.2006.06.025

Wilson, J. Q., & Kelling, G. L. (1982). Broken windows. *The Atlantic*, (March).

Woldoff, R. A., & Weiss, K. G. (2018). Studentification and disorder in a college town. *City & Community*, *17*(1), 259–275. https://doi.org/10.1111/cico.12279

Wortley, R., & Mazerolle, L. (2008). Environmental criminology and crime analysis: Situating the theory, analytic approach and application. In R. Wortley & L. Mazerolle (Eds.), *Environmental Criminology and Crime Analysis* (pp. 1–18). Willan Publishing.

Wu, C., Ren, F., Hu, W., & Du, Q. (2019). Multiscale geographically and temporally weighted regression: Exploring the spatiotemporal determinants of housing prices. International *Journal of Geographical Information Science, 33*(3), 489-511. https://doi.org/10.1080/13658816.2018.1545158

Wu, Q., Zhang, X., & Waley, P. (2016). Jiaoyufication: When gentrification goes to school in the Chinese inner city. *Urban Studies*, *53*(16), 3510–3526. https://doi.org/10.1177/0042098015613234

Wyly, E. K., & Hammel, D. J. (2004). Gentrification, segregation, and discrimination in the American urban system. *Environment and Planning A: Economy and Space*, *36*(7), 1215–1241. https://doi.org/10.1068/a3610

Yang, B., Liu, L., Lan, M., Wang, Z., Zhou, H., & Yu, H. (2020). A spatio-temporal method for crime prediction using historical crime data and transitional zones identified from nightlight imagery. *International Journal of Geographical Information Science*, *34*(9), 1740–1764. https://doi.org/10.1080/13658816.2020.1737701

Zandiatashbar, A., & Hamidi, S. (2018). Impacts of transit and walking amenities on robust local knowledge economy. *Cities*, *81*, 161–171. https://doi.org/10.1016/j.cities.2018.04.005

Zandiatashbar, A., & Hamidi, S. (2022). Impact of transit quality on anchor-mediated knowledge economies across large U.S. cities. *Transportation Research Record*, *2676*(4), 763–775. https://doi.org/10.1177/03611981211065440

Zandiatashbar, A., Hamidi, S., Foster, N., & Park, K. (2019). The missing link between place and productivity? The impact of transit-oriented development on the knowledge and creative economy. *Journal of Planning Education and Research*, *39*(4), 429–441. https://doi.org/10.1177/0739456X19826271

Zhang, J., Ma, Z., Li, D., Liu, W., Tong, Y., & Li, C. (2020). Young pioneers, vitality, and commercial gentrification in Mudan Street, Changchun, China. *Sustainability*, *12*(8), 3113. https://doi.org/10.3390/su12083113

Zhang, J., & Wu, L. (2025). Gentrification outcomes of greening in different urbanization stages: A longitudinal analysis of Chinese cities, 2012–2020. *Environment and Planning B: Urban Analytics and City Science*, *52*(1), 231–246. https://doi.org/10.1177/23998083241258683

Zhang, L., Tan, P. Y., & Richards, D. (2021). Relative importance of quantitative and qualitative aspects of urban green spaces in promoting health. *Landscape and Urban Planning*, *213*, 104131. https://doi.org/10.1016/j.landurbplan.2021.104131

Zuk, M., Bierbaum, A. H., Chapple, K., Gorska, K., & Loukaitou-Sideris, A. (2018). Gentrification, displacement, and the role of public investment. *Journal of Planning Literature*, *33*(1), 31–44. https://doi.org/10.1177/0885412217716439

Zuk, M., Bierbaum, A., Gorska, K., Loukaitou-Sideris, A., Ong, P., Thomas, T., & Chapple, K. (2015). *Gentrification, Displacement and the Role of Public Investment: A Literature Review*. https://doi.org/10.13140/RG.2.2.12408.60168

Appendix A. Census data harmonization

Census data from earlier years were harmonized to the 2021 DA boundaries in the first and second manuscripts. Figure A1 illustrates the 2021 DAs (476 in total) based on DA boundary consistency. 398 DAs have 2021 boundaries that are identical to or fully contained within all previous boundaries, allowing direct data alignment with no additional harmonization steps. 74 DAs have 2021 boundaries that are identical to or fully contained within the 2016 and 2011 boundaries, but not the 2006 or 2001 boundaries, requiring additional harmonization steps in the first manuscript. 4 DAs have 2021 boundaries that are not fully contained within the 2016 or 2011 boundaries, requiring additional harmonization steps in both the first and second manuscripts. Boundary reconfigurations confined to areas without dwellings are not considered as changes.

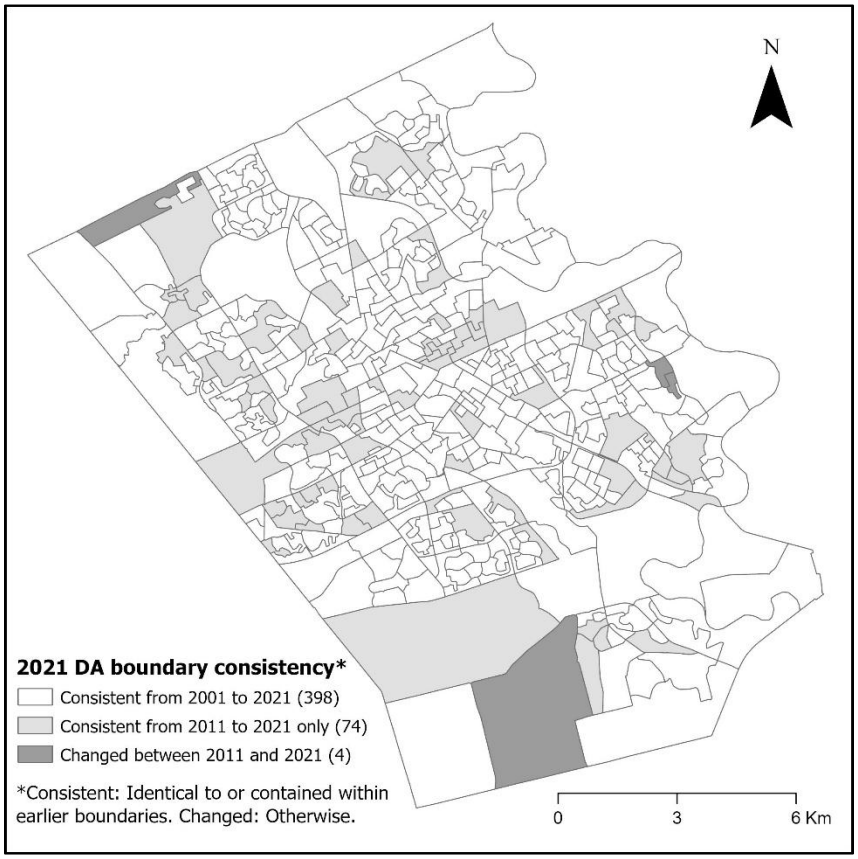


Figure A1: Dissemination area boundary consistency between 2001 and 2021.

The method used by Allen and Taylor (2018) to create the Canadian longitudinal census tract database was adapted in this research to harmonize DA data. For DAs with inconsistent boundaries over time, data values were apportioned from earlier DAs and spatially joined to the intersecting 2021 DAs to obtain previous year census data aligned with the 2021 boundaries. Let A denote a 2021 DA and let B_k $(k = 1,2, \dots, n)$ denote DAs from a previous census year that spatially intersect with A. The census variable values from the previous census year allocated to the boundaries of A are given by Equation A1 below.

$$W_{A,B_k} = \frac{P_{A,B_k}}{P_{B_k}}$$

$$C_A = \sum_{k=1}^{n} W_{A,B_k} C_{B_k}$$

$$R_A = \frac{\sum_{k=1}^{n} W_{A,B_k} P_{B_k} R_{B_k}}{\sum_{k=1}^{n} W_{A,B_k} P_{B_k}}$$

(A1)

W_{A,B_k} is the apportionment weight used to allocate data from B_k to A. P_{B_k} is the total population or dwelling count in B_k, and P_{A,B_k} is the population or dwelling count of B_k that falls within the boundaries of A. Population is used for population-based variables (age group, personal income, etc.), while dwelling count is used for dwelling- or household-based variables (tenure, dwelling value, etc.). C_{B_k} represents the value of a count variable (senior population, number of condominium units, etc.) in B_k, and C_A represents the value of this variable allocated to the boundaries of A. R_{B_k} represents the value a ratio variable (average income, percentage of low income, etc.) in B_k, and R_A represents the value of this variable allocated to the boundaries of A.

The only required parameter in Equation A1 that is not directly available or calculable from DA-level census data is P_{A,B_k}, which must be calculated or estimated using data at the dissemination block (DB) scale. The DB is the smallest census geographic unit for which population and dwelling counts are available, with no other variables reported at this scale, and all DBs are nested within DAs of the same census year. Most DAs that have undergone boundary

changes maintain alignment with DB boundaries from previous census years. For these DAs, P_{A,B_k} can be calculated as the sum of population or dwelling counts of DBs that are nested within B_k and also fall within the boundaries of A. Figure A2 illustrates an example of calculating apportionment weights and joining previous census data to the 2021 boundaries using this method.

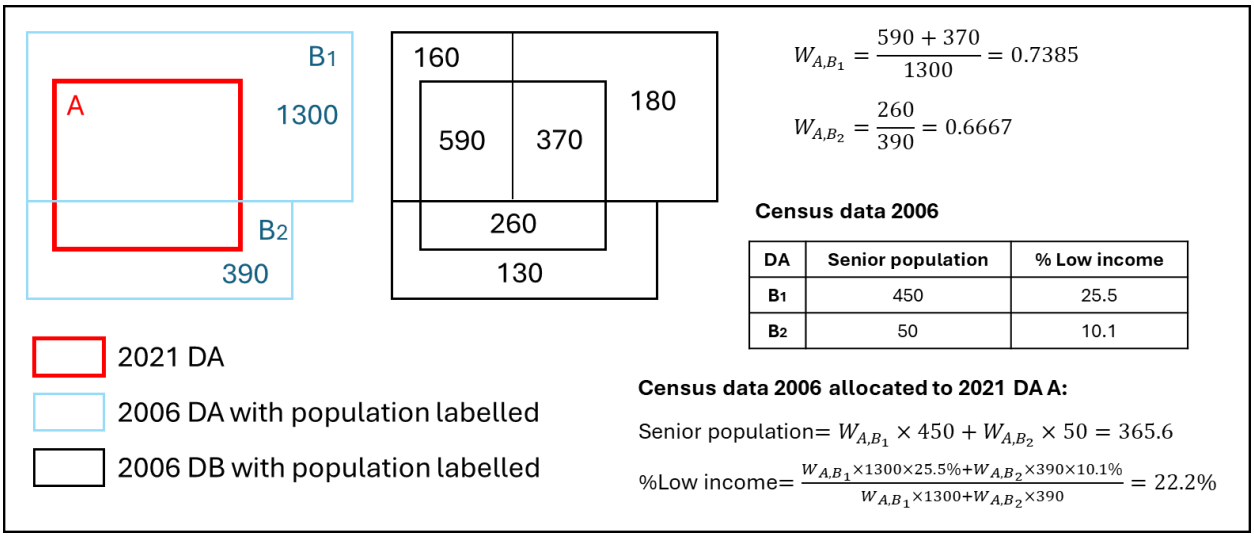


Figure A2: Dissemination area boundary consistency between 2001 and 2021.

For DAs that intersect, but do not fully encompass, one or more previous DBs, a decision must be made to apportion the affected DBs. Allen and Taylor (2018) allocated DB-level population in proportion to built-up area, an approach well suited to automated processing of large national datasets. Given the much smaller study area of Kitchener–Waterloo, this research instead employed building permits, remote sensing data, and Google Earth Timelapse imagery to count or estimate the number of residential dwellings within each portion of a DB that falls inside the boundaries of each intersecting 2021 DA. These estimates were then used to proportionally allocate DB-level population and dwelling counts to subareas fully contained within the 2021 DAs. The resulting subareas replaced the original DBs and were then used to calculate P_{A,B_k}.

Appendix B. Supplementary material to Chapter 2

Validating the regression model

Moran's I test was used to confirm the presence of spatial autocorrelation in the dependent variables. Significantly positive Moran's I values indicate positive spatial autocorrelation. Table A1 shows the Moran's I statistics and the associated p-values. Significantly positive Moran's I statistics were the found in both the change in average income ($I = 0.23$; p-value < 0.001) and the change in average dwelling value per room ($I = 0.14$; p-value < 0.001), validating the assumption of positive spatial autocorrelation in the regression model.

The Variance Inflation Factor (VIF) was used to test for multicollinearity, which refers to the correlations between explanatory variables that could potentially lead to unreliable regression results. VIF values are provided in Table B1. Most VIF values were below 3, indicating little to no concern about multicollinearity for most variables, and none exceeded 10, indicating no significant multicollinearity.

Table B1. VIF values of explanatory variables in regression.

Variable	Regression 1: Change in average income	Regression 2: Change in average dwelling value per room
Distance to LRT	1.77	1.82
Average income	2.07	
Dwelling value per room		1.38
Children	2.09	2.06
Youths	1.33	1.15
Renters	6.82	5.98
Low-income population	2.76	2.35
Movers	3.88	3.83
Population density	1.41	1.38
Apartments	7.25	6.45
Attached dwellings	1.85	1.82
Dwelling in disrepair	1.32	1.38
New dwellings	2.71	2.97
Commercial districts	1.33	1.29
Accessibility to buses	1.34	1.34

Posterior predictive checks were conducted by simulating replicated datasets from the full posterior predictive distribution and comparing observed summary statistics to their simulated counterparts. As shown in Table B2, posterior predictive p-values were computed for both the mean and SD as the proportion of replicated values exceeding the observed values. Both p-values were close to 0.5, indicating that the generated data were consistent with the observed data.

Table B2. Posterior predictive p-values for the current model

Dependent Variable	Mean	SD
Change in average income	0.47	0.51
Change in dwelling value per room	0.46	0.49

The deviance information criterion (DIC) and Watanabe–Akaike information criterion (WAIC), computed in R-INLA, were used to compare the performance of the current model to a base model and models incorporating other types of space-time interactions. The base model is the current model excluding the spatiotemporally random slope term. The current model assumes Type I space-time interaction, meaning that the space-time interaction term is independent across time and space. Types II, III, and IV interactions assume the space-time interaction term to be interdependent only over time, only over space, and over both space and time, respectively (Haining and Li, 2020; Knorr-Held, 2000). Changing the interaction types in the model involves modifying the prior settings for the space-time interaction term. Table B3 presents the DIC and WAIC results, with lower values indicating better model performance. The current model outperforms all other models.

Table B3. DIC and WAIC tests.

Model	**Regression 1: Change in average income**		**Regression 2: Change in average dwelling value per room**	
	DIC	WAIC	DIC	WAIC
Current model	-10291	-10696	-10136	-10634
Base model	-10094	-10431	-9993	-10351
Type II Interaction	-10186	-10541	-10076	-10437
Type III Interaction	-10109	-10521	-10056	-10432
Type IV Interaction	-10281	-10548	-9995	-10501

Appendix C. Supplementary material to Chapter 4

The academic calendar

The academic calendar used in this study is based on the UW calendar, which follows a three-term system. The start and end dates of each term are listed below, with the days between terms viewed as term breaks.

2015: Winter (Jan 05–Apr 26), Spring (May 04–Aug 16), and Fall (Sep 14–Dec 23).

2016: Winter (Jan 04–Apr 24), Spring (May 02– Aug 14), and Fall (Sep 08–Dec 23).

2017: Winter (Jan 03–Apr 26), Spring (May 01– Aug 12), and Fall (Sep 07–Dec 22).

2018: Winter (Jan 03–Apr 25), Spring (May 01– Aug 12), and Fall (Sep 06–Dec 22).

2019: Winter (Jan 07–Apr 28), Spring (May 06– Aug 17), and Fall (Sep 04–Dec 22).

Crime and disorder statistics

Table C1 details the specific offence types included under acquisitive crime, expressive crime, and disorder, along with their total counts during the five-year study period. Table C2 presents Moran's I test results for the three offence types, both overall and by day category, all of which show significantly positive spatial autocorrelation, indicating the need to account for spatial dependence in modelling.

Table C1. Offence types and counts included in this study

Offence	**Count 2015-2019**
Acquisitive crime	
Total	61256
Theft	36763
Motor vehicle theft	5156
Fraud	9461
Break and enter	8677
Robbery	966
Extortion	233
Expressive crime	
Total	11507
Assault	5440
Threatening	3494
Criminal harassment or stalking	470
Sex offence	2103
Disorder	
Total	126495
Indecent act	530
Drugs	5748
Liquor offence	4738
Property damage	9160
Gaming and betting	11
Unwanted contact	3485
Disturbance	10819
Dispute	13788
Intoxicated person	4867
Unwanted person	31683
Graffiti	1149
Bylaw complaint	40517

Table C2. Spatial autocorrelation (Moran's I) test results

Offence type	**Total**	**Term - business**	**Term - non-business**	**Break-business**	**Break - non-business**
Acquisitive	0.20 ($p<0.001$)	0.19 ($p<0.001$)	0.22 ($p<0.001$)	0.17 ($p<0.001$)	0.19 ($p<0.001$)
Expressive	0.25 ($p<0.001$)	0.22 ($p<0.001$)	0.27 ($p<0.001$)	0.25 ($p<0.001$)	0.29 ($p<0.001$)
Disorder	0.40 ($p<0.001$)	0.37 ($p<0.001$)	0.46 ($p<0.001$)	0.36 ($p<0.001$)	0.33 ($p<0.001$)

Regression results

Tables C3-C5 present the regression results using campus proximity, student-oriented housing, and student-aged population as the studentification indicators, respectively. The tables also report ΔDIC values, defined as the difference between the DIC of the current models, and the DIC of the models where regression coefficients for studentification indicators are held constant across day categories. Lower DIC values generally indicate model improvements and the interpretation of ΔDIC can follow the same rules used for Akaike information criterion (AIC) comparisons (Spiegelhalter et al., 2002). Values between 0 and -2 indicate no substantial difference, values between -4 and -7 suggest the current model is moderately better, and values lower than -10 indicate the current model is strongly better (Burnham & Anderson, 2002).

Table C3. Regression coefficient estimates (posterior means and 95% CIs of relative risks) for model specifications using campus proximity as the studentification indicator.

Variables	**Acquisitive crime**	**Expressive crime**	**Disorder**
Campus proximity as the studentification indicator (time-varying effects)			
λ_1 (term - business)	1.214 (0.902, 1.634)	1.068 (0.738, 1.545)	1.254 (0.928, 1.695)
λ_2 (term - non-business)	1.288 (0.941, 1.762)	1.302 (0.892, 1.907)	1.472 (1.096, 1.975)*
λ_3 (break - business)	1.093 (0.805, 1.483)	0.785 (0.503, 1.225)	1.082 (0.796, 1.471)
λ_4 (break – non-business)	1.103 (0.784, 1.550)	1.050 (0.674, 1.636)	1.230 (0.909, 1.663)
Intercept			
α_1 (term - business)	0.559 (0.550, 0.568)*	0.469 (0.451, 0.489)*	0.388 (0.383, 0.394)*
α_2 (term - non-business)	0.396 (0.386, 0.407)*	0.371 (0.346, 0.396)*	0.565 (0.556, 0.575)*
α_3 (break - business)	0.601 (0.580, 0.624)*	0.399 (0.360, 0.446)*	0.422 (0.409, 0.435)*
α (break – non-business)	0.385 (0.366, 0.406)*	0.353 (0.311, 0.398)*	0.528 (0.510, 0.546)*
Control variables (consistent effects over time)			
Population size	1.070 (1.055, 1.084)*	1.063 (1.046, 1.080)*	1.067 (1.053, 1.081)*
Residential instability	1.330 (1.191, 1.485)*	1.417 (1.240, 1.619)*	1.553 (1.394, 1.729)*
Material deprivation	1.056 (0.937, 1.190)	1.202 (1.043, 1.387)*	1.093 (0.972, 1.228)
Dependency	0.954 (0.852, 1.069)	0.904 (0.788, 1.037)	0.864 (0.773, 0.965)*
Ethnic concentration	0.996 (0.868, 1.143)	0.982 (0.831, 1.160)	0.961 (0.840, 1.100)
Distance to CBD	0.853 (0.804, 0.904)*	0.877 (0.816, 0.942)*	0.885 (0.834, 0.939)*
Parks	1.228 (1.038, 1.454)*	1.255 (1.023, 1.541)*	1.305 (1.107, 1.539)*
Bus stops	1.010 (1.003, 1.017)*	1.012 (1.004, 1.020)*	1.011 (1.004, 1.017)*
Model performance			
ΔDIC	-2.8	-5.4	-8.9

Note: All covariates were mean-centred. * represents significance at the 95% CI.

Table C4. Regression coefficient estimates (posterior means and 95% CIs of relative risks) for model specifications using student-oriented housing as the studentification indicator.

Variables	Acquisitive crime	Expressive crime	Disorder
Student-oriented housing as the studentification indicator (time-varying effects)			
λ_1 (term - business)	1.732 (1.043, 2.878)*	1.410 (0.763, 2.603)	1.827 (1.088, 3.070)*
λ_2 (term - non-business)	1.728 (1.016, 2.941)*	1.887 (1.009, 3.533)*	2.281 (1.380, 3.772)*
λ_3 (break - business)	1.332 (0.797, 2.226)	0.922 (0.463, 1.835)	1.301 (0.770, 2.197)
λ_4 (break – non-business)	1.435 (0.820, 2.509)	1.252 (0.632, 2.484)	1.293 (0.775, 2.156)
Intercept			
α_1 (term - business)	0.559 (0.550, 0.568)*	0.472 (0.452, 0.492)*	0.388 (0.383, 0.394)*
α_2 (term - non-business)	0.397 (0.386, 0.407)*	0.368 (0.345, 0.392)*	0.565 (0.555, 0.574)*
α_3 (break - business)	0.602 (0.580, 0.624)*	0.405 (0.367, 0.448)*	0.423 (0.410, 0.437)*
α (break – non-business)	0.386 (0.366, 0.407)*	0.354 (0.312, 0.400)*	0.530 (0.512, 0.548)*
Control variables (consistent effects over time)			
Population size	1.069 (1.055, 1.083)*	1.063 (1.046, 1.079)*	1.065 (1.052, 1.079)*
Residential instability	1.307 (1.168, 1.463)*	1.385 (1.209, 1.586)*	1.527 (1.367, 1.706)*
Material deprivation	1.063 (0.944, 1.197)	1.213 (1.053, 1.398)*	1.089 (0.969, 1.225)
Dependency	0.957 (0.855, 1.072)	0.904 (0.789, 1.036)	0.871 (0.779, 0.973)*
Ethnic concentration	0.976 (0.849, 1.121)	0.958 (0.810, 1.132)	0.965 (0.841, 1.109)
Distance to CBD	0.850 (0.802, 0.902)*	0.875 (0.815, 0.939)*	0.882 (0.831, 0.935)*
Parks	1.231 (1.041, 1.456)*	1.265 (1.032, 1.551)*	1.314 (1.113, 1.551)*
Bus stops	1.010 (1.003, 1.017)*	1.013 (1.004, 1.021)*	1.011 (1.005, 1.018)*
Model performance			
ΔDIC	-7.2	-4.3	-14.9

Note: All covariates were mean-centred. * represents significance at the 95% CI.

Table C5. Regression coefficient estimates (posterior means and 95% CIs of relative risks) for model specifications using student-aged population as the studentification indicator.

Variables	Acquisitive crime	Expressive crime	Disorder
Student-aged % as the studentification indicator (time-varying effects)			
λ_1 (term - business)	1.008 (0.995, 1.021)	1.009 (0.994, 1.025)	1.017 (1.003, 1.030)*
λ_2 (term - non-business)	1.009 (0.995, 1.022)	1.016 (1.000, 1.032)*	1.024 (1.011, 1.037)*
λ_3 (break - business)	1.002 (0.989, 1.015)	0.999 (0.983, 1.015)	1.010 (0.997, 1.024)
λ_4 (break – non-business)	1.005 (0.991, 1.019)	1.006 (0.989, 1.022)	1.010 (0.997, 1.023)
Intercept			
α_1 (term - business)	0.559 (0.550, 0.568)*	0.472 (0.454, 0.491)*	0.388 (0.383, 0.394)*
α_2 (term - non-business)	0.396 (0.386, 0.407)*	0.364 (0.343, 0.386)*	0.565 (0.555, 0.574)*
α_3 (break - business)	0.601 (0.580, 0.623)*	0.416 (0.381, 0.453)*	0.423 (0.411, 0.436)*
α (break – non-business)	0.386 (0.366, 0.406)*	0.355 (0.317, 0.395)*	0.531 (0.514, 0.548)*
Control variables (consistent effects over time)			
Population size	1.070 (1.056, 1.085)*	1.065 (1.049, 1.082)*	1.069 (1.055, 1.084)*
Residential instability	1.328 (1.185, 1.489)*	1.376 (1.203, 1.573)*	1.505 (1.344, 1.684)*
Material deprivation	1.056 (0.936, 1.191)	1.221 (1.062, 1.405)*	1.101 (0.978, 1.240)
Dependency	0.963 (0.860, 1.078)	0.910 (0.796, 1.039)	0.881 (0.788, 0.986)*
Ethnic concentration	0.981 (0.839, 1.146)	0.928 (0.773, 1.114)	0.911 (0.781, 1.063)
Distance to CBD	0.852 (0.804, 0.904)*	0.877 (0.818, 0.939)*	0.886 (0.836, 0.940)*
Parks	1.222 (1.032, 1.446)*	1.258 (1.032, 1.533)*	1.302 (1.102, 1.538)*
Bus stops	1.010 (1.003, 1.017)*	1.013 (1.005, 1.021)*	1.011 (1.005, 1.018)*
Model performance			
ΔDIC	-13.2	-1.9	-15.0

Note: All covariates were mean-centred. * represents significance at the 95% CI.