Spatial and spatio-temporal variability in social, emotional and behavioural development of children

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Abstract

Neighbourhood differences in early development can be explored by incorporating spatial and spatio-temporal information with population data. Spatial refers to the relationship between neighbouring areas, while spatio-temporal refers to the relationship between neighbouring areas over time. At the time of writing, most population studies have focused on spatial variation in early development over a single year or short time period.

This project identifies spatial and spatio-temporal referenced data that can be linked with population data on child social, emotional and behavioural difficulties in Glasgow, United Kingdom (UK). The Child Mental Health in Education (ChiME) study is a unique resource that can be used to model long term trends in a preschool population. In the ChiME study, Strengths and Difficulties Questionnaire (SDQ) forms were analysed for 35,171 children aged 4–5 years old across 180 preschools in Glasgow, UK, between 2010 and 2017 as part of routine monitoring. Using ChiME data, this work examined how early development varies over space and time, how the neighbourhood is defined, how important the neighbourhood is and what neighbourhood characteristics are related to early development.

A literature review of 71 studies (from 2012-2022) in Chapter 2 discusses the neighbourhood constructs that are associated with variation in early development for children in Scotland. These constructs included the physical environment (e.g. greenspace) and social environment (e.g. social networks). The availability of data and the strength of evidence to support each construct varied. For many constructs, there was limited understanding of their relevance to younger children as opposed to adolescent or adult populations. There are gaps in the literature in the extent that neighbourhood con-

structs relate to developmental outcomes at an individual level or how this may change over time. To address these gaps, much more multilevel research, using population data is required.

Chapter 3 provides a methodological review of the multilevel spatio-temporal approaches used to date. There is limited methodological guidance on how to model spatio-temporal variation for multilevel data. There is a risk of over complicating the model when attempting to account for spatial, temporal and/or spatio-temporal effects. Choosing the appropriate spatio-temporal multilevel model depends on the structure of the data, the degree of correlation, the goal of the analysis and overall model fit. Using a Bayesian workflow, each component of the model is reviewed in an iterative process to provide the best model for the data in Chapter 4. This includes evaluation of the outcome (total difficulties scores vs high scores) and comparing discrete distributions (Poisson, Negative Binomial and Zero-Inflated Negative Binomial models). Workflow analysis supported the use of Zero Inflated Negative Binomial distribution for total difficulties scores and the use of approximation methods for estimation.

The total difficulties score for an individual child nested in their preschool, electoral ward and ward:year was modelled using a multilevel model with the components selected in Chapter 4. In Chapter 5, models were built incrementally, considering the value of each context. Boys, those of increasing deprivation and children outside the average age, had more difficulties on average. Preschool and ward variation, although minimal, highlight potential priority areas for local service provision. After consideration of demographics (sex, age, and deprivation), the overall spatial effect found the electoral wards of Anderston, Craigton, North East and Pollokshields were worse than expected (Relative Risk > 1) from 2010 to 2017. There were 72 preschools that were worse than expected based on their demographics. Approximately half of the children who lived in a ward that was worse than expected also attended a preschool that was worse than expected.

There were independent spatio-temporal patterns in total difficulties, that exist in addition to the overall spatial effect. Spatial effects were not solely due to consistently poor performing areas. Instead, there is evidence of yearly variations in performance.

Spatial analysis using only a single or few years may lead to misleading conclusions about area level variability. For example, once considering the spatio-temporal effect, Pollokshields was no longer considered worse than expected.

There were differences in spatial and spatio-temporal variation depending on the neighbourhood definition (electoral ward, locality, Intermediate Zone (2001 and 2011) and Consistent Areas Through Time (CATTs)) found in Chapter 6. Looking at the different spatial scales together, can help support diffuse or more concentrated intervention delivery. Localities and 2011 Intermediate Zones had a similar spatial distribution to the ward. The relative importance of the neighbourhood compared to other contexts can be quantified through the Variance Partition Coefficient (VPC). Estimated VPC of the neighbourhood on early development was expected to be between 0 and 9% according to recent literature. Though the typical VPC equation does not apply to discrete distributions, recent approximations have been developed. Using these approximations, it was found that proportionally, the neighbourhood context alone does not make a considerable contribution to variation in difficulties scores. VPC values ranged from 0.39-1.1% depending on the neighbourhood definition. From the perspective of decision-making, the partitioned variance suggests that considering the neighbourhood along with other contexts would be more meaningful than the neighbourhood alone.

Preschool and neighbourhood characteristics are thought to provide a more feasible target for intervention compared to individual level characteristics. Cross-level effects (which describe the association between a higher level covariate and a lower level outcome) are investigated in Chapter 7. Preschool and neighbourhood indicators were derived from openly available administrative data. The quality of these indicators and their relevance to this project varied. Preschools were classified as small/medium/large local authority, private business or voluntary. Most children were in local authority preschools. Total difficulties scores were lower in private business compared to small local authority preschools. Spatial variation was in part explained by a child's prosocial behaviour and its interaction with their preschool provider. The mechanisms underlying these differences are at present unknown. There were ecological correlations between total difficulties and the neighbourhood indicators (participation, child poverty, domestic abuse, free time places, vandalism and proximity to greenspace (at 400 m and 800m)). These correlations did not translate to a cross-level association with individual level total difficulties.

In conclusion, there are multiple contexts that account for variation in total difficulties. The preschool and spatio-temporal context and their composition could provide additional information about how the neighbourhood relates to early development. There is a need for more spatio-temporal data, that can be linked to population data, to understand how the neighbourhood is associated with development at an individual level, beyond deprivation. Multi-level spatio-temporal models can be used to understand early development and support the selection of delivery areas for place-based interventions.

Dedication

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination, which has led to the award of a degree.

This thesis consists in part of previously published work:

Ofili, S., Thompson, L., Wilson, P., Marryat, L., Connelly, G., Henderson, M. and Barry, S.J., 2022. Mapping Geographic Trends in Early Childhood Social, Emotional, and Behavioural Difficulties in Glasgow: 2010–2017. *International journal of environmental research and public health*, 19(18), p.11520.

I have been responsible for conducting the analysis, interpretation of results and preparing the first draft of the manuscript. An abridged version of this paper can be found in Chapter 5.

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Chapter 1

Introduction

1.1 Childhood Social, Emotional and Behavioural Development in the Population

Population health describes the distribution of health and well-being among groups of individuals. Using population data, we can understand why some groups of individuals have better outcomes than others. Promoting positive outcomes and reducing negative outcomes where there is the greatest inequality allows efficient allocation of resources.

Early childhood represents a key period in development as a child will rapidly evolve physically, socially, emotionally, cognitively and behaviourally. During this developmental period, inequalities can emerge [1].

Monitoring early child development is an integral part of achieving the United Nations' Sustainable Development Goals (SDG) [2]. Historically, population level data about early child development has been scarce [3]. Limited data availability inhibits the ability to identify patterns within the population and develop policies and interventions. Recently, there has been a rise in population monitoring of child development [4]. Internationally, there are now several surveillance programmes to monitor health and development across childhood [5, 6].

The Early Development Index (EDI), which was specifically designed as a population measure, has collected data for over 1 million children in Canada at school entry [7]. The tool has been adapted for use in several countries including Australia, Mexico, and the United States [8]. In other regions such as China and Brazil, early development has been measured using the population tool the early Human Capability Index (eHCI) [9].

This project is focused on the developmental difficulties of children in preschool (aged 3–5 years). Developmental problems predict school exclusion [10] and later mental health conditions [11] at an individual level, and lead to higher healthcare and social welfare costs at a societal level [12–14]. The transition from preschool to primary school is a critical period in development, as it introduces a significant change in social and physical environment. Developmental inequalities can be exacerbated while at primary school [15] supporting the need for earlier intervention.

Mental well-being in early childhood is an important part of development that is not well understood [16]. Signs of anxiety, depression and behavioural problems can be seen by preschool age, though symptoms may manifest differently than in older children and adults [17–19]. For young children, some of these symptoms (for example, irritability or aggression) may represent a transient state as the child develops emotional regulation and behavioural control. But there are cases where symptoms are enduring and indicate likely mental health difficulties. According to a recent meta-analysis, 1 in 5 children under 7 years old have symptoms that would meet the criteria for a diagnosis [17]. There are a variety of screening tools that measure social, emotional and behavioural development to estimate levels of mental well-being at the population level [20]. Monitoring average social, emotional and behavioural development in the population can provide meaningful insight to population mental health [21, 22].

1.2 Neighbourhood Differences in Early Child Development

Population level data supports analysis of regional inequalities in developmental outcomes, as there is adequate sample size to provide small area estimates. Regional variation in developmental outcomes can be expected as the neighbourhood environment influences the day to day social and physical experiences of the child and their caregiver. For example, neighbourhoods can influence access to play areas, local amenities and exposure to crime and violence. These experiences can be transforming, enriching, reinforcing, impairing or damaging to development [23]. There has been considerable research on how the characteristics of a neighbourhood are associated with child mental health and well-being [24, 25], though deprivation remains the most commonly researched neighbourhood factor [26].

We can use population data to develop policies and monitor the success of different initiatives that focus on where people live (i.e. "place-based" initiatives). Place based approaches in early childhood (used alongside universal policies) are on the rise [27, 28]. Komro, Flay and Biglan suggest focusing on high poverty neighbourhoods to promote child development [29]. However, the evidence to support place-based interventions targeting early developmental outcomes in deprived neighbourhoods is insufficient [27]. Evaluating place-based initiatives can be challenging due to the variety of components that need to be considered in the delivery and evaluation of the intervention [30]. Kwan [31] summarises key issues in neighbourhood research:

- Individual level factors that may mitigate or mediate neighbourhood effects have to be considered
- Other neighbourhood characteristics can result in a relationship that is better or worse than expected (i.e. areas of high deprivation with positive outcomes or vice versa)
- The neighbourhood effect is likely to vary over space and time
- The neighbourhood effect is likely to vary depending on how space and time are defined
- There is a publication bias towards significant neighbourhood effects

Therefore, we need further population research on how the neighbourhood relates to variation in development to implement evidence based interventions. An emerging position in the literature is to move beyond only asking why a neighbourhood has poor outcomes to asking the additional questions: where, when, and for whom? [26, 32] i.e. the role of spatial, spatio-temporal and individual effects.

1.3 Individual, Spatial and Spatio-temporal Variation in Early Child Development

Understanding child mental health requires investigation of the different contexts that may contribute to pathology. A variety of factors at individual, family, learning environment, community and structural level can be protective from or put children at greater risk of poor mental health outcomes.

The Canadian Neighbourhoods and Early Child Development Database (CanNECD) has aggregated neighbourhood level EDI outcomes, socioeconomic and demographic data across Canada from 2003/4-2014 [33]. This database has been used to understand the positive relationship between neighbourhood socioeconomic status and early development [34, 35]. However, the contextual level examined can influence the strength of association. For example, the socioeconomic status of the child tends to be more important to development than the socioeconomic status of their neighbourhood [36].

Building on the ecological model presented by Bronfenbrenner [37], conceptual frameworks have been developed (e.g. [34] and [38]) to describe the relationship between the contexts. Figure 1.1 shows an adaptation of the framework presented by Minh et al., [34]. These contexts can inform and constrain one another and are likely to have bidirectional relationships [39]. Therefore, where possible, these additional contexts should be considered for precise policymaking [40].

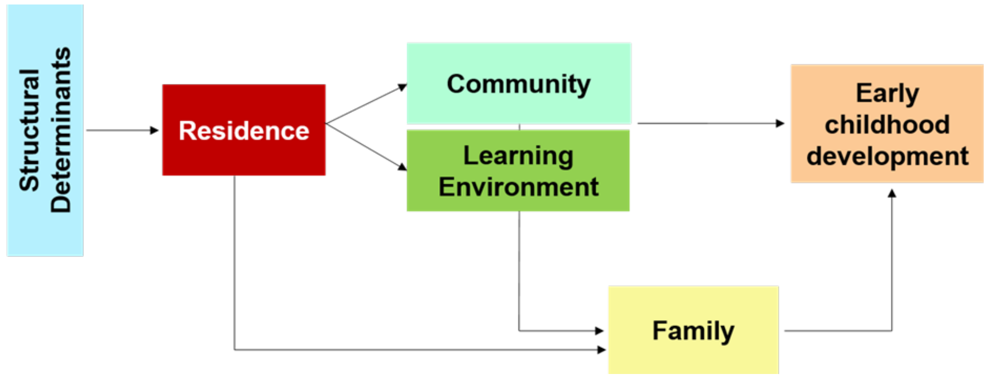

Figure 1.1: Contexts that influence early child development adapted from Minh et al., [26]

Population studies can opt for a multilevel approach, where information is retained about each individual child. This avoids relying solely on aggregation, which can lead to ecological fallacy [41]. Some place-based initiatives delivered in deprived neighbourhoods were associated with positive outcomes at the aggregate level (e.g. neighbourhood or school) but not at an individual level [28]. Therefore, multilevel approaches lead to more informative statistical models. There have been more multilevel approaches to early developmental research in recent years. From 1990-2003, there were 13 studies that considered the individual and neighbourhood context [25]. From 2009-2015, there were an additional 31 multilevel studies [26]. In 2022, the Australian Early Development Census (an adaptation of the EDI) was linked with indicators of the built environment of 21 large cities (AEDC-BE) to create a multilevel dataset. The AEDC-BE is the first of its kind to have national coverage [42]. Using the AEDC-BE, Alderton et al., [43] found inequalities in access to public open space (after considering the effects of child's demographics) that were associated with mental health difficulties.

Spatial analysis means not only considering the role of a neighbourhood independently, but also the relationship between neighbourhoods i.e. the spatial distribution. Visualising spatial inequalities through mapping provides an accessible way to highlight areas in need of further action that can be interpreted by a variety of stakeholders. Despite this, a recent review found that only roughly 1 in 4 studies on neighbourhood health inequalities from 2000-2020 provided a map [44]. Maps can promote community awareness and strategic development [45]. In Australia, mapping showed there was a cluster of poor aggregated EDI outcomes in neighbourhoods in the city of Sydney, but not Canberra. This led the authors to conclude that "spatial targeting" of policy and resources was not a strategy that is appropriate in all cities [46]. While some studies have used multilevel spatial approaches (e.g. [47]), overall it has been noted that the spatial mechanisms that account for neighbourhood inequalities in early development (at an individual level) are under-researched and require further investigation [26].

There is increasing literature on the importance of considering time in neighbourhood research [48]. The relationship between space and time is complex and there is not a common theoretical or methodological framework [26]. The age group, the cohort an individual belongs to and, the time period of study reflect changing biological, social and environmental contexts over time [49, 50]. Even neighbourhoods are not static. The composition and characteristics of neighbourhoods change over time. In addition, there may be an interaction between spatial and temporal variation (i.e. spatio-temporal effects) meaning neighbouring areas can change over time in opposing ways. Neighbourhood changes can impact the effectiveness of place-based initiatives, as the priorities of an area can change as the initiative is being implemented [28]. Spatio-temporal interactions have been examined in other related outcomes, such as child maltreatment [51]. Data with the temporal and spatial detail to answer these questions in early development are often not available. Existing multilevel spatial databases have yet to look at longer term effects. The AEDC-BC has only been linked for 2015 and the data is collected every 3 years [42]. As a result, there is limited information on spatio-temporal interactions in relation to early childhood mental well-being.

1.4 Early Child Development Statistics in Scotland

There are several initiatives in Scotland that aim to improve social, emotional and behavioural development. These include universal approaches (e.g. needs assessments and health promotion) and those that are more targeted to children at high risk of developmental difficulties (e.g. specialist care) [52]. It is believed that both universal and targeted approaches combined will lead to long term change [53]. So far, the existing data to monitor social, emotional and behavioural development for preschool age children at a population level in Scotland is not sufficient to support the development of early intervention [52, 53]. Two out of the seven indicators for the Children and Young People National Performance Outcomes in Scotland are related to early social, emotional and behavioural development:

1. Child social and physical development measured by reported developmental concerns at 27–30 months

2. Child well-being and happiness measured by likely mental health difficulties at 4–12 years

These indicators were taken from child health reviews and the Scottish Health Survey [54], respectively. However, for each indicator, there is a limited ability to estimate spatial and spatio-temporal variability in preschool social, emotional and behavioural development, for reasons outlined below.

1.4.1 Child Health Reviews

Official early child development statistics in the United Kingdom (UK) are derived from child health surveillance programmes. In the UK, devolution has resulted in separate child health surveillance programmes [55]. This has led to different outcomes collected for different groups of children. For example, in England, outcomes are only monitored for children aged 2-2.5 years old. In 2017, Scotland joined Northern Ireland and Wales to include reviews at 4-5 year olds. Implementation of the health review for 4-5 year olds in Scotland was not initially mandated by the government and varied across health boards. Some regions only started conducting the 4-5 year reviews from 2020, therefore coverage in the first years of implementation was low. Further, there are differences in the breadth of the data that is recorded at review. Northern Ireland routinely measures social-emotional problems, while in Scotland, these outcomes were initially only measured at the discretion of the health visitor [55]. Health reviews are offered to all eligible children, but the representativeness can vary, with children living in the most deprived areas being the least likely to take part [56]. The coverage of the 4-5 year reviews among eligible children in Glasgow, Scotland increased from 12.4% in 2018/2019 (the year of its initial introduction) to 77.8% in 2020/2021 [57].

There is currently insufficient data for the analysis of spatio-temporal variation in preschool social, emotional and behavioural difficulties using child health reviews. Scotland's 27-30 month review data show it would be possible to compare small areas and monitor their progress over time [58]. Figure 1.2 shows a map of Glasgow and the comparisons between developmental concerns across areas and years. There is evidence of potential spatial and spatio-temporal variation. Panel A shows different areas were found to be better (blue) or worse (orange) than the city average in 2013/14-2015/16 (i.e. spatial variation). Panel B shows areas that got better (blue) over time from 2013/14-2015/16 to 2017/18-2019/20 (i.e. spatio-temporal variation).

The health review data is largely descriptive and only provided at an aggregate level, meaning analysis of the multiple contexts that may contribute to these area level differences cannot be examined.

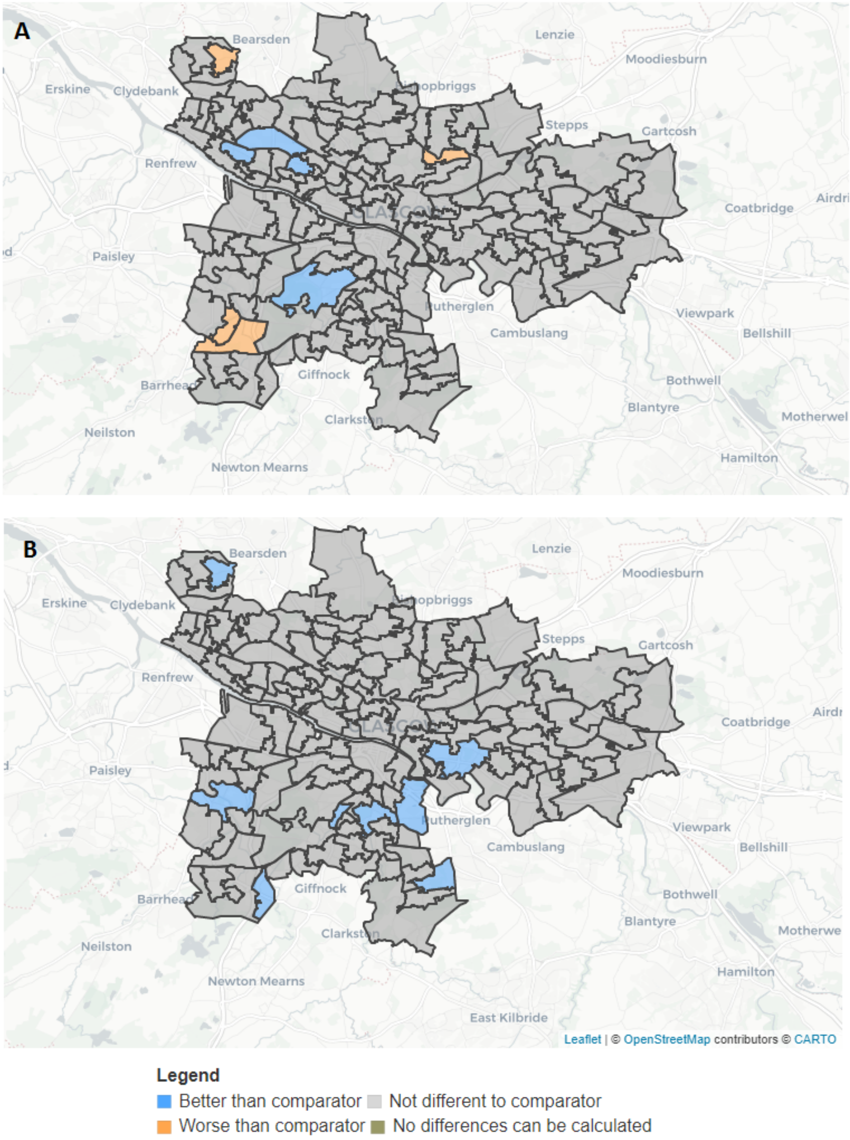

Figure 1.2: Spatial (A) and Spatio-temporal (B) variation in developmental concerns in Glasgow at 27-30 month reviews

A comparator is Glasgow average (2013/14-2015/16). B comparator is areas in 2017/18-2019/20 compared to 2013/14-2015/16 created from Scottish Public Health Observatory [58]

1.4.2 Population Surveys

At the time of writing, there are not any comparable population-level studies to the EDI and eHCI currently running in the United Kingdom. In 2013, a feasibility study for the EDI was conducted in a school district in Edinburgh [59] with no further action to date. The Scottish Health Survey [54], used to measure child well-being and happiness, can only provide health board level data if several years are aggregated. Population-based sampling in studies such as the Millennium Cohort Study (MCS) [60] and Growing Up Scotland [61] provide insight into preschool-aged mental health in UK populations. Eight multilevel studies (considering individual and neighbourhood context) from the United Kingdom were found in reviews from 1990-2003 [25] and 2009-2015 [26]. Four of those studies included children from Scotland using the MCS data. However, sample sizes do not always permit analysis at the neighbourhood level across all regions of the UK. Both cohort studies are susceptible to attrition and differential response rates that can affect representativeness at the small area level. For example, for a complete case analysis of individual and neighbourhood effects in the MCS, 698 out of 4,748 3-year-old children were from Scotland, this sample size would not support analysis at a regional or city level [62]. For Growing up Scotland, sub-national data is not available.

Routine population data was collected from preschool and primary school aged children across Glasgow city from 2010-2017 as part of the Child Mental Health in Education (ChiME) study [63]. This was the first routine collection of children's social and emotional functioning at school entry in Scotland. The ChiME study is a unique resource in its ability to address questions about long term trends in population mental health in preschool children, in a UK city with varying levels of deprivation. The ChiME data set is discussed further in the chapter.

The 2010-2012 subset of ChiME data was, as far as we are aware, the first time individual and spatial variation in early social, emotional and behavioural problems were mapped across a city [64]. It was noted that differences between neighbourhoods remained after accounting for the demographics of the children, providing evidence that some areas of high deprivation had better than expected outcomes and vice-versa [64]. This effect is described by Kershaw et al., [65], in Canada as "off-diagonal" where there is a buffering process at the neighbourhood level that reduces the relationship between deprivation and development. Similarly, in the United Kingdom, cities with similar levels of deprivation do not have similar health outcomes, suggesting there are contributing factors beyond deprivation [66].

1.5 Place-based Initiatives in Glasgow

There has been a variety of place-based interventions implemented in Scotland. Local level action has been a policy interest in Scotland for several years, with councils given increasing autonomy and more unallocated funding [53]. 2003 saw the introduction of Community Planning Partnerships (CPPs). There is a CPP for every council in Scotland. In Glasgow City Council, the CPP has split the city into 3 sectors: North West, North East and South and 56 localities for planning. Each locality has roughly 10,000 residents.

Shortly after, in 2005 the 10-year programme GoWell began [67]. GoWell selected 14 deprived communities to monitor the impact of regeneration on the residents' health and well-being. Though the areas selected were not aligned with administrative or statistical boundaries, the interventions covered the following localities: Drumchapel, Castlemilk, Greater Gorbals, Greater Govan, Haghill & Carntyne, Sighthill, Roystonhill & Germiston.

Ten localities were selected by Glasgow CPP to reduce inequalities as part of the 2013 Thriving Places initiative [68]: Ruchill/Possilpark, Drumchapel & Lambhill/Milton, Parkhead/Dalmarnock, Easterhouse, Springboig & Barlanark, Priesthill/Househillwood, Greater Gorbals & Govan. Each place was selected based on small area data, mainly the 2012 Scottish Index of Deprivation [69]. Every Thriving Places' locality has its own 10-year plan. Approaches include universal strategies and more targeted interventions for neighbourhoods with specific needs. Key outcomes (e.g. income deprivation, employment deprivation, multiple deprivation and mental and emotional well-being of adult residents) are monitored for improvement.

The same year saw the introduction of the Place Standard Tool by the Scottish Government, NHS, and Architecture and Design Scotland. The Place Standard Tool is a community assessment based on 14 themes which include feeling safe, social contact and natural space [70].

In 2011, Geddes et al., suggested that the neighbourhood context should be considered as a level of action for interventions to improve social, emotional and behavioural outcomes in early childhood [52].

CPPs have been encouraged to deliver programmes which promote positive outcomes in early years through initiatives such as the Early Years Change Fund [71] and the Children and Young People Improvement Collaborative (CYPIC) [72]. For example, CYPIC set a target of 90% for each CPP to reach developmental milestones ahead of starting primary school by 2017. Since 2016 Children in Scotland (CIS) has led the CHANGE (Childcare and Nurture Glasgow East) project [73] which focuses on nurseries in deprived neighbourhoods (Parkhead/ Dalmarnock, Calton/ Bridgeton and Tollcross/ West Shettleston). CHANGE supports knowledge exchange and assesses the impact on outcomes for individuals, families, and the community.

Children's Neighbourhood Scotland (CNS) focused on improving outcomes in two neighbourhoods in Glasgow with high deprivation (Bridgeton and Dalmarnock) between 2018 and 2022. The neighbourhoods were selected by CNS to deliver tailored place-based solutions [74]. Notably, the boundaries for these neighbourhoods were not fixed to allow the approach to be inclusive for all children and young people.

Figure 1.3 shows the CPP localities with the areas mentioned highlighted with a red circle.

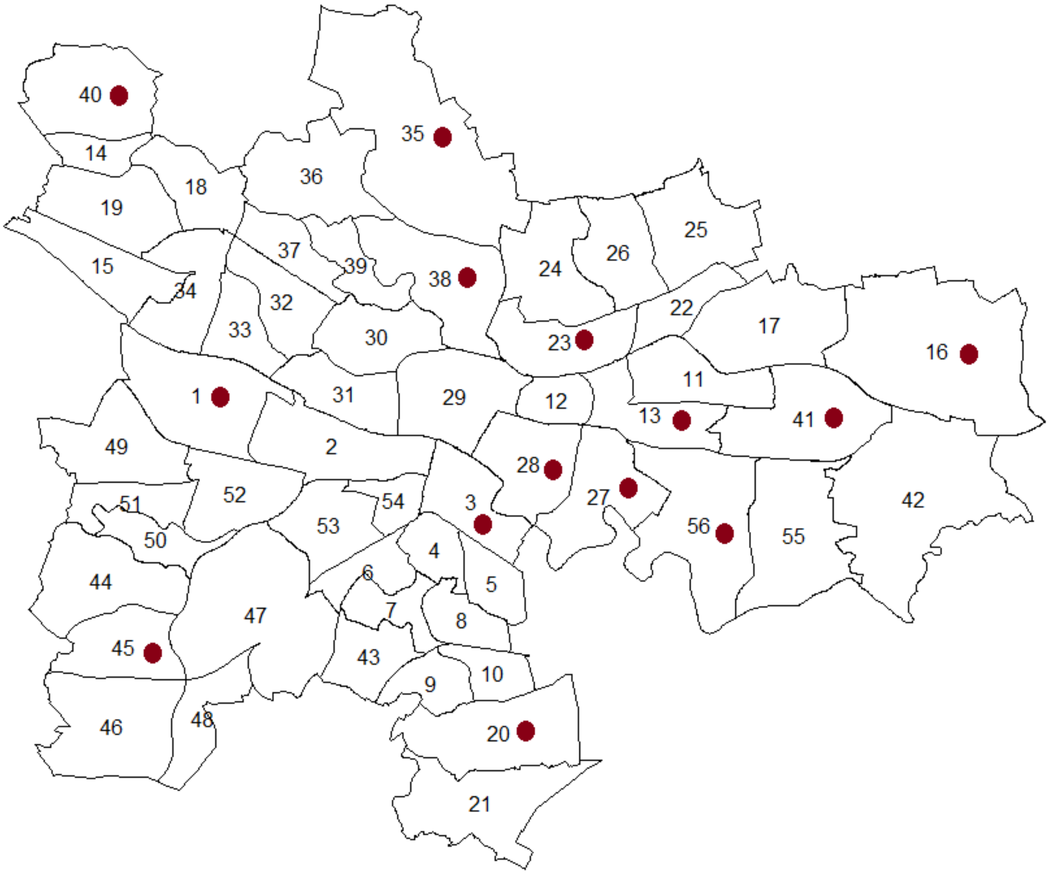

Figure 1.3: Localities in Glasgow
1.Greater Govan, 2.Ibrox / Kingston, 3.Greater Gorbals, 4.Govanhill, 5.Toryglen, 6.Shawlands / Strathbungo, 7.Langside / Battlefield, 8.King's Park / Mount Florida , 9.Cathcart / Simshill, 10.Croftfoot, 11.Riddrie / Cranhill, 12.Dennistoun, 13.Haghill / Carntyne, 14.Blairdardie, 15.Yoker / Scotstoun, 16.Easterhouse, 17.Ruchazie / Garthamlock, 18.Temple / Anniesland, 19.Knightswood, 20.Castlemilk, 21.Carmunnock, 22.Blackhill / Hogganfield, 23.Sighthill / Roystonhill / Germiston, 24.Springburn, 25.Robroyston / Millerston, 26.Balornock/ Barmulloch, 27.Parkhead / Dalmarnock, 28.Calton/ Bridgeton, 29.City Centre/ Merchant City, 30.Hillhead/ Woodlands, 31.Yorkhill/ Anderston, 32.Hyndland / Dowanhill/ Partick East, 33.Broomhill/ Partick West, 34.Anniesland / Jordanhill/ Whiteinch, 35.Lambhill/ Milton, 36.North Maryhill / Summerston, 37.Kelvindale / Kelvinside, 38.Ruchill / Possilpark, 39.Maryhill Road Corridor, 40.Drumchapel, 41.Springboig/ Barlanark, 42.Baillieston/ Garrowhill, 43.Newlands / Cathcart, 44.Pollok, 45.Priesthill/ Househillwood, 46.South Nitshill / Darnley, 47.Pollokshaws/ Mansewood, 48.Arden/ Carnwadric, 49.North Cardonald / Penilee, 50.Corkerhill/ North Pollok, 51.Crookston/ South Cardonald, 52.Bellahouston/ Craigton / Mosspark, 53.Pollokshields West, 54.Pollokshields East, 55.Mount Vernon / East Shettleston, 56.Tollcross/ West Shettleston

Despite the focus on inequalities, there has been an implementation gap in Scotland, where intervention does not necessarily lead to progress [75]. A 2018 briefing by Policy Scotland [76] highlighted issues that should be addressed in future local level action in Scotland. They recommended comparing relative inequalities at the small area to support the development of localised initiatives. While the availability of small area level data has improved, neighbourhoods are often defined by where there is available data rather than meaningful communities. There is a need for clearer definition of what the neighbourhoods of interest are, and how these are defined. Policy Scotland mention the changing neighbourhood profiles in Glasgow. Areas typically associated with poverty and inequality are evolving because of population changes (e.g. Calton and Govanhill) and regeneration strategies (e.g. Gorbals). Similarly, Glasgow Centre of Population Health highlighted Drumchapel, Easterhouse, Bridgeton & Dalmarnock, and Anderston & Finnieston as areas with a history of relatively high deprivation that have undergone both small and extensive change over the years [77].

1.6 Project Overview

Matthews et al., [78] highlight various opportunities for improving spatial analysis related to maternal and child health. This includes the use of temporally referenced data, better defined boundaries and visualisation through quality mapping and documentation of spatial modelling processes. This project aims to build on the initial ChiME spatial research [64] to investigate long-term multilevel spatial and spatio-temporal variation in child social, emotional and behavioural difficulties that could support policymaking. This project aims to address the following research questions:

1.6.1 How Does Early Development Vary Over Space and Time?

Spatial analysis on the ChiME study has so far only looked at the 2010-2012 subset [64]. This project investigates the long term spatial effects from 2010-2017, and the potential spatio-temporal interaction associated with developmental difficulties. The methodologies used in the literature are described in Chapters 3 and 4. The spatial and spatio-temporal variation of ChiME population mental health is evaluated in Chapter 5.

1.6.2 How Can We Define the Neighbourhood?

Various boundaries have been used for existing place-based interventions in Glasgow. A key challenge in this research area is defining the neighbourhood, which should ensure a balance between comprehensive use of information and policy impact. The areas defined and estimates from those areas may be biased. This is known as the Modifiable Areal Unit Problem (MAUP). Using smaller areas can help to identify social effects [79]. Different neighbourhood definitions and their impact on decision-making are discussed in Chapter 6.

1.6.3 How Much Does the Neighbourhood Matter?

Considering the variety of contexts that are at play (Figure 1.1), this project aims to examine how much the neighbourhood contributes to child mental health compared to other contexts. Often, studies of neighbourhood effects focus on the neighbourhood characteristics that significantly relate to the outcome. Recently, Merlo et al., [80] made the case to consider how meaningful the neighbourhood context is on individual outcomes too. While characteristics may be significant, if the role of the neighbourhood is minimal, then concentrating on other contexts for intervention may be more impactful. The importance of the neighbourhood environment is examined in Chapter 6.

1.6.4 What Neighbourhood Characteristics Are Related to Variation in Child Development?

Off-diagonal effects point to the potential presence of other factors that contribute to the residual spatial variation. It is yet to be determined what neighbourhood characteristics could contribute to the spatial variation in this population [64]. Chapter 2 provides an overview of what is currently known about the neighbourhood characteristics that influence child mental health in Scotland. Chapter 7 will investigate what characteristics are most relevant for the preschool aged children in Glasgow.

1.7 Discussion

Identifying developmental difficulties in preschool aged children, and delivering early interventions, could reduce the individual and societal impact. Population data is useful in monitoring early child development. This has been demonstrated globally through the use of the eHCI and EDI.

Neighbourhoods can influence a child's social and physical environments. There is growing interest in understanding the relationship between the residential neighbourhood and developmental inequalities. Factors such as neighbourhood deprivation and the built environment have been associated with early development [26, 38]. The impact of neighbourhood-level characteristics on developmental outcomes could be used to identify areas of interest for evidence-based interventions. At the moment, evidence to support the effectiveness of interventions that target early development is limited [27, 28]. Evaluating place-based initiatives can be challenging due individual level factors, differences over space and time and defining space and time.

Population data can be linked with spatial data. These linked databases can identify the neighbourhoods associated with poorer outcomes, the neighbourhood characteristics associated with poor outcomes, and visualise the impact through mapping. Analysis can be more informative when multilevel approaches are used, as a variety of factors at the individual, family, learning environment, community and structural level influence development. Various conceptual frameworks have been suggested in the literature to guide analysis (e.g. [34, 37, 38]).

The population of interest for this work is preschool aged children in Glasgow, Scotland. Analysis will be conducted using the ChiME (Child Mental Health in Education) study, a population dataset collected as part of routine data collection in Glasgow City, Scotland, from 2010 to 2017. In Glasgow, there is already an interest in local level action alongside universal strategies that aim to improve early development. Many place-based initiatives were delivered during the ChiME sample's early development, such as GoWell [67] and Thriving Places [68].

There is limited population data in Scotland to allow long-term spatio-temporal effects in child development to be examined [52]. This is not unique to Scotland, while population datasets have been routinely collected at school start in Canada [7] and Australia [42], there is at present no long term spatial or spatio-temporal analysis of social, emotional and behavioural difficulties. Health reviews are the norm, but the data are not always complete or accessible. Scotland's 27-30 month review data in Figure 1.2 (whose population will include the later cohorts of the ChiME sample) show some evidence of potential spatio-temporal variation in younger age groups.

ChiME data has already been used to map social, emotional and behavioural difficulties in the short term [64]. Building on that initial research, this project aims to examine the long-term spatial and spatio-temporal variation.

This research will contribute to our understanding of spatial patterns in child development and the role of demographics. Further, it adds to the currently limited literature on how spatial patterns in development can fluctuate over time and the importance of the spatio-temporal context relative to persistent spatial patterns.

1.8 Description of the data

The work uses secondary analysis from the 2010-2017 population dataset: Child Mental Health in Education (ChiME).

1.8.1 Setting

The area of interest is Glasgow City, the most populated city in Scotland, from 2010-2017. Like the rest of Scotland, Glasgow demonstrates area level disparities in health outcomes that appear to be driven by socioeconomic factors [81]. Levels of social, emotional and behavioural difficulties in Glasgow are similar to the rest of the United Kingdom at preschool age [82].

1.8.2 Study Participants

Approximately 90% of 4-year-old children in Scotland are registered in some form of early learning and childcare [83]. Local authorities in Scotland ensure children aged 3 and 4 years old are entitled to funded sessions of preschool. The hours of funded preschool have increased from 475 hours per year, to 600 in 2014 to 1,140 in the year 2021. And the age range has expanded to include eligible 2-year-olds, such as those with looked after status. Preschools can be classified according to their provider:

1. Local Authority - Run by the local authority
2. Private Business - Run on a profit-making basis
3. Voluntary - Run on a not for profit basis (e.g. by a charity), with profits reinvested into services

Voluntary and private preschools can operate in partnership with the local authority to offer funded places [84]. These are known as partnership preschools. All children living in Glasgow, who were attending a local authority or partnership preschool from 2010-2017, and who were due to start school the following academic year, were eligible for the study. Of the included preschools, 60 returned data every year, while the others were involved for a subset of the study years. Children in preschools without funded places or those not in preschool (e.g. use childminders or playgroups) were not part of the study. In total, data were collected from 41 128 children at 182 preschools in the study.

1.8.3 Study Design

NHS Greater Glasgow and Clyde and the City Council set up a framework with the aim of improving child outcomes, at a population level, through parenting support. The framework, applied the international Triple P Parenting Programme from 2010-2014. Data collection continued to 2017, to monitor the impact of the intervention post implementation. An evaluation of the programme [63] found no evidence that the Triple P Parenting programme had an impact on population SDQ scores [63]. The data collected formed the Child Mental Health in Education (CHiME) population database. Preschool staff were asked to complete the teacher version of the Strengths and Difficulties Questionnaire (SDQ) [85]. Forms were completed on paper (2010), through a mix of paper and electronic submissions (2011) or solely electronically (2012-2017) using the education services' information management system. For 2010 and 2011 the SDQ version used was for 4–16-year-olds. This was changed to the version for 2–4-year-olds in subsequent years due to staff perception that question wording for conduct problems in 2–4-year-olds version (which asked about being spiteful and argumentative with adults) version was more developmentally appropriate than the 4–16-year-olds version (which asked about stealing, cheating and lying). The SDQ questionnaire for 2-4 year olds is attached in the appendix.

1.8.4 Outcome

There are 25 questionnaire items and 6 impact questions. Scores were generated for each domain - emotional symptoms, conduct problems, hyperactivity/inattention, peer problems and prosocial behaviour [86]. Answers were scored according to the SDQ guidance so that the Not True is coded as zero, Somewhat True as one and Certainly

True as two. The mean score generated for Emotional symptoms (Items 3, 8, 13, 16 and 24) Conduct problems (Items 5, 7, 12, 18, 22), Hyperactivity/inattention (2, 10, 15, 21, 25), Peer relationship problems (6, 11, 14, 19, 23) were multiplied by five and added together to get a total difficulties score out of 40. Scoring was based on the code provided on the SDQ website [87].

SDQ scores as an outcome can be expressed in different ways. For example, it could be used to describe the number of total difficulties, the individual domain scores, internalising (peer relationship problems and emotional symptoms) and externalising scores (conduct problems, and hyperactivity/inattention). Alternatively, scores can be categorised based on whether a child is above or below a threshold. New banding classifies scores from 0-10 as close to average, 11-14 as slightly raised, 15-17 as high and 18 and above as very high for 2–4-year-olds in the UK [88]. A score of 15 or above indicates a high likelihood of psychiatric diagnosis.

1.8.5 Variables

Biological sex at birth and date of birth were obtained from educational services' administrative databases and were linked to the ChiME database. Age was calculated in years from date of birth to planned start in primary school (1st August following data collection) .

The postcode of residence was linked to a Data Zone – a small area geography provided by the Scottish Government that represents a population of 500-1000. Over the course of the study, there was a change in the locations of the boundaries, resulting in 2 sets of data zone boundaries: Data Zones 2001 and Data Zones 2011. Data zones are the geography level at which the Scottish Index of Multiple Deprivation (SIMD) is provided [69]. The SIMD identifies areas of multiple deprivation across several domains including income, employment, health, education, housing, geographic access and crime. Individual scores across the domains are combined to create a single SIMD score. Areas are ranked from the most to the least deprived according to their score, then categorised by quintiles (e.g. the 20% most/least deprived of the data).

SIMD scores are updated at four yearly intervals to reflect population changes, updated measurement tools and new geographical boundaries. Over the course of the study, 3 iterations of the SIMD were generated. Therefore, each release uses data that corresponds to a specific time period and boundary [89]. The iteration of the SIMD, the corresponding boundary and years for this analysis are shown in Table 1.1.

Table 1.1: Corresponding Years for SIMD iterations

SIMD	Data Zone	Relevant Years
2012	2001	2010-2013
2016	2001	2014-2016
2020	2011	2017 - present

SIMD Scottish Index and Multiple Deprivation

In order for the data to reflect the local share of relative deprivation within Glasgow, deprivation scores for each data zone were categorised into quintiles within the council area of Glasgow rather than for the whole of Scotland [90]. In the absence of household data, deprivation quintiles were used as a proxy for household socioeconomic status.

Of the 41 128 in the initial dataset, children were excluded if they lived outside of Glasgow, were missing date of birth or were under 4 or over 6 years old at primary school entry, had a missing or invalid postcode or were missing a total difficulties score (n=5957), resulting in 35 171 included children in 180 preschools (Figure 1.4).

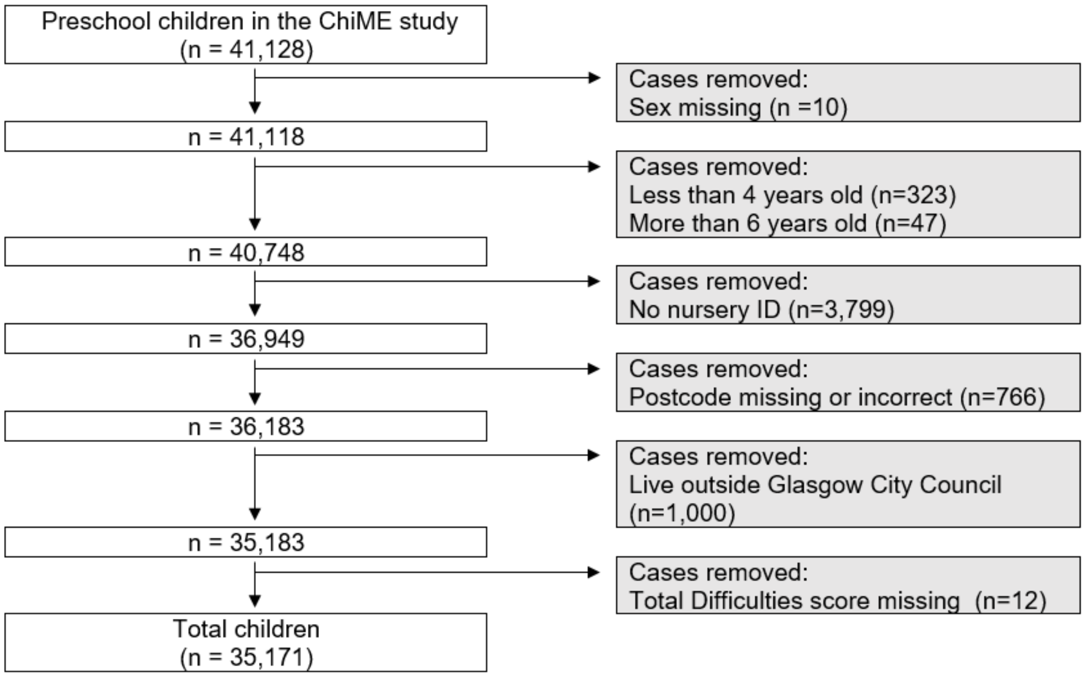

Figure 1.4: Sample flow

The demographics of the included sample are shown in Table 1.2. Scores were higher among children who were expected to start school over 5.5 years old or under 4.5, boys and children in higher deprivation quintiles. These demographic patterns in social, emotional and behavioural scores are consistent with the literature [8, 91, 92].

Table 1.2: Sample demographics

Demographic		N	High SDQ (%)	Median SDQ (IQR)
Total		35171	3149 (9.0%)	4(1-9)
Age (years)	4-4.5	2112	212 (10.0%)	6 (2-10)
	4.5-5	16 456	1541 (9.4%)	5 (2-9)
	5-5.5	15 297	1160 (7.6%)	4 (1-8)
	5.5-6	1306	236 (18.1%)	6 (2-12)
Sex	Female	17 210	877 (5.1%)	3 (1-7)
	Male	17 961	2272 (12.6%)	6 (2-10)
Deprivation Quintile	5 (least deprived)	5071	289 (5.7%)	3 (0-7)
	4	5610	424 (7.6%)	4 (1-8)
	3	6696	605 (9.0%)	4 (1-9)
	2	8179	808 (9.9%)	5 (2-9)
	1 (most deprived)	9615	1023 (10.6%)	5 (2-10)
Cohort	2010	3082	232 (7.5 %)	4 (1-9)
	2011	3336	299 (9.0%)	5 (2-9)
	2012	3882	348 (9.0%)	5 (2-9)
	2013	3899	327 (8.4%)	4 (1-8)
	2014	5275	459 (8.7%)	4 (1-9)
	2015	5246	473 (9.0%)	4 (1-9)
	2016	5480	534 (9.7%)	5 (2-9)
	2017	4971	477 (9.6%)	4 (1-9)

Table A.1 shows the distribution of the demographics over each year. While the distribution of sex over the years was consistent, there were differences in the proportion of children in each age group and deprivation quintile across the cohorts. These differences are thought to be, at least in part, due to varying preschool samples each year. This is explored in Chapters 5 and 7. Table 1.3 shows the number of children and preschools involved in each year of the study. The Scottish Government provides estimates of the number of children registered in local authority and partnership preschools in Glasgow who are due to start school from 2010-2013 (shown in Table 1.3 as the Target Population) [93]. The initial years of the sample include 54.2% to 69.6% of the target population.

For the remaining cohorts, the Scottish Government statistics on the number of children registered at preschool included 'ante pre-school' (i.e. 3-year-olds) [93]. The target population for 2014-2017 in Table 1.3 was estimated based on the fact that in 2010-2013, between 65% and 69% of the combined 'ante pre-school' and 'pre-school' registrations were due to start school [93].

Table 1.3: Sample representativeness each year

Cohort	ChiME Preschools	ChiME Sample	Target Population	% of Target
2010	120	3082	5690	54.2%
2011	102	3336	5830	57.2 %
2012	101	3882	5574	69.6%
2013	101	3899	5920	65.9%
2014	161	5275	*6151-6540	*80.7-85.8%
2015	156	5246	*5941-6317	*83.0-88.3%
2016	154	5480	*5875-6247	*87.7-93.3%
2017	142	4971	*5837-6207	*80.1-85.2%

Target Population = number of children in local authority and partnership preschools in Glasgow who are due to start school (excluding those with deferred school entry).
*Estimated values assuming 65-69% of preschool registrations (excluding 2-year-olds, and deferred entry) are due to start school. [83].

In January 2010, there were 235 preschools in Glasgow City, 125 were local authority, 85 were partnership and 43 were neither [94]. In 2013, there were 226 preschools in Glasgow, 113 local authority, 78 partnership, and 37 were neither [95]. The study collected data from 120 out of 210 (57.1%) eligible preschools in 2010 and 101 out of

191 (52.9%) in 2013.

1.8.6 Geography

Electoral Wards were selected as the primary geography. A limitation of the use of the CPP localities (Figure 1.3) is that they were created 20 years ago and do not take into account population changes that have occurred since their creation [96]. Further, they are not typically used in academic research, limiting the comparability of the results to other boundaries used in the rest of Scotland and the United Kingdom.

At the time of the study, there were 21 electoral wards within Glasgow City. The boundaries for the wards were consistent across the study period. New ward boundaries were introduced after the study period in 2017 creating 23 boundaries, with a new ward created in both the east and west of the city.

Electoral wards align with policymaking and have been updated to reflect population change. The formal structure of the Glasgow CPP includes Area Partnerships. Each Area Partnership is given a budget to support its local communities. Area Partnerships are structured based on electoral wards to allow councillors to be more involved in community planning [97]. A comparison between the electoral ward boundaries and the localities is shown in Figure 1.5. The majority of the localities nest within the electoral wards except for Shawlands/Strathbungo, Bellahouston/Craigton/Mosspark and Lambhill/Milton.

The relationship between current place-based programmes referred to earlier in the chapter and electoral wards is shown in Table 1.4. Chapter 6 discusses the use of smaller geographies, such as Glasgow CPP's localities.

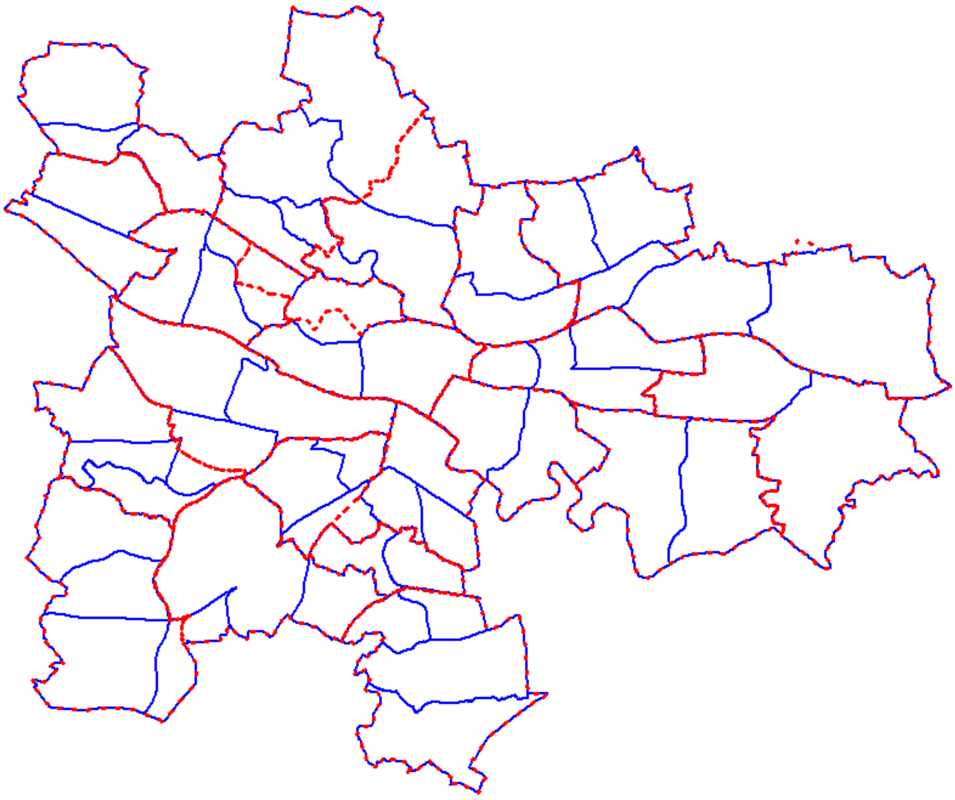

Figure 1.5: Glasgow CPP Localities boundaries (blue) compared to electoral wards (red)

CPP Community Planning Partnership. Electoral wards boundaries were used from 2007 to 2017.

Table 1.4: Ward locations of place-based programmes

Sector	Locality	Ward
North West	Drumchapel	Drumchapel/Anniesland
North West	Lambhill/Milton	Canal and Maryhill/Kelvin
North West	Ruchill/Possilpark	Canal
North East	Easterhouse	North East
North East	Sighthill / Roystonhill / Germiston	Springburn
North East	Parkhead/Dalmarnock	Calton
North East	Calton/Bridgeton	Calton
North East	Haghill/Cartyne	East Centre
North East	Springboig / Barlanark	Baillieston
South	Priesthill/Househillwood	Greater Pollock
South	Govan	Govan
South	Greater Gorbals	Southside Central
South	Castlemilk	Linn

1.8.7 Data Limitations

The main limitations of the study are those associated with the use of routinely collected data. Not all variables of interest were available [98]. Family-level variables could not be used in the analysis. Family is an important context in early development and its omission in this analysis will impact how the relative importance of the other contexts is interpreted. There was missing data such as geographic or demographic data which meant some children were excluded from the analysis.

The ChiME data has a narrow range of developmental outcomes. The SDQ indicates more generalised symptomatology related to mental well-being [99]. Mental well-being is a component of early development, that includes the domains of social, emotional and behavioural development. There are other important domains of development, including physical and cognitive development that have not been measured or investigated in this study. However, domains of development are inter-related [29]. Measures of social, emotional and behavioural problems are correlated with more holistic measures of development such as the eHCI and EDI [100, 101].

There are several considerations associated with the use of the teacher assessed

SDQ score. Community screening is most effective when multiple informants (parent and teacher) are used [99]. Teacher reported scores differ from parental scores, each having different advantages. For example, the teacher is not able to comment on the child's behaviour at home; therefore the scores can only represent the child's state at preschool. The choice of rater results in differences in performance according to SDQ domains. Despite this, the overall predictive validity is similar for each informant [99]. Further, teachers are used as raters for the EDI, so this improves comparability.

The study is susceptible to selection bias. Children and preschools were not randomly selected. Not all preschools responded to the invitation to return data for every year. The characteristics of the preschools that returned data yearly differed from those that did not. The initial years of the sample were predominately local authority preschools, with fewer children living in the most deprived quintiles [63]. This may be due to issues in staff capacity. A qualitative study on collecting SDQ forms in Glasgow found that preschool staff were concerned about how completing the forms would add to their workload [102]. In partnership preschools, there were fewer full-time equivalent staff in 2010 [94]. The representativeness of the sample is likely to vary each year, depending on which preschools took part.Analysis conducted as part of the evaluation of the Triple P programme found there were no considerable differences in the SDQ scores at a population level between the preschools that remained in the study during every cohort and those that did not [63]. However, the changing sample may bias the spatial, temporal and spatio-temporal estimates from the data. This is explored in section 5.4.3 in Chapter 5. The impact of provider type on variation in scores by preschools and neighbourhoods is explored in Chapter 7.

Chapter 2

Neighbourhood Constructs Related to Child Mental Health and Well-being in Scotland: A Literature Review

Previous research has highlighted the importance of using a theoretical framework for selecting the neighbourhood characteristics for investigation [103, 104]. The characteristics selected, and how they are defined and measured, can influence the research findings.

At the neighbourhood level, there are several mechanisms that are thought to impact early child development that may, partly, explain any spatial variation. These have been classified in different ways over the years (e.g. [26, 105, 106]):

- Social-Interactive: social aspects of the community e.g. social networks, social support, trust, and participation
- Physical: the built and natural environment e.g. housing, greenspace, and routes
- Structural: neighbourhood socioeconomic status and intersectionality e.g. deprivation and discrimination

- Institutional: institutions e.g. libraries and community centres

The relationship between the neighbourhood and early development has been the focus of several international reviews (Table 2.1).

Table 2.1: Summary of reviews on relationship between neighbourhood and early development

Year	Author	Age group	Mechanisms	Studies (Scotland)
2006	Sellstrom and Bremberg [25]	0-18	All	13
2006	Rajartnam [104]	NS	All	31
2013	Vyncke [107]	0-18	Social-Interactive	8
2014	Pillas [1]	0-8	Social-Interactive	201
2014	van Vuuren [103]	0-18	Structural	19
2015	Christian [108]	0-7	Physical	32
2017	Minh [34]	0-6	All	42 (4)
2019	Alderton [38]	0-8	Physical	14
2021	Janus [8]	School Entry	Structural	133 (1)

NS Not Specified. Brackets show the number of studies that included populations from Scotland.

Across these reviews, many studies have found an association between development and the neighbourhood socioeconomic status (SES) [8, 25, 103]. In earlier research, there was a need for more understanding of this relationship in theory [25]. Since then, studies have suggested factors that may explain this association. Firstly, once considering the SES of the family, the neighbourhood SES is smaller, but still present [103]. Secondly, the social-interactive aspects of the neighbourhood have been found to partly explain neighbourhood SES and development [26, 107]. There may also be independent associations between development and the neighbourhood social context [1], though there is a need for more data [8]. The physical environment is proposed to promote (or inhibit) behaviours that are related to development, especially for physical health and social competence [108]. There is less information on the neighbourhood institutions (e.g. early learning and child care, child services) that could support development [26, 38]. Alderton et al., [38] found this to be a significant gap in the literature related to early mental health.

Consistently, across the reviews, there are calls for research that is theory driven and relevant to the population of interest. The reviews cover different outcomes that relate to early development, well-being, and health, this can make comparisons between studies difficult. Rajartnam, Burke, and O'Campo determined that each developmental outcome will need its own theoretical framework [104]. Frameworks may also vary across people and places. Few reviews conducted on neighbourhood effects in the last 10 years have featured research from Scotland (Table 2.1). It is unclear if this is due to restrictive search criteria or lack of qualifying evidence, as much of the research for Scotland is available in grey literature. As a result, there are gaps in the literature into the specific relationships that underlie neighbourhood differences in social, emotional and behavioural development in Scotland.

NHS Scotland's Children and young people's mental health indicators [109], released in 2012, highlight neighbourhood related constructs that are associated with mental health outcomes (including social, emotional and behavioural development). These include social networks, safety, and housing conditions (Table 2.2). These constructs were developed through consultation with field experts and stakeholder groups and designed to align with existing policies such as the Scottish Government National Performance Framework [110] and the UN's Sustainable Development Indicators [2]. Constructs were intended to be used to create mental health profiles at a local level and inform local strategy.

The accompanying literature review conducted to form the rationale for the constructs showed the quality of evidence varied considerably [109]. Limitations included a lack of longitudinal research, lack of data on children and young people, or lack of information on positive mental health. It was recommended that the evidence should be updated to reflect advances in the literature.

Shortly after, the Good Places Better Health – Child Mental Health and Well-being Evidence Assessment [111] using data from the Office of National Statistics [112] and Growing Up in Scotland survey [61] highlighted 4 key influences for children up to age 9:

- Homes
- Green (e.g. parks and gardens), blue (e.g. rivers, lochs, sea) , and play spaces

Table 2.2: NHS Scotland Children and young people's mental health indicators related to neighbourhood

Mechanism	Construct	Indicator
Community	Participation	Sense of agency: Belief in ability to make a positive difference
		Respect of children's rights
		Influencing local decisions
		Participation in clubs, groups, organisations
	Social networks	Contact with peers
	Social Support	Social Support
	Trust	Neighbourhood trust
		Community Cohesion: people in area stop and speak in the street
		Informal social control : Willingness of adult residents to intervene in neighbourhood-threatening scenarios
	Safety	Neighbourhood safety
Structural	Equality	Absolute poverty
		Income inequality
		Relative poverty
		Persistent poverty
	Discrimination	Discrimination and harassment
		Perception of attitude of adults towards children and young people
		Stigma towards children and young people
	Physical Environment	Neighbourhood satisfaction
		Free time places
		Greenspace
		House condition: design and maintenance
		Over crowding
	Violence	Domestic abuse
		Child protection
		Neighbourhood violence

- Routes (transport and access)
- Amenities and Facilities

Apart from 'Routes' (which was not listed as an NHS indicator), these all fall within the 'physical environment' construct previously identified in the NHS Scotland framework. More recently, the Child and Adolescent Health and Well-being in Scotland Evidence Review [113] provided national level indicators for area factors related to well-being, though these were not specific to child mental health:

- Neighbourhood safety
- Access to greenspace and play areas
- Public attitudes to young people
- Involvement in decision-making
- Involvement in volunteering and leisure activities
- Housing conditions
- Poverty
- Neighbourhood Relations

These align with the NHS Scotland constructs, but the list is not exhaustive.

The conceptual pathways developed by Alderton et al., [38] and Minh et al., [26] describe how structural mechanisms (e.g. equality and discrimination) can influence child mental health through family mental health or via the physical (e.g. neighbourhood safety) and social-interactive mechanisms (e.g. trust). Here, the pathways are adapted to reflect the constructs of interest for decision makers in Scotland [109, 111, 113]. Figure 2.1 shows how the contexts in Figure 1.1 can be expanded to include the neighbourhood constructs that could interact with one another to influence child mental health in Scotland. While the family context cannot be investigated with the ChiME data, there is an opportunity to explore the relationships between the other constructs. There is not one clear pathway. There are likely to be multiple constructs that influence mental health positively and negatively, operating at the same time or through multi-directional pathways.

The evidence reviews indicate there are two main challenges in identifying which neighbourhood factors are most important locally for children in Scotland. Though constructs were selected on the basis of existing international evidence, historically there has not been consistent availability of data to monitor these (i) across all age groups and (ii) at a small area level, restricting the ability to understand which neighbourhoods and children may be most affected in Scotland.

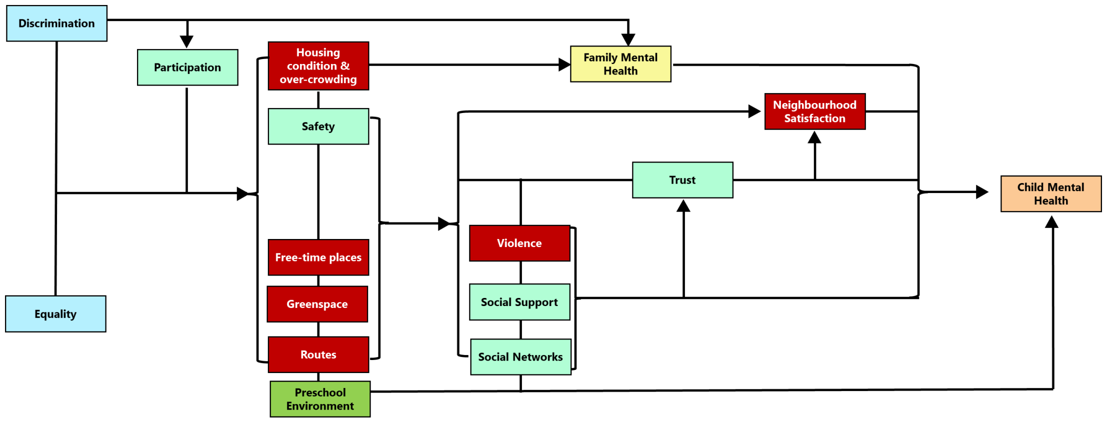

Figure 2.1: Proposed pathways for the influence of neighbourhood on child mental health in Scotland

This review aims to summarise recent literature on the effect of neighbourhood constructs on child mental health and well-being in Scotland.

2.1 Methods

2.1.1 Eligibility Criteria

The main population of interest was pre and primary school-aged children (aged approximately 4 to 12 years), living in Scotland. The main outcome of interest was mental health and well-being. If there were no relevant studies on mental health and well-being, outcomes related to child health and development were included. Where there was limited research from Scotland, evidence from rest of the United Kingdom (UK) or international populations were discussed.

Neighbourhood differences were defined by any sub-national geographic boundaries, which included:

- Health geographies (e.g. health boards)
- Administrative geographies (e.g. council areas/local authorities and electoral wards)
- Statistical boundaries (e.g. intermediate zones and data zones)

Where there were not geographically defined neighbourhoods, but information on neighbourhood attitudes were collected, this was included.

2.1.2 Information Sources

The review focuses on reports published since the NHS Scotland indicators were developed (2012 to present) and covers the most recent developments in the literature. Studies that have already been discussed in the Good Places Better Health Evidence Assessment, or the Child and Adolescent Health and Well-being in Scotland Evidence Review were excluded. As a result, some evidence related to the earlier ChiME cohorts (2010-2011) is omitted.

Electronic databases searched were PubMed, PsycInfo, GEOBASE, ASSIA and ERIC. Grey literature searches and hand searched sources were:

- OpenGrey http://www.opengrey.eu/
- NHS Health Scotland http://www.healthscotland.scot/publications
- Scottish Government https://www.gov.scot/publications/
- Glasgow Centre for Population Health https://www.gcph.co.uk/publications
- Scottish Public Health Observatory (ScotPHO) https://www.scotpho.org.uk/publications/
- Audit Scotland https://www.audit-scotland.gov.uk/report/search
- Growing Up in Scotland https://growingupinscotland.org.uk/publications
- Centre for Research on Environment, Society and Health https://cresh.org.uk/
- Big Urban Data Centre https://www.ubdc.ac.uk/research/publications/

2.1.3 Search Strategy

Titles and abstracts were searched for key terms (Table 2.3). References lists from identified papers were hand-searched.

Table 2.3: Search term categories

Population	Exposure	Outcome
Early years	Neighbourhood	Well-being
Young	Residence	Mental
Nursery	Community	Psychological
Children	Inequalities	Development
Pre-school	Area	Conduct
Primary School	Geographic	Mood
	Spatial	Emotional
	Ecological	Social
	environment	Behaviour
	Map/mapping	Strengths & difficulties
	Postcode	
	Nature	
	Urban	
	Socioeconomic	
	Scottish Index of Multiple Deprivation	

2.1.4 Data Synthesis

Due to heterogeneity in studies, evidence is summarised through narrative synthesis using the construct headings defined according to the NHS Scotland Children and young people's mental health indicators [109]. The construct 'Routes' has been added to this review according to evidence from the Good Places Better Health review [111].

2.2 Current Evidence on Neighbourhood Constructs

2.2.1 Summary of Included Studies

There were 23 papers and reviews identified that explored the association between the constructs of interest and child (mental) health and development. These are summarised in Table 2.4 and discussed in further detail in rest of the chapter. The remaining 47 papers discuss recent developments in how the constructs are defined, measured and related to one another to further develop the theoretical framework proposed in Figure 2.1. All academic reviews were international, and all grey literature reviews were from Scotland.

Table 2.4: Summary of studies: association between child health & development and neighbourhood

Author	Year	Source	Age group	Region	Construct	Outcome	Multilevel
Ehsan et al., [114]	2019	Review of reviews	General population	International	Social Capital	Health	Y
Pérez et al., [115]	2019	Review of reviews	General population	International	Social Capital	Health	N
Marryat et al., [116]	2014	Academic paper	4-5 years	Scotland	Social Support	Social, emotional and behavioural difficulties	N
Rueger et al., [117]	2016	Meta-analysis	< 20 years	International	Social Support	Depression	N
Kosher and Ben-Arieh [118]	2017	Academic paper	8-12 years	International	Participation	Well-being	Y
Flouri et al., [119]	2015	Academic paper	3-7 years	England	Trust	Social, emotional and behavioural difficulties	Y
Shortt and Ross [120]	2021	Academic paper	10-13 years	Scotland	Safety	Health	N
Maantay and Maroko [121]	2015	Academic paper	Adults	Scotland	Safety	Mental Health	N
O'Brien et al., [122]	2019	Meta-analysis	General population	International	Safety	Health	Y
Odgers et al., [123]	2012	Academic paper	5-12 years	UK	Safety	Health	N
Clery et al., [36]	2022	Systematic Review	0-5	UK	Equality	Health	Y
Bécares et al., [124]	2015	Academic paper	5-11 years	UK	Discrimination	Social, emotional and behavioural difficulties	N
Cave et al [125]	2020	Systematic Review	<18 years	International	Discrimination	Health	N
Scottish Government [126]	2020	Grey Literature	8-12 years	Scotland	Neighbourhood satisfaction	Mental Health	N
Richardson [127]	2017	Academic paper	4-6 years old	Scotland	Greenspace	Social, emotional and behavioural difficulties	N
Roberts et al., [128]	2019	Systematic Review	<21 years	International	Greenspace	Well-being	N
Hossain et al., [129]	2020	Review of reviews	General population	International	Greenspace	Mental Health	Y
McCormick R [130]	2017	Systematic Review	< 18 years	International	Greenspace	Mental Health	Y
Clair [131]	2019	Literature Review	Children (undefined)	International	Housing condition and overcrowding	Well-being	Y
Marsh et al., [132].	2019	Academic paper	2-3 years	England	Housing condition and overcrowding	Social, emotional and behavioural difficulties	N
Weitzman [133]	2013	Literature Review	Children (undefined)	International	Housing condition and overcrowding	Health	N
Schubert et al., [134]	2019	Meta-analysis	<18 years	International	Routes	Mental Health	N
Freeman [135]	2013	Review	General population	International	Violence	Mental health	Y

Multilevel refers to sources that do (Y) or do not (N) include consideration or investigation of multiple contexts.

2.2.2 Community Constructs

Community constructs align with how the Scottish Government now defines social capital: social networks, community cohesion, community empowerment, and social participation. Social capital is measured over time using the Scottish Household Survey, though this is primarily collected in adults [136]. How these themes relate to health and well-being have been examined extensively in the literature. A review of reviews conducted in 2019 identified 20 papers on the relationship between social capital and mental and physical health status and found evidence of an association [114]. In the same year, for another review of reviews focusing on the role of community, a further 8 papers were identified. Three of the papers included research on children (though these were published between 2008 and 2011 so are not discussed here) and again the overall evidence suggested social environment of the community is associated with more positive developmental outcomes [115].

Social Networks & Social Support

NHS Scotland define social support as the quality of relationships with members of the community, for example, if a child could ask a neighbour for help [109]. The association between social support (both theorised positive effects and protection from negative effects) and depression in children and adolescents has been supported in a meta-analysis of over 300 papers [117]. The authors recommended more research on younger people, as only 20 of the included studies were on children under the age of 12. The effects of different sources of support varied by age group. Peer group support was one of the strongest sources of support for younger children [117]. Data on community social support for children in Scotland is limited. In Glasgow, social and emotional functioning in pre-school children was associated with social isolation, measured through the Strengths and Difficulties questionnaire [116]. The mechanism for the effects of social interactions on mental health and how this may differ by area requires further investigation [114]. For example, area level differences in the provision, quality, and affordability of spaces that promote interaction.

Participation

Feeling responsible and respected are indicators of child well-being according to the Scottish Government's Getting it Right for Every Child (GIRFEC) policy [137]. In line with the Scottish Government model of engagement [138], children should be involved in shaping how their local services are delivered. This can include being involved in decision-making (e.g. consultation) and participation in groups or voluntary work that can help children feel listened to and that they belong in their community. Children's Neighbourhood Scotland [74] aimed to strengthen the agency of children through their involvement in shaping neighbourhood improvements and reducing inequalities. The impact of the programme was assessed through bespoke surveys and qualitative research. The Children and Young People Mental Health Indicator Framework [109] recommended collecting data on sense of agency and whether children have their rights respected. Since then, the Children's Measurement Framework identified 50 statistical indicators for children's rights in Scotland, England, and Wales using administrative and survey data sources across 10 domains including 'participation, influence and voice' [139]. The authors found evidence to support monitoring all indicators, and measurement at a local level requires further research [139]. The progress of children's rights in Scotland was reviewed recently by the Scottish Government [140] and Together (Scottish Alliance for Children's Rights) [141]. A review of town planning in Scotland found children's rights, according to the UN Convention on the Rights of the Child [142], were not always reflected in planning policy [143]. The relationship between children's rights and their well-being was analysed using data from the International Survey on Children's Well-Being (ISCWeB) [144]. The UK sample includes children from England only. Across the whole sample, subjective well-being in 8 to 12-year-old children was associated with how they viewed their rights and that feeling heard in their community was correlated to neighbourhood satisfaction and overall subjective well-being [118].

Trust

Trust for residents in the neighbourhood and community cohesion was previously measured in secondary school aged children [109, 113] in Scotland through studies such as the Health Behaviour in School-aged Children [145]. A lack of community cohesion can be considered social fragmentation. Using a census-based index for fragmentation [146] (which includes measurement of population turnover and single households) and data from 3, 5 and 7-year-old English children from the Millennium Cohort Study, it was found that social fragmentation has little role in emotional or behavioural development [119]. The index provides small area level data on social fragmentation, allowing analysis of its spatial distribution. However, there are challenges in interpretation. The measures focus on aspects relevant to adult residents, the extent that it captures fragmentation may vary regionally and, it may not reflect perceptions of fragmentation [147].

NHS Scotland indicators [109] recommended the collection of national data on informal social control such as willingness to intervene when children are misbehaving, however, there continues to be limited available data. The 2006 Scottish Social Attitude survey found that 9% of adults felt very comfortable intervening in a hypothetical scenario of teenagers vandalising a bus shelter [148], but has not been included in further rounds of the survey. More recent studies have focused on how informal social control contributes to neighbourhood collective efficacy. Informal social control and community cohesion are two main components of neighbourhood collective efficacy. Both play a protective role against child maltreatment as found in a systematic review of 21 papers from the US and Asia [149]. Authors highlighted the distinction between willingness to intervene (which is typically how informal social control is measured) and actual action in community-based child protection. Another important consideration is how neighbourhood collective efficacy is measured at the neighbourhood level. A study conducted in London used data from the UK Metropolitan Police Public Attitude Survey to generate a measure of collective efficacy. How this was rated was shown to vary by neighbourhood and by residents within the same neighbourhood [150].

Safety

Both the physical and social aspects of the neighbourhood environment contribute to whether residents feel safe. Though no longer collected as part of the Scottish Household Survey, the descriptive analysis showed in 2016 two-thirds of households considered local play areas safe for 6-12-year-olds to go with friends and roughly one-third were concerned about bullying and being harmed by adults [151]. A meta-analysis on the effects of neighbourhood disorder on child and adult health outcomes found that both social and physical disorder were associated were poor mental health outcomes [122]. Aspects of neighbourhood design such as surveillance and security may be associated with crime, e.g. enclosed spaces and vacant property. Just over half of those who live in proximity (500 m) to derelict land live in the most deprived areas in Scotland [152]. Conditions of facilities, streets, spaces, and play areas could create health and safety risks and spatial stigma. It has previously been shown that living near vacant and derelict land is associated with prescribing adult mental health medication in Glasgow [121]. In the last few years, there have been developments in the understanding of the condition of places on child mental well-being. The Local Environmental Audit and Management System measures local authority standards in indicators of cleanliness [153]. Approximately 1 in 3 of the local authorities audited in 2018/2019 had issues with litter, weed, or detritus. Littering can affect children and young people in the community in many ways. The items discarded may be harmful (e.g. drug related litter); children may feel that there is a lack of care about their area; and it can diminish the quality of neighbourhood spaces [120]. Physical disorder and decay rated using

Google Street View were associated with anti-social behaviour, while 'child safe' streets were associated with prosocial behaviour in 12-year-old children living in England and Wales [123].

2.2.3 Structural constructs

Equality

Existing literature supports a significant relationship between child health and socioeconomic indicators including income, education, and employment [103] though effects were often attenuated by family-level indicators. There are differences in individual level income measures and those analysed at area level [154]. Individual measures tend to be more strongly associated with child health outcomes [36]. There has been a drive from the Scottish Government to monitor child poverty at a local level. The Child Poverty Strategy 2014 [155] called for the local level poverty estimates. The Scottish Household Survey [156] was adapted to include measures of material deprivation. The Child Poverty (Scotland) Act 2017 requires local authorities and health boards to develop appropriate measures for local action reports [138]. An evidence review on causes, consequences, and prevention of local child poverty conducted by What Works Scotland highlighted that there is limited academic research for Scotland specifically compared to the UK as a whole [157].

Discrimination

Much of the research on neighbourhood identity is focused on adults [158, 159]. The 2018 Scottish Household Survey found that adult experiences of discrimination and harassment occurred more in areas of higher deprivation [160]. There is evidence to support exposure to racial discrimination being associated with negative mental health outcomes for children and adolescents in longitudinal studies [125]. Findings from the UK Millennium Cohort Study suggest this is due to ethnic minority family members being impacted by racism (for example worsening maternal mental health) rather than living in an area where racial attacks are more prevalent [124].

Children and young people recognise feeling included in their community as an important component of their health and well-being [113]. The physical neighbourhood environment can promote a sense of belonging through local structures that facilitate social interactions. Play Scotland describes the important role that play areas and the natural environment have in helping children develop a sense of belonging in their neighbourhood. As a result, it is integral that these spaces are inclusive [161]. A survey on inclusivity in play asked adults in Scotland about barriers to play in the community, the most commonly selected reasons were: fear, poor outdoor environment and poor resources [162].

Physical Environment

Neighbourhood Satisfaction The neighbourhood satisfaction is collected from adolescents, and the determinants of satisfaction may differ for younger populations or their caregivers. In the Growing Up in Scotland survey, elements of parental satisfaction with the area included opinions on reputation, community spirit and desire to move [163]. For children, these determinants may align with what is considered a 'child-friendly' environment. Han and Kim identified 4 emotional experiences from child-friendly environments when reviewing the literature: sociality, wellness, development, and independence. Through child-friendly spaces, children are recognised as stakeholders in their community and have improved experiences with their environment [164]. The Realigning Children's Service programme conducted well-being surveys in primary and secondary school children in 5 local authorities in Scotland. It found that children in Primary 5 -7 were twice as likely to have a lower mood if they did not like their area, but that family, school, and peer level risk factors were stronger indicators of mood [126].

Free time places The NHS review describes free time places as neighbourhood facilities and amenities where children spend time outside the home or learning environment example, leisure centres, shops and parks [109]. A review of the effects of neighbourhood environment on health highlighted the positive role of local amenities (e.g. childcare, recreation centres, libraries) in health and development for young children [108]. Deprived areas can have more amenities or be in closer proximity to recreational facilities such as playgrounds, swimming pools and courts compared to less deprived areas [165]. In Scotland, deprived areas can be closer to public physical activity facilities [166] and have better walk-ability than more affluent areas [167]. Deprived neighbourhoods may experience a higher presence of facilities that may have a negative impact on community health. In Glasgow, the clustering of gambling, fast food and alcohol, and tobacco outlets increases with deprivation [168]. GPS tracking of 10-11-year-olds in Scotland found that children from more deprived areas are exposed to more tobacco outlets than those from less deprived areas [169]. Future research on the direct impact of neighbourhood amenities in Scotland should consider the quality of facilities, purchasing behaviour [170] and the ratio of healthy to unhealthy outlets in an area [171].

Greenspace The impact of natural space, in particular greenspace like parks, gardens, woodlands, and vegetation on mental health has been explored in many research studies. In an umbrella review, the authors identified 20 systematic reviews and meta-analyses on the topic [129]. There seems to be a positive association between access to greenspace and positive mental health outcomes.

For children, reviews have shown these effects could be direct or via their parents or caregivers [128, 130]. Good Places Better Health Scotland highlights the importance of the physical aspects of the natural environment (e.g. fresh air, sunlight) and how it provides a space for imaginative play and joint play with others, which promote healthy development [111]. A longitudinal study found, after considering individual and household demographics, having access to private gardens is associated with lower social, emotional and behavioural difficulties for children living in urban areas in Scotland, after accounting for household income and neighbourhood deprivation [127]. Families may experience variations in the quality of accessible natural space. Glasgow Centre for Population Health developed an indicator which shows there are geographic differences in the proportion of children under 16 living near quality greenspace. In some Glasgow neighbourhoods, 100% of the children live within 400 m to the highest quality greenspace while in others it is as few as 10% [172]. Access to quality space may depend on cost of facilities, transport needs and safety concerns. Further research is needed to address associations between natural environment and mental health that may differ due to population disparities such as ethnicity or socioeconomic status.

Housing condition and over crowding Housing can be considered a psycho-social environment as well as a physical environment. As such, there are a variety of ways in which housing can impact mental well-being. Young children spent a lot of time at home. Consequently, children may be more exposed to aspects of housing that relate to their health and development [133]. Housing conditions should create a stable and safe environment for children. This includes limiting damp, noise and cold, and having sufficient lighting. Poor housing conditions put children at risk of exposure to environmental hazards and toxins, which can affect several child health outcomes [133]. In addition, children may be indirectly affected by the impact of housing on their caregiver [131]. Liddell and Guiney [173] summarise the theoretical models that link poor energy efficiency with adult mental well-being. Contributing factors include stress over bill payments, damage from damp and mould, and health concerns from the cold.

Crowding limits physical activity in children living in low-cost housing [174]. In the UK, 3-year-old children in households with a greater number of people per room developed more behavioural difficulties [132]. Sleep and maternal stress were found to partly mediate this association [132]. Though it should be noted that the number of people per room may not fully represent overcrowding and the feeling of being crowded may be better reflected through consideration of the number of children, the relationship between occupants and cultural norms [111].

Routes The Scotland Health and Inequality Impact Assessment Network (SHI-IAN) highlight the impact of public transport to the wider community [175]. Public transport infrastructure can facilitate the local economy but also create psychological and physical barriers resulting in community severance [175]. Transport choices can impact community health air pollution levels and risk of injury. At an individual level, the ability to use public transport is determined by the availability, affordability, and practicality of services. Public transport plays an important role in facilitating access to work, education and recreation and health services. Transport can impact social well-being through the activities that take place during the trip and facilitating access to destinations for social interactions. As a result, lacking appropriate public transportation within a neighbourhood can play a role in social exclusion. Households with better access to transport had lower rates of adverse childhood experiences (ACEs) [176].

A caregiver's decision to allow their children to walk to school is influenced by distance, traffic, safety and parents' convenience. Contrary to what would be predicted, if traffic is slow and safe, this was negatively associated with active travel [177] which may reflect the impact this has on the parent's convenience to drive the child [178]. Notably, as active travel research in Scotland largely focuses on school commutes, there is much less research on recreational travel and how this may vary [179].

Traffic is an important aspect of the route environment. Traffic can directly impede the ability to actively travel and restrict opportunities to play in outdoor neighbourhood areas, affecting physical activity and social interaction [108]. A meta-analysis found rising road traffic noise (per 10 dB) associated with an 11% and 9% increase in the odds of high scores in hyperactivity/inattention and total difficulties, respectively [134]. However, only 3 studies were eligible for inclusion in the meta-analysis and evidence from the remaining studies was methodologically heterogeneous, and their findings were inconclusive. In addition to the physical impact of road traffic injuries, there is a psychological impact on children who survive accidents. A meta-analysis found that roughly 1 in 5 children and adolescents had post-traumatic stress disorder following a road traffic accident [180].

Violence

Previously, there was no suitable data on the number of children living in a household where there is domestic abuse, the need for child protection or exposure to neighbourhood violence [109]. However, at a local level, there is available information on the number of children on the child protection register and child protection referrals. The Child and Adolescent Health and Well-being Evidence Review [113] notes that the number of children on the child protection register could reflect greater family instability, need, or identification of cases. Local variations in child protection referral processes make national monitoring and comparison between local areas difficult. By the age of 8, approximately 9% of children from the Growing Up in Scotland 2004/5 cohort had experienced domestic abuse [181]. Research suggests neighbourhood effects are associated with child maltreatment [135]. In England, adverse childhood experiences (ACEs) which include abuse, neglect and household adversities at the local authority level were higher in areas with greater population density [182].

2.3 Discussion

In recent years, there has been growing literature on neighbourhood effects on health and well-being. The impact of neighbourhood effects may differ across people and places. This work aimed to review the existing literature on how neighbourhood characteristics relate to child social, emotional and behavioural development in Scotland since the NHS Scotland Children and young people's mental health indicators were established [109]. This review looked at 71 studies from grey and academic literature relevant to Scotland published from 2012 to 2022. There were six key findings from the review.

1. For some constructs, there continues to be limited data specifically about young children (Table 2.4). There was one study on the association between participation and well-being, compared to several reviews on greenspace. The quantity of evidence supporting different constructs is variable (Table 2.4). There was more evidence supporting the role of structural constructs (shown in red in Figure 2.1) than community constructs (shown in turquoise in Figure 2.1). There were methodological challenges in measuring community constructs in a way that is meaningful to younger children. Data related to older children and adults may be easier to collect, but may not reflect the experience or perspectives of preschool aged children/their caregivers. It is unclear if the weaker associations when using constructs derived from older populations are due to a genuine lack of association or an inability of the data to capture neighbourhood effects in the target age group. For example, where collective efficacy was measured by surveying

families in the same neighbourhood, it was negatively associated with anti-social behaviour [183].

2. Most of the evidence found was academic literature (Table 2.4). The inclusion of grey literature allowed more research from Scotland to be reviewed. Evidence on the role of neighbourhood satisfaction was only possible through the inclusion of grey literature. Some of the studies from Scotland were smaller or of lower methodological quality, so may have been excluded from other reviews. Including sources across the hierarchy of evidence resulted in varying quality of evidence. Constructs such as greenspace are supported by several systematic reviews, while other constructs rely on individual cross-sectional studies or descriptive reports (e.g. participation). As the latter evidence is less robust, some neighbourhood effects may be due to confounding or other sources of bias.

3. There is evidence for multiple contexts being involved in neighbourhood effects in Scotland, aligning with the multiple contexts included in Figure 2.1. This supports the use of multilevel approaches to neighbourhood effects research. The neighbourhood can affect the mental health of the caregiver, which could impact the child at a family/household level. Discrimination, housing, and routes appear to be more related to the household or caregiver rather than directly relating to the child. At an individual level, children in specific demographic groups or differing levels of mental health difficulties may be more susceptible to neighbourhood factors. And there is a distinction between the neighbourhood environment (neighbourhood deprivation) and individual circumstances (individual deprivation). Most of the single studies in Table 2.4 do not consider the individual and neighbourhood contexts in their methodology. Though previous reviews such as Sellstrom and Bremberg [25] have focused specifically on multilevel studies. Most of the reviews included here featured some discussion or consideration of multiple contexts. The distinction between the levels may not always be clear, e.g. the learning environment could be considered a feature of the neighbourhood and a separate context, and individual characteristics both shape and are shaped by

the neighbourhood.

4. As research has developed, how these constructs are defined has evolved. A recent review highlighted the differences in how indicators of community well-being were defined within the UK over 5 years [184]. This may impact what data is collected in the long term. In some cases (e.g. ratings of local play areas) the data was previously collected, but not at present. Structural indicators are moving away from objective measures (such as distance to amenities). For both greenspace and free time places, it was highlighted that there is a need for evidence beyond accessibility and towards differences in perceptions of quality and barriers to use. This creates new challenges as individual perceptions may not lead to a consensus at the neighbourhood level, this inhibits the ability of the construct to reliably measure neighbourhood differences. Individuals between neighbourhoods can also differ in their interpretation of a construct, as mentioned with collective efficacy. Multi-level data would support the analysis of the reliability of a measure at a neighbourhood level, considering both the individual and neighbourhood level variance in perceptions [185].

5. Many of the constructs overlap and connect - as initially proposed in Figure 2.1. For example, the pathways linking social capital, safety, and violence to child mental health outcomes may overlap. Similarly, a systematic review of measures of adolescent social environment found considerable overlap between the items used to measure different constructs [186]. As a result, it may be difficult to attribute neighbourhood differences to solely one construct without considering the profile of the neighbourhood as a whole. Taking into account multiple constructs would help to explore confounding, though this is dependent on the availability of contextual level data on key confounders.

6. Local level data is not available for all the constructs. In Scotland, there was a lack of local level data related to child poverty, though recently policy has been put in place to address this [138]. There is a similar need for local level data related to exposure to violence, where the literature suggests area level dif-

ferences are expected. Where local data were available, studies considered the spatial distribution of the physical environment constructs within the cities (e.g. [121, 127, 167, 170]). How these small areas are defined varied across studies (for example, distance from home [127], data zones [121, 167] and intermediate zones [170]), even for analysis conducted in the same city ([121, 170]). As previously discussed, there is limited research on how spatial relationships may evolve. Neighbourhood constructs changing over time could support the inclusion of the temporal or spatio-temporal context (for example living in a neighbourhood at a specific point in time) to Figure 2.1.

The current evidence supports the notion that inequalities in the constructs of a neighbourhood can be associated with the mental health and well-being of preschool-aged children. Further investigation of these constructs within a multilevel context and using data from a preschool-aged population could help to identify priority areas for intervention. Where possible there is a need to consider the role of time as a context (i.e. spatio-temporal variation) and as an aspect of neighbourhood composition (i.e. spatio-temporal characteristics). Spatio-temporal characteristics should be explored from a variety of data sources such as those from the grey literature to fill in some of the research gaps in the academic literature. The remaining chapters discuss the methodology to address these research needs and the application of the methodology to the ChiME data.

Chapter 3

Modelling Individual, Spatial and Spatio-temporal Variability: A Methodological Review

The research questions for this project will be primarily answered using regression modelling. The modelling strategy requires consideration of the data structure. Take a regression model equation, used to estimate the value of y given x, here a linear model is used for simplicity:

$$\begin{aligned} y &= \beta_0 + \beta_1 x_1 + \epsilon \\ \epsilon &\sim N(0, \sigma^2) \end{aligned} \tag{3.1}$$

Where y is the response variable, x is the explanatory variable. The βs are the regression coefficients. β_0 is the intercept which describes the average value of y when x is zero. β_1 is the coefficient for x, it is the slope of the line describing the change in average y when there is a unit change in x, ϵ is the error term which is normally distributed with mean zero and variance (σ^2).

The equation describes the regression relationship, so that the estimated value of y for the i th observation for $i = 1,\ldots,n$, is:

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{i1} \tag{3.2}$$

The hat notation $\wedge$ indicates the estimates for y and the regression coefficients.

Covariance describes the variance between two variables. In a regression model, the covariance of the response is estimated after adjustment for explanatory variables. This is equivalent to the predicted value being subtracted from the observed value. This results in the error term. The covariance of the error term for the same observation (i.e. with itself) is its variance:

$$Cov(y_1 - \hat{y}_1, y_1 - \hat{y}_1)) = Cov(\epsilon_1, \epsilon_1) = Var(\epsilon_1) = \sigma^2 \tag{3.3}$$

In a simple linear model, the covariance of two different observations is assumed to be zero:

$$Cov(y_1 - \hat{y}_1, y_2 - \hat{y}_2)) = Cov(\epsilon_1, \epsilon_2) = 0 \tag{3.4}$$

The covariance structure for the error terms can be represented as follows:

Table 3.1: Linear model covariance structure

i	1	2	3	4
1	σ^2	0	0	0
2	0	σ^2	0	0
3	0	0	σ^2	0
4	0	0	0	σ^2

The correlation is calculated by dividing the covariance by the total variance. In this example, the correlation between an observation with itself is one, and with all other observations is zero. For each observation, there is random error. The differences between the values predicted by the equation and the observed values are known as the residuals. These are estimates of the error, or the variation in the data that is not explained by the regression equation. The performance of a model can be assessed by evaluating the residuals. In a linear model, it is assumed that the residuals are independent. The value of one observation does not give information about any other.

When two observations have a correlation that is not equal to zero, they are considered dependent. Within the CHiME data, there are four key sources of dependence that require a different modelling approach:

- Cluster
- Spatial
- Temporal
- Spatio-temporal

Identifying and measuring these sources of dependence and how these can be addressed within the model are discussed in the rest of this chapter.

3.1 Clustered Data

Child development is influenced by multiple different contexts, such as preschool and neighbourhood [37]. Therefore, variation in development can be attributed to contextual differences.

Observations taken from children in the same neighbourhood are expected to be more similar than those taken from children in different neighbourhoods. If this is the case, observations from children belonging to the same neighbourhood cluster together. Similarities between children in the same neighbourhood could be due to shared exposure to neighbourhood-level factors or due to 'residential selection' whereby there are similarities between households who choose to live in a certain area [187].

For preschools, the needs, or facilities of the preschool, catchment areas and parental selection may result in similar outcomes in the children who attend. In the case of the CHiME project, where SDQ scores are recorded by the teacher, there may be preschool and teacher level differences in SDQ measurement practices.

These similarities between children in the same cluster violate the assumption of independence described in the linear model. As a result, in a standard regression where clustering is ignored, the standard error estimates are underestimated. There are different modelling approaches to deal with clustering in the data.

- Separate analyses: Analysing each cluster separately is the simplest approach, but this does not allow within-cluster effects to be estimated.

- Cluster-robust standard errors: Using the cluster residuals, within cluster variability can be taken into account to provide larger, more robust standard errors. However, this does not have an effect on the parameter estimates.

- Generalized Estimating Equations (GEE): In GEEs, clustering is not the main interest. Parameter estimates and standard errors are adjusted for clustering. This is commonly achieved by specifying a correlation structure for the mean and variance of outcome within clusters. As only the mean and variance are used, parameter estimates reflect population averages.

- Multilevel models: The multilevel model is also known as a mixed effect, variance components, random effect, hierarchical or nested model. Multilevel modelling explicitly allows the effects of multiple clusters to be modelled at the same time and estimates cluster specific effects via a few parameters. These clusters can form a hierarchy of different levels. Within each level, similarities between observations from the same cluster are allowed. Depending on the complexity of the data, specification of the random effects can be challenging.

For this work, which is interested in understanding the role of clusters on individual heterogeneity, the multilevel approach was considered the most suitable. This approach is discussed in more detail in the next section.

3.1.1 Multilevel Modelling

Using multilevel models to identify sources of variation in health and well-being outcomes can help the development of policies that address inequalities [188]. Multilevel models have been used extensively in neighbourhood research [25, 189–191].

In multilevel modelling, random effects are added to the model to give structure to the cluster-level residuals. Random effects allow dependency in the model through the covariance structure so that individuals or observations within the same cluster can be modelled as more similar than those across clusters. This means that the independence assumption holds for the individual level errors. Explanatory variables at different levels of hierarchy can be added to the model.

The primary interest is not in the estimates for each cluster, but the variation. The clustering effect can be included in the model via a single or small number of variance parameters. Rather than estimating a random effect for each cluster, the model splits the variation in the outcome into variance components attributable to the differences between the levels. This models the between-cluster variation and within-cluster variation. By accounting for the cluster level correlation, including random effect variances allows the independence assumption for the individual level errors to be met. The random effects can be introduced in different ways [192]:

Random Intercept Model

A random intercept model allows varying intercepts for each cluster. For $i = 1, \ldots, n$ individuals in $j = 1, \ldots,$ clusters:

$$\begin{aligned} y_{ij} &= \beta_0 + u_j + \beta_1 x_{1ij} + \epsilon_{ij} \\ u_j &\sim N(0, \sigma_u^2) \\ \epsilon_{ij} &\sim N(0, \sigma_\epsilon^2) \end{aligned} \tag{3.5}$$

There is now a two-level structure. Subscript i indicates the i th unit in level 1 and j is the cluster in level 2 that the i th belongs to. For example, if individuals were nested within neighbourhoods, i represents the individual and j their neighbourhood. Therefore, y_{ij} is the value of y for individual i in neighbourhood j. There is an overall intercept β_0 and a cluster effect u_j so that the intercepts can vary across the clusters. The slope β_1 estimates the average relationship between y and x. The slope is assumed to be the same across all clusters.

Random effects are assumed to be normally distributed. The variance components represent how an individual differs from their cluster mean (within-cluster variance σ_ϵ^2), and how cluster means differ from the overall mean distribution (between-cluster variance σ_u^2). A two-level random intercept model, as above, assumes the covariance between observations from different clusters or individuals is zero. For the same observation, the covariance is the variance of the cluster and individual random effects $\sigma_u^2 + \sigma_\epsilon^2$. And for two individuals in the same cluster, the covariance is σ_u^2 (Table 3.2).

Table 3.2: Random intercept covariance structure

j		1	1	1	2	2	2
	i	1	2	3	1	2	3
1	1	$\sigma_u^2 + \sigma_\epsilon^2$	σ_u^2	σ_u^2	0	0	0
1	2	σ_u^2	$\sigma_u^2 + \sigma_\epsilon^2$	σ_u^2	0	0	0
1	3	σ_u^2	σ_u^2	$\sigma_u^2 + \sigma_\epsilon^2$	0	0	0
2	1	0	0	0	$\sigma_u^2 + \sigma_\epsilon^2$	σ_u^2	σ_u^2
2	2	0	0	0	σ_u^2	$\sigma_u^2 + \sigma_\epsilon^2$	σ_u^2
2	3	0	0	0	σ_u^2	σ_u^2	$\sigma_u^2 + \sigma_\epsilon^2$

The residual is now decomposed into residuals at level i, and at level j. The individual level errors are independent, given the cluster level errors. The average cluster-level residuals describe the variation (after accounting for covariates) that is not explained by the model.

Random Slope Model

In a varying slope model, the slope of the regression can vary between clusters.

$$\begin{aligned} y_{ij} &= \beta_0 + (\beta_1 + u_{1j})x_{1ij} + u_{0j} + \epsilon_{ij} \\ \begin{pmatrix} u_{0j} \\ u_{1j} \end{pmatrix} &\sim N(0, \Omega_u) \text{ where } \Omega_u \begin{pmatrix} \sigma_{u0}^2 & \sigma_{u01}^2 \\ \sigma_{u01}^2 & \sigma_{u1}^2 \end{pmatrix} \\ \epsilon_{ij} &\sim N(0, \sigma_\epsilon^2) \end{aligned} \tag{3.6}$$

There is now an overall slope β_1 and a cluster effect u_{1j} so that the slopes can vary between clusters. This allows the explanatory variable x (which in this example is continuous) to have varying cluster effects. The random effects assume a bivariate normal distribution with covariance matrix Ω_u. σ_{u01}^2 describes the covariance between the intercept and slope. When x is a categorical variable, this is referred to as a random coefficient.

3.2 Complex Data Structures

In conventional multilevel analysis, individuals are nested into clusters by levels, as in Figure 3.1. For example, a child (level 1) is nested within a preschool (level 2) which is nested within their neighbourhood (level 3) [192].

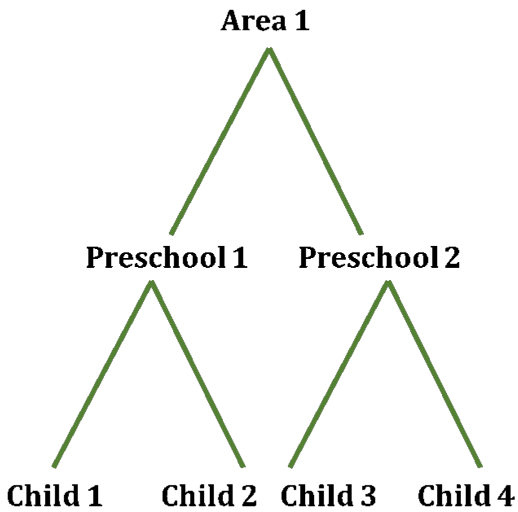

Figure 3.1: Nested data structure

In Glasgow, children will normally attend the primary school for their local catchment area. However, this is not the case for preschool, where cross-boundary arrangements mean that children can attend preschools outside their local authority. According to a report by the Scottish Government, the most frequently cited reason for choosing an Early Learning and Childcare (ELC) provider was the proximity to home [193]. This may not follow a strict hierarchy, for example, the preschool may be close to home but over the boundary of their local neighbourhood. Thus, children can attend the same preschool while living in different neighbourhoods; or live in the same neighbourhood but attend different preschools. Omitting these non-nested structures can affect estimates of covariate effects and variance components [194, 195].

In cross-classified relationships, the higher levels do not need to be nested. For example, in Figure 3.2, children are nested within preschools and within neighbourhoods, but preschool and neighbourhood are not nested [192, 196].

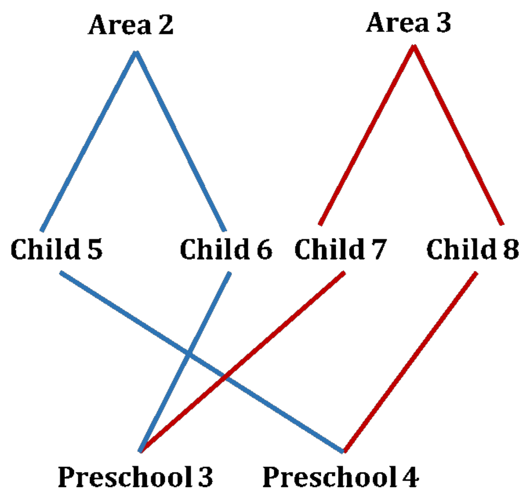

Figure 3.2: Cross-classified data structure

This approach has been used in educational research and is increasingly used in health research [197]. In a cross-classified model, (where school and neighbourhood were cross classified) authors found that the percentage of social housing in the neighbourhood was positively associated with more social and emotional difficulties in the Millennium Cohort Study [198].

Using multiple subscript notation [199], the subscript $(j1, j2)$ represents a cross-classified relationship:

$$\begin{aligned} y_{i(j1,j2)} &= \beta_0 + u_{j1} + u_{j2} + \epsilon_{i(j1,j2)} \\ u_{j1} &\sim N(0, \sigma^2_{u(1)}) \\ u_{j2} &\sim N(0, \sigma^2_{u(2)}) \\ \epsilon_{i(j1,j2)} &\sim N(0, \sigma^2_{\epsilon}) \end{aligned} \tag{3.7}$$

Using the example provided in Figure 3.2, where preschool is u_{j1} and area is u_{j2}, the covariance between Child 6 and 7 who attend the same preschool would be $\sigma^2_{u(1)}$, for Child 5 and 6 in the same area it would be $\sigma^2_{u(2)}$. There is no covariance between the preschool and area effects. If two children attended the same preschool and lived in the same area, the covariance would be the sum of the separate effects $\sigma^2_{u(1)} + \sigma^2_{u(2)}$.

In instances where an individual belongs to more than one higher level unit, this is known as a multiple membership model [199] (Figure 3.3).

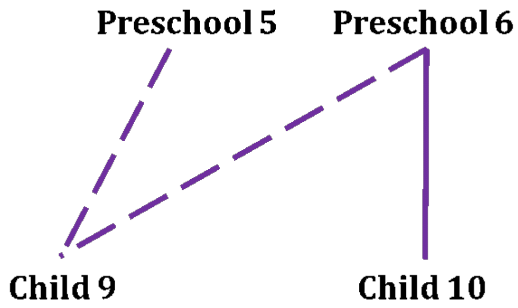

Figure 3.3: Multi-membership data structure

The multiple membership model can be shown as:

$$
\begin{aligned}
y_{ij} &= \beta_0 + \sum_{j=1}^{J} W_{j,i} u_j + \epsilon_i \\
u_j &\sim N(0, \sigma^2_u) \\
\epsilon_{i(j1,j2)} &\sim N(0, \sigma^2_\epsilon)
\end{aligned}
\tag{3.8}
$$

In this model, weights $W_{j,i}$ are assigned based on the degree to which an individual i belongs to a specific cluster j. Any cluster-level variables added to the model are weighted. The overall mean intercept according to membership to u_j is $\beta_0 + \sum_{j=1}^{J} W_{j,i} u_j$. Different methods can be used to assign the weights, for example the proportion of time spent in each cluster. Using the example provided in Figure 3.3, assuming Child 9 spent 0.5 of their time in preschool 5 and preschool 6, would have the following model: $y_9 = \beta_0 + W_{5,9}u_5 + W_{6,9}u_6 + \epsilon_9 = \beta_0 + 0.5u_5 + 0.5u_6 + \epsilon_9$

Unlike the cross-classified model in Equation 3.7, there is only one random effect for preschool and a single variance component. The total variance is not constant and varies by child according to their weighted membership to a cluster.

3.3 Correlation Structures for Modelling Dependence

Traditional multilevel modelling assumes independence between clusters, however there may be sources of dependence to consider. For example, residuals closer together in time or space may be more similar. Spatial correlation may be introduced in data collected at neighbourhood and preschool level, and temporal correlation may be introduced in longitudinal or repeated cross-sectional data which has been pooled over time. Covariates may account for some of this variability but might not explain all of it, resulting in spatially or temporally correlated residuals. A multilevel model that ignores the residual spatial and/or temporal correlation will violate the independence assumption. This can cause the standard error estimates to be inaccurate. The effects of space and time can be modelled through the specification of random effects. By using random effects, as opposed to fixed effects, the between-cluster differences can be estimated and varying slope effects can be included.

3.3.1 Spatial Multilevel Modelling

Neighbourhood effects can be described as platial (also known as unstructured or heterogeneity) or spatial [200]. Platial refers to the similarity of individuals in the same neighbourhood. Therefore, this is an examination of the correlation within neighbourhoods. This is addressed through the multilevel models that have been discussed so far. Spatial refers to the relationship between neighbouring areas. According to Tobler's first law [201], neighbourhoods that are closer in space are more likely to be similar, causing spatial dependence. Each type of effect provides different types of information about the neighbourhood. Even with the inclusion of neighbourhood-level covariates, ignoring the spatial correlation when modelling could result in spatially correlated residuals.

Spatial correlation of residuals aggregated by area can be estimated through Moran's I statistic [202]. The value of I measures the correlation between adjacent areas. Take a dataset where $i = 1,\ldots,n$ individuals are nested in $j = 1,\ldots,J$ areas, and the interest is to measure the spatial correlation of variable y_j which has been aggregated at the area level.

$$\mathrm{I} = \frac{J}{\sum_{j=1}^{J}\sum_{j=1}^{J} w_{j,j'}} \frac{\sum_{j=1}^{J}\sum_{j'=1}^{J} w_{j,j'}(y_j - \bar{y})(y_{j'} - \bar{y})}{\sum_{j=1}^{J}(y_j - \bar{y})^2} \tag{3.9}$$

In this example, y_j and $y_{j'}$ represent observations of y from different regions. To calculate Moran's I, observations are centred on $\bar{y}$ (the sample mean from $y_1, \ldots, y_J$). $w_{j,j'}$ represents the jj'-element (row j and column j') of an adjacency matrix w, to identify adjacent or neighbouring areas. The value of I indicates where neighbouring areas are similar (I $\approx$ 1); dissimilar (I $\approx$ -1); or have no association (I $\approx$ 0). The Moran's I test the null hypothesis that the value of I that was observed is equal to zero i.e. there was no spatial association.

Moran's I is an example of a global measure of spatial correlation. This means correlation is measured for the whole region of study. However, uneven distribution of spatial effects across the study area can cause clustering. Local indicators of spatial autocorrelation can detect the presence of these clusters in the data [203]. Global tests such as Moran's I can be broken down into local relationships. For region j, Localised Moran's I is:

$$I_j = \frac{(y_j - \bar{y})\sum_{j'=1}^{J} w_{j,j'}(y_{j'} - \bar{y})}{\frac{\sum_{j=1}^{J}(y_j - \bar{y})^2}{J}} \tag{3.10}$$

Spatial Random Effects

The spatial structure of the data can be incorporated in many ways [204]. Through use of a multiple membership model – individuals are nested within an area and assigned to neighbouring or proximal areas. This creates a spatially structured residual. Alternatively, using Eigenvector Spatially Filtered Multilevel Models a matrix of Eigenvectors that describe how the spatial weights matrix is distributed are added to the multilevel model in a linear combination as explanatory variables [205]. Eigenvectors are selected based on Moran's I [202] so that the values that best account for correlation are included and the spatial correlation is filtered out. This was used to explore the spatial distribution of self-rated health in South Korean adults [206]. The most common methods used is through the random effects where, different structures are specified for the effects.

Random effects are frequently modelled using a conditional autoregressive (CAR) model [41]. Individuals are nested within areal units. To add the spatial structure to the model, each area-level observation has a specific random effect, which is given a CAR distribution. The spatial effect is common to all individuals nested within that area.

If $\mathbf{u}$ is a vector of areas $\{u_1,\ldots,u_J\}$, using a CAR specification, an area u_j would have the following conditional distribution given the distribution of the other areas u_{-j}:

$$u_j|\mathbf{u}_{-j} \sim N(\frac{\sum_{j'=1}^{J} w_{j,j'}u_{j'}}{\sum_{j'=1}^{J} w_{j,j'}}, \frac{\tau^2}{\sum_{j'=1}^{J} w_{j,j'}}) \tag{3.11}$$

This can also be written in the following form, for $\mathbf{u}$:

$$u \sim MVN(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \text{ where } \boldsymbol{\Sigma} = \tau^2\boldsymbol{(D - W)}^{-1} \tag{3.12}$$

The mean of each random effect is conditional on the mean of its neighbouring areas. The spatial covariance structure is calculated by adding the matrix $\mathbf{D}$ and the negative of the matrix $\mathbf{W}$ and taking the inverse. Each element is then multiplied by τ^2 the conditional variance parameter. $\mathbf{D}$ represents a diagonal matrix where the diagonal elements are the number of neighbours a region has, therefore non-diagonal entries are zero. Spatial dependence matrix structure is typically defined through an adjacency matrix $\mathbf{W}$ though other weighting options could be considered such as threshold distances between centroids [207]. $w_{j,j}$' is the jj' th element of the adjacency matrix. The value of the weight is one if the regions j and j' share a border, and zero if the regions do not share a border. The more neighbours an area has, the smaller its variance will be. A large variance indicates low spatial correlation, while a variance near zero indicates that neighbouring regions tend to be similar.

For example, for the areas A, B and C in Figure 3.4 their matrices would be D

$$\begin{pmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \text{ and W } \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}.$$

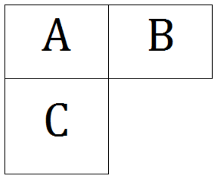

Figure 3.4: Border matrix example

Multilevel CAR allows individual and spatial variation [208]. Spatial correlation is modelled through the random effect which allows the j th region to deviate from the overall mean, and is common to all individuals within the region. For example, to study variability in neighbourhood perceptions in adolescents, Fagg et al., used a multilevel model that allowed adjustment for individual, family and area-level effects with spatial correlation modelled using a CAR distribution [209].

There are various types of spatial structures using CAR models including:

- The Intrinsic CAR (ICAR) described above: $\boldsymbol{\Sigma} = \tau^2(\boldsymbol{D} - \boldsymbol{W})^{-1}$
- Leroux CAR which has a spatial dependence parameter ρ for varying autocorrelation strengths [210]. Values of ρ range from zero to one. Larger values mean data are clustered within-areas while small values show that differences between-areas are low: $\boldsymbol{\Sigma} = \tau^2(\boldsymbol{D} - \boldsymbol{\rho W})^{-1}$
- Convolution or BYM model [211] where spatial dependence is represented by the sum of structured spatial random effect u_j and the unstructured effect v_j: $v_j \sim N(0, \boldsymbol{\Sigma})$ where $\boldsymbol{\Sigma} = \begin{pmatrix} \sigma_1^2 & \sigma_{21}^2 & \sigma_{31}^2 \\ \sigma_{21}^2 & \sigma_2^2 & \sigma_{32}^2 \\ \sigma_{31}^2 & \sigma_{32}^2 & \sigma_3^2 \end{pmatrix}$

Spatially Varying Coefficients

In addition to local spatial effects, the association between a covariate and an outcome may vary locally. For example, the role of ethnicity on a health condition may depend on the area [212]. In the CAR models described so far, random intercepts are allowed, and it is assumed that coefficients are constant over the region of study. However, it may be the case that coefficients vary across areas. Recently, the CAR model has been extended to allow spatial random slopes. Using a multivariate CAR (MCAR), covariate effects can vary spatially [213]. In the multilevel multivariate version of the Leroux CAR model, multiple response variables can be modelled simultaneously. The area-level random intercept and slope u_0j and u_1j are represented by u and follow a multivariate normal distribution.

$$u \sim MVN(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \text{ where } \boldsymbol{\Sigma} = [\boldsymbol{D} - \boldsymbol{W}]^{-1} \otimes \Gamma^{-1} \tag{3.13}$$

μ is the mean of the intercept and slope distributions and Σ is the variation of the intercepts and slopes calculated through a Kronecker product of the inverse matrices. Further details on MCAR are provided elsewhere [212, 214]. An alternative approach to allow both the intercept and slope to vary by location was recently suggested by Janko et al., [215].

3.3.2 Spatio-temporal Multilevel Modelling

A random variable can be indexed in time and space, therefore the data can be correlated in both space and time. Including spatial and temporal effects add further complexity to the multilevel model as the dependence structures for spatial, temporal and spatio-temporal interactions need to be considered. Challenges include random effects competing with fixed effects [216]; spatial confounding (a spatially structured fixed effects correlates with a spatial random effect, thus giving overlapping information about the outcome and inaccurate fixed effect estimates) [217] and; competition between random effects that are collinear (causing a random effect to be eliminated by the addition of another captures the same variation [216]).

Measures of spatial correlation can be extended for application to spatio-temporal correlation [218–220]. In spatio-temporal Moran's I (I_{st}), spatial adjacency w_{ij} is measured as described before, and temporal adjacency t_{ij} is determined by whether the data lies within a difference in time. Spatio-temporal weights can be multiplicative or additive [218]. However, this brings additional challenges of computational load and integrating the spatial and temporal data.

Where there is spatio-temporal correlation, there are several factors in choosing the appropriate covariance structures between a set of spatio-temporal data points. Across disciplines, several methods have been developed in recent years to account for spatio-temporal variability [221]. There are a number of papers reviewing the methodologies for estimating space-time covariance structures [222–225]. However, creating realistic covariance structures, especially where there are large data sets with many observations, can be challenging [226].

Knorr—Held describes four types of spatio-temporal interactions, depending on whether the spatial and temporal effects are structured or unstructured [227]. The structures are visualised in Figure 3.5.

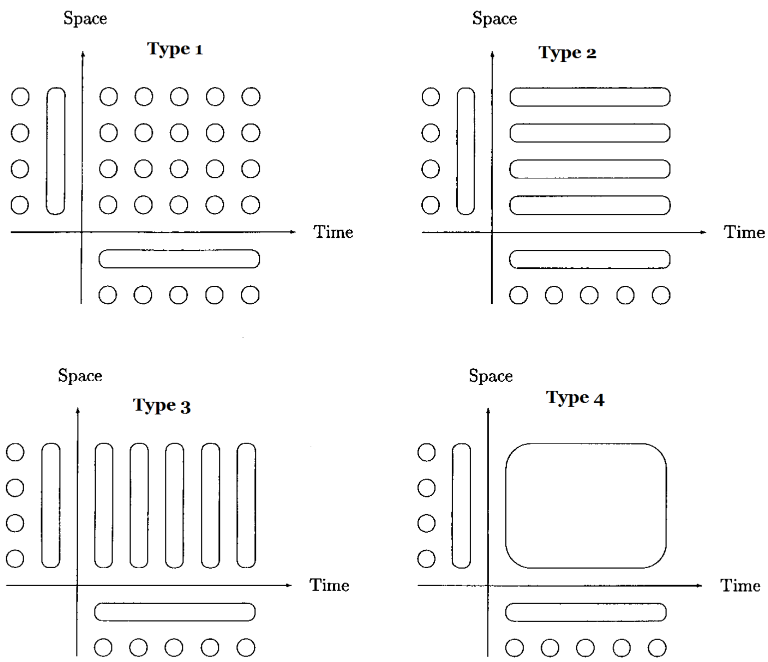

Figure 3.5: Spatio-temporal interactions from Knorr—Held [227]
Circles are unstructured, and the ovals are structured.

In the Type 1 interaction, the two unstructured effects interact. This means that there is not a spatial nor temporal structure to the interaction. This could be defined using a normally distributed random effect. In Type 2, the temporal effect is structured but the spatial is unstructured. Meaning that the temporal structure (e.g. autoregressive) for individual areas are independent of each other. In Type 3, the temporal effect is unstructured, and the spatial effect is structured (e.g. CAR specification) resulting in a spatial structure that is temporally independent. In Type 4, interaction is calculated through the Kronecker product of structured temporal and structured spatial so that there is dependence in both space and time. The spatio-temporal covariance matrix can be generated through the weighted sum or Kronecker product of the spatial and temporal covariance matrices [224]. For example, the Kronecker product of a $n_s x m_s$ spatial covariance matrix S and a $n_t x m_t$ temporal covariance matrix T would be defined as:

$$\mathbf{\Sigma} = S \otimes T \begin{bmatrix} S_{11}T & \cdots & S_{1m_s}T \\ \vdots & \ddots & \vdots \\ S_{n_s m_1}T & \cdots & S_{n_s m_s}T \end{bmatrix} \tag{3.14}$$

There is a risk of over-modelling the data if all interaction types were included, so the most appropriate for the data should be selected.

There has been extensive literature on spatio-temporal modelling in single level or aggregated models [228]. However, as discussed earlier, aggregation can lose information about the individual and can result in inferences incorrectly made at an individual-level causing ecological fallacy. Often there is insufficient spatial detail to investigate these effects within a multilevel structure.

Spatio-temporal Random Effects

Recently, approaches using aggregated data have been adapted to fit within a multilevel data structure. Schmidt-Catran and Fairbrother [229] present a number of multilevel structures for how spatio-temporal effects can be modelled, represented in Figure 3.6.

There are four key approaches according to Figure 3.6. Firstly to ignore the presence of spatio-temporal effects as in Model B. Secondly, to consider separable spatial and temporal effects such as Model E. Thirdly to consider a spatio-temporal interaction as in Model A. And finally to consider a combination of effects as in the remaining Models

Random effects	Model A	Model B	Model C	Model D	Model E	Model F
Country		✓		✓	✓	✓
Year			✓		✓	✓
Country-year	✓		✓	✓		✓
Structure						

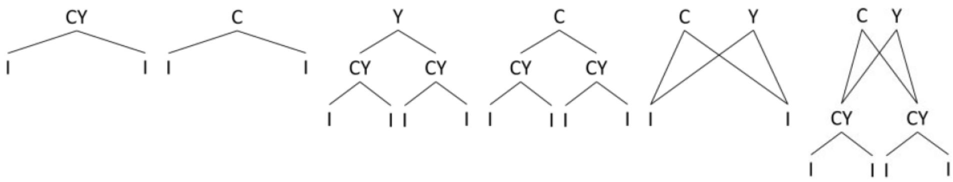

Figure 3.6: Spatio-temporal data Structures by Schmidt-Catran and Fairbrother [229]
C= Country, Y=year, CY= country-year, I=individual

C, D and F. Each approach makes difference inferences about how much similarity is expected for individuals within the same area during a specific year.

Schmidt-Catran and Fairbrother [229] took a social science perspective, using simulations to explore the different modelling structures for independent spatio-temporal random effects. In 2022, Djeudeu et al., [230] developed a decision tree for spatio-temporal multilevel models known, as MLM tCARs, based on correlated temporal and spatial structures in the data. These spatio-temporal models with varying degrees of complexity are discussed in further detail in this final section.

Spatial effects e.g. Model B

This model may be considered temporally independent. This would follow the spatial models that have been discussed so far in the chapter. For example, Ruiz-Castell et al. aimed to estimate area variability in depression symptoms using data collected from cross-sectional surveys conducted in 2013-2015 [231]. Participation rates for each survey were low, so data was pooled over time. Individual-level symptoms were adjusted by individual and area-level effects and the spatial structure was modelled using an analogue of a CAR model with no term included to account for time. To account for the effect of time (but not temporal variation), a fixed effect can be added to the model so that the random effects represent spatial variation after accounting for time.

Separable spatial and temporal effects e.g. Model E

Separable effects model time and space covariance structures separately. This is shown in Model E in Figure 3.6. An advantage of this approach is its simplicity. This is useful when spatial and temporal effects are not considered to be simultaneous, for example when examining change in a single area over time or at a single time point across space.

Growth Curves are used in cases where the outcome demonstrates a change over time. As in the random intercept model in Equation 3.5 assuming for every $j = 1,\ldots,n$ areas there is a measurement at $t = 1,\ldots,T$ time points:

$$\begin{aligned} y_{jt} = \beta_0 + u_j + \beta_1 time_{jt} + \epsilon_{jt} \\ u_j \sim N(0, \sigma_u^2) \\ \epsilon_{jt} \sim N(0, \sigma_\epsilon^2) \end{aligned} \tag{3.15}$$

Where $time_{jt}$ is the time for measurement occasion t in area j and β_1 is the growth rate. It is assumed that for ϵ_{jt} different measurements from the same area are independent given the random effect. So far, this assumes change over time is linear. To allow non-linear changes over time, the model can be extended to include a polynomial such as $\beta_{2j} time_{jt}^2$ or a spline -a non-parametric function – which allows different polynomials at intervals (knots) for a more flexible shape.

The growth curve in Equation 3.15 can be expanded to a random slope model as in Equation 3.6, implying a Type 2 or 4 interaction. This allows the growth rate to vary by area to show areas that have increasing or decreasing trends over time, called the differential time trend. The differential time trend represents the interaction between the linear trends and the spatial effect.

Meng et al. aimed to calculate the spatial patterns of temporal effects [232]. In this repeated cross-sectional study, individuals were nested within census areas to estimate smoking status from 2003-2008. The model included a spatial random intercept for census area. The slopes of the (linear and polynomial) time trend were included as spatially varying. Structured effects were modelled using a ICAR so that neighbouring regions were given similar trends. This meant that time trends were specific to each area. This allowed the authors to estimate the spatial pattern of the time trend at the census area-level.

In addition to the linear or polynomial trends, a temporal random intercept can be added, creating a temporal effect that is common across all areas [230].

If there are sufficient time points, temporal correlation in residuals aggregated by time can be measured through tests such as the Durbin-Watson test or the autocorrelation function (ACF) which calculates how related a value is to its measurement at previous time points [226]. Temporal correlation can be structured similarly to spatial effects using CAR structures (such as ICAR or Leroux CAR) [233]. In an Autoregressive process (AR), the temporal effect at time t is equal to a linear combination of weighted past observations plus random noise [234].

$$\mathbf{\Omega} = \sigma_\epsilon^2 \begin{pmatrix} 1 & \rho & \rho^2 \\ \rho & 1 & \rho \\ \rho^2 & \rho & 1 \end{pmatrix} \tag{3.16}$$

The correlation between measurement occasions is dependent on their distance in time. ρ is an estimate of the correlation and falls between zero and one. Time points closer together are more closely related. The correlation between occasion 1 and 2 is ρ whereas the correlation between points 1 and 3 decreases to ρ^2. A special case of the autoregressive model is the Random Walk (RW). In the RW model, the past observations are not weighted, so the effect of time t is the effect at the previous time point(s) plus random noise. Where there is more temporal correlation between time-points, this suggests the spatial effects do not change over time. Djeudeu et al., refer to this model was MLM ANOVA [230].

Spatio-temporal Effect e.g. Model A

Spatial structures can be expanded for spatio-temporal data [230, 235]. Djeudeu et al., refer to this model was MLM CONVO [230] where an independent spatial structure for each time point could be estimated. A spatio-temporal convolution structure was developed for a three-year household panel study, where individuals were nested within counties in Germany at each year [235]. The model included individual and time-varying county level covariates. Spatial random effects were modelled using a convolution structure consisting of an ICAR and unstructured random effect that was assumed to be common across all time points. The random effect was expanded (following Type 1 and Type 3 interactions) so that the spatial random effect was calculated for each county and year.

Spatial, Temporal and Spatio-temporal Effects e.g. Models C, D and F Schmidt-Catran and Fairbrother, [229] recommend using Model F, the fullest model. Similarly, the MLM ANOVA can be expanded to include a Type 1 spatio-temporal effect [230]. The spatio-temporal interaction can estimate the residual non-separable variation that has not been explained by the separable spatial and temporal effects [227]. Where there is no spatial and temporal structure, Model D may provide a suitable simplification [229].

For Type 4 spatio-temporally structured interaction, Neelon et al., developed a spatio-temporal regression model, for repeated cross-sectional data where patients were nested within census areas [236]. Spatial and temporal random effects were included, and both were given ICAR structures. The model included non-separable spatio-temporal effects as an interaction to identify deviations from the overall effects. The random effect for spatio-temporal interaction was given a multivariate ICAR distribution. This covariance was calculated through the Kronecker product of the spatial and temporal random effect structures matrices. Therefore, the spatio-temporal random effect is dependent over space and time through the combination of a spatial ICAR and temporal ICAR i.e. following a smooth spatio-temporal evolution. Using this approach, the authors were able to identify years and areas that deviated from the average (in this case, the average assumed that there was no spatial or temporal effect). While this approach uses a minimal number of parameters, there still needs to be cautiousness around the number of parameters included.

3.4 Discussion

This chapter introduced the multilevel model and how it deals with dependence structures in the data. Multi-level modelling is considered a suitable approach for this data to model the correlation structures between children in the same preschool, neighbourhood, and neighbourhood-year. In conventional multilevel analysis, individuals are assigned to clusters by contextual levels (e.g. children in neighbourhoods). Random effects are added to the model for each level. This allows the variation in the outcome to be split into variance components attributable to the differences between levels.

When considering the role of multiple contexts, data can follow different structures e.g. nested, cross-classified (non nested level) and multi-membership (individual belongs to more than one cluster). The independence assumption is that the value of one observation does not give information about any other, i.e. they are independent. However, observations taken from children in the same neighbourhood or preschool are expected to be more similar than those taken from children in different neighbourhoods or preschools. At each contextual level, random effects allow observations to be grouped into clusters while assuming independence between clusters. These are known as unstructured (or independent) random effects.

Different random effect structures could exist in the ChiME data. Spatial correlation is dependence between neighbouring areas. Spatially structured random effects are frequently modelled using a conditional autoregressive (CAR) model [211] where each random effect is conditional on its neighbouring areas. Where there is no correlation between neighbouring areas, this effect can be described as platial (also known as unstructured or heterogeneous). Spatio-temporal correlation is dependence in time and space. There are different ways that space and time can interact. Knorr-Held [227] describe four types of interaction, depending on whether time and/or space are correlated.

There is a risk of over-complicating the model when attempting to account for independent, spatial, and/or spatio-temporal effects. The strategies to incorporating different structures of spatio-temporal dependence differ across disciplines. For example, Schmidt-Catran and Fairbrother [229] provide an overview assuming all random effects are unstructured, while Djeudeu et al., [230] provide options assuming there is separate spatial and temporal correlation. Neither approach encompasses all possible multilevel spatio-temporal structures that could occur, but together cover those that are most common in the literature to date.

Choosing the appropriate model depends on the structure of the data, the degree of correlation, the goal of the analysis and overall model fit, which will require an iterative approach of model building and evaluation. The next chapter discusses the model building approach.

Chapter 4

Model Building using a Bayesian Workflow

This chapter introduces the model building process used in this project known as Bayesian Workflow [237]. As shown in the previous chapter, there are several different spatial and spatio-temporal models with varying levels of complexity. Here, using the workflow, each component of the model can be reviewed in an iterative process to provide the best fitting model for the data.

4.1 Bayesian Approach

In the Frequentist approach, parameters are fixed but unknown. For example, the estimate for the unknown parameter β_1 is $\hat{\beta_1}$. In Bayesian statistics, parameters are random with an unknown distribution. The distribution of the parameter given the data is estimated by combining information about the parameter with prior information. Bayes' Theorem [238] states:

$$\pi(\theta|x) = \frac{f(x|\theta)p(\theta)}{f(x)} \tag{4.1}$$

Where the posterior distribution of parameter θ given data x is $\pi(\theta|x)$. Through the posterior distribution, unknown parameters such as regression coefficients can be estimated. $f(x|\theta)$ is the likelihood of observing data x given the parameters (determined by the distributional assumption of the outcome). Using prior information, prior distributions p(θ) for each parameter can be assigned independently of the data. The prior can have strong information about the parameter or be uninformative e.g. given a distribution with a large variance. Finally, $f(x)$ is a normalising constant.

The Bayesian approach is useful in decomposing complex multilevel modelling into a hierarchy of stages:

1. **Data model** specifies the true process of the observational data and the measurements error. E.g. $Y_{ij} \sim Normal(\mu_{ij}, \sigma^2)$
2. **True process** is specified by the regression parameters and random process. E.g. $\mu_{ij} = \beta_1 x_{1i} + \beta_2 x_{2i} + u_j$
3. **Model parameters** are specified using priors e.g. $u_j \sim Normal(0, \sigma_u^2)$. The means, variances and other distributional terms underlying the parameters are the hyper-parameters, when the hyper-parameters are given distributions this can be modelled as a hyper-prior e.g. $\frac{1}{\sigma_u^2} \sim \Gamma^{-1}(1, 0.0005)$.

This hierarchical approach allows the structure of the random effects to be flexibly determined [239, 240].

Bayesian modelling is widely used in spatial and spatio-temporal research. In the spatio-temporal models discussed in the previous chapter, all used Bayesian estimation. There is increasing interest in applying the Bayesian approach in child psychology research [241] to support the analysis of complex data structures e.g. nested random effects, cross-classified effects, multilevel explanatory variables and spatial correlation [64, 209, 242].

4.2 Bayesian Workflow

The process of developing Bayesian models can be described as an iterative process that follows a "tangled workflow" [237]. Multiple models are fit through a series of model building, inference, checking and improvement that involve adapting the components of the model.

In this project, the starting point is the model used in Barry et al., [64] for the 2010-2012 subset of the ChiME data, which will now be referred to as the initial model. For modular construction, the components of the initial model are as follows:

- Estimation: Markov Chain Monte Carlo (MCMC)
- Data model: Individual Total Difficulties Scores follow a Negative Binomial Distribution in a Generalised Linear Mixed Model (GLMM)
- True process: Average individual total difficulties score is modelled by individual characteristics, neighbourhood effects and preschool effects
- Model parameters: Neighbourhood effects are the sum of spatially structured and unstructured random effects while preschool effects are unstructured.

Modular construction focuses on changing and reviewing components of the model. This is an important consideration for this project as there have been over 20,000 additional data points since 2012 that need to be incorporated in the data and may alter the model required. Furthermore, recent reviews of statistical modelling in psychology have found a lack of transparency [243] and poor reporting quality in GLMMs [244]. This section hopes to address this by evaluating the assumptions made in the components of the initial model that have not been reported elsewhere. While later chapters focus on the true process of the model, this section discusses the estimation, data model, and model (hyper-)parameters.

4.3 Estimation

From the posterior distribution, summary statistics (for example, a point estimate and a credible interval) can be derived to describe its location and spread. Repeated sampling from the joint distribution of all the parameters provides clearer estimates of the underlying distribution. In Bayesian statistics, this is typically implemented using MCMC algorithms such as Gibbs sampler and Metropolis-Hastings [245, 246]. The samples are not drawn from the joint posterior distribution (occurring simultaneously) but rather the conditional (or marginal) posterior distribution of each parameter. For example, for β_0 the conditional posterior distribution would be given the other parameters:

$$\pi(\beta_0|y, \beta_1, u_j, \sigma_u^2, \sigma_e^2) \tag{4.2}$$

In an MCMC algorithm, each sample drawn from the distribution is correlated to the last. The more samples drawn, the more the sequence converges to represent the desired posterior distribution. Samples drawn before convergence (burn-in) can be discarded, so they do not contribute to the estimate. Achieving convergence can be computationally intensive and difficult to evaluate, though statistics have been developed to disprove convergence has been reached. As a result, there is often a trade-off between inference, model complexity and computational effort.

Bayesian workflow [237] highlights the value of approximate estimation methods in developing complex models, whereby models may be less accurate, but they are computationally faster. Integrated Nested Laplace Approximations (INLA) are deterministic rather than probabilistic like MCMC, meaning the same results it produced each time the model is run. Using numerical integration, INLA calculates approximate values for the marginal posterior distributions of the parameter of interest, irrespective of other parameters. The marginal probability, can in most cases be sufficient to make model inferences compared to joint probability use in MCMC. Its main advantages are its ease in incorporating random effects and being less computationally intensive than MCMC [247]. Though there is less flexibility in specification of hyperparameters compared to other software.

The suitability of INLA depends on the software and the type of model. Estimates from INLA in multilevel spatial models were found to be robust and closely match those provided by MCMC software WinBUGs when using vague priors [41]. When compared to JAGS and STAN, similar results were produced, with INLA providing the best results in all scenarios [248]. However, in disease mapping models, random effect precisions were not as well estimated by INLA compared to OpenBUGs until more informative priors were used [249].

Therefore, while an MCMC estimation approach was used in the initial model [64], as this project is focused on adding and changing components of the model, approximations will be used.

4.4 Data Model

4.4.1 Outcome

Defining the outcome is a key consideration in model building. Total difficulties scores are often dichotomised to indicate the number or proportion of children that reach a threshold of likely psychiatric diagnosis. The Scottish Government, as part of a National Performance Framework [110], uses the number of children with high scores as a metric. From an analytical perspective, this would mean examining what influences an individual child's score to be above vs below the cut-off for high number of difficulties. With dichotomised scores comes a loss of information, changes to understanding of individual differences and potentially differing results [250]. The impact of this distinction can be seen when looking at ward level summary statistics for this sample (Figure 4.1).

There is less variation in median scores. Notably, Shettleston (19) appears to be worse than other areas in the city using the proportion but not the median. This difference is more clear when viewing the box plots of ward level scores (Figure 4.2). Here you can see how higher scores vary and that median scores do not necessarily relate to high scores.

While a first impression may be that there is insufficient variation in median scores to model change, an advantage of the multilevel model is that it does not solely use the ward level summary statistic as the outcome. Using individual raw scores in a multilevel approach, the variation between individual scores in the same ward and between the wards can be captured.

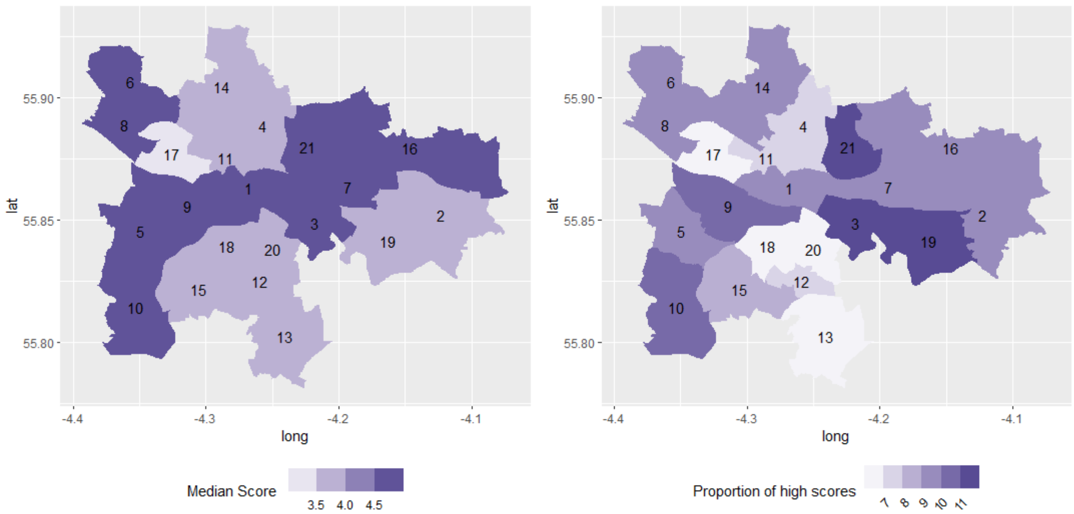

Figure 4.1: Median and high scores by electoral ward in Glasgow
Median scores (left) and proportion of children with high scores (right) from 2010-2017. 1 Anderston/City, 2 Baillieston, 3 Calton, 4 Canal, 5 Craigton, 6 Drumchapel/Anniesland, 7 East Centre, 8 Garscadden/Scotstounhill, 9 Govan, 10 Greater Pollok, 11 Hillhead, 12 Langside, 13 Linn, 14 Maryhill/Kelvin, 15 Newlands/Auldburn, 16 North East, 17 Partick West, 18 Pollokshields, 19 Shettleston, 20 Southside Central, 21 Springburn. The ward boundaries were obtained from SASPAC (Small Area Statistics PACkage) at `https://saspac.org/` using the boundaries at 2011.

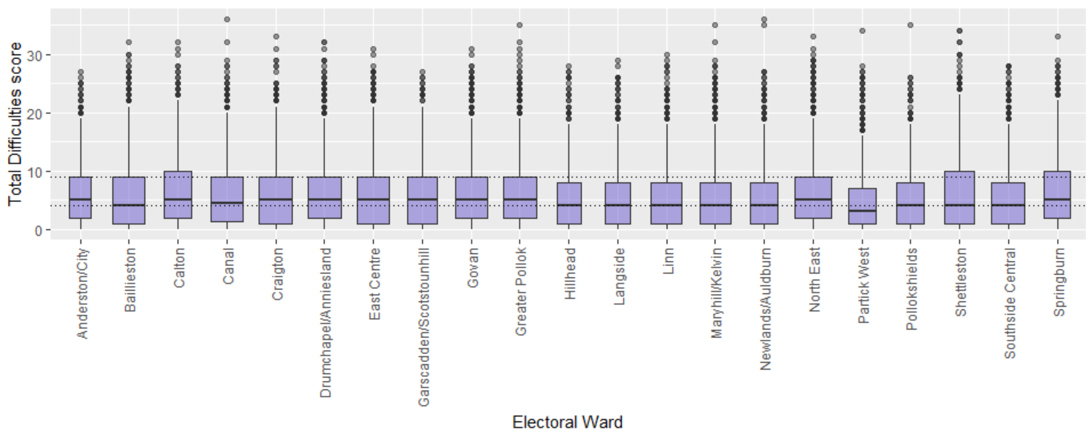

Figure 4.2: Box plot of total difficulties scores by ward
Dashed lines represent the sample median and 75th quantile.

For example, in a separate publication from this work (see Ofili et al., [251]) there was no variation between ward scores when the outcome was aggregated to median difficulties per ward. However, using the same sample, there was variation between the wards when a multilevel model was used. The multilevel model changed the outcome to individual scores, and ward-level variance to how, on average, scores in each ward differ from the overall city mean. Therefore where the difference between average ward scores is small, a multilevel approach can be used to capture variation.

Table 4.1: Ward Variance using Aggregate versus Multilevel Models

Model	Outcome	Structure	Ward-level variance (95% CrI)
Aggregate	Median ward scores	Wards	0.000(0.000–0.074)
Multilevel	Individual scores	Children in wards (and preschools)	0.011(0.004–0.021)

CrI Credible Intervals. Further details on the models are in Chapter 5 and in Ofili et al., [251].

With raw scores, the focus of analysis becomes average scores rather than the proportion most at risk. There is value in showing what is happening on average. However, there may be differences in covariate effects for scores that are close to the centre of a distribution (i.e. median or average scores) compared to scores that are closer to the tails of the distribution (i.e. those who are captured in dichotomised scores). Analysis from the Millennium Cohort Study (MCS) shows that the effects of deprivation and maternal health are more pronounced in children with scores in the upper quartile i.e. those with likely difficulties [252].

Though average scores typically mean there are no likely mental health difficulties, scores are dimensional [21]. An increase in average scores in the population is related to rising rates of psychiatric diagnosis at a constant rate (Figure 4.3) [22]. Population average scores were found to be more clinically relevant than measures using the dichotomised scores [22].

For this analysis, raw scores were considered the most informative outcome. Using raw scores means there needs to be consideration of the distribution of the raw scores. In 2016, Tzavidis et al., [252] noted that none of the MCS studies using raw SDQ scores to date accounted for the asymmetry of the distribution. This is discussed in the next section.

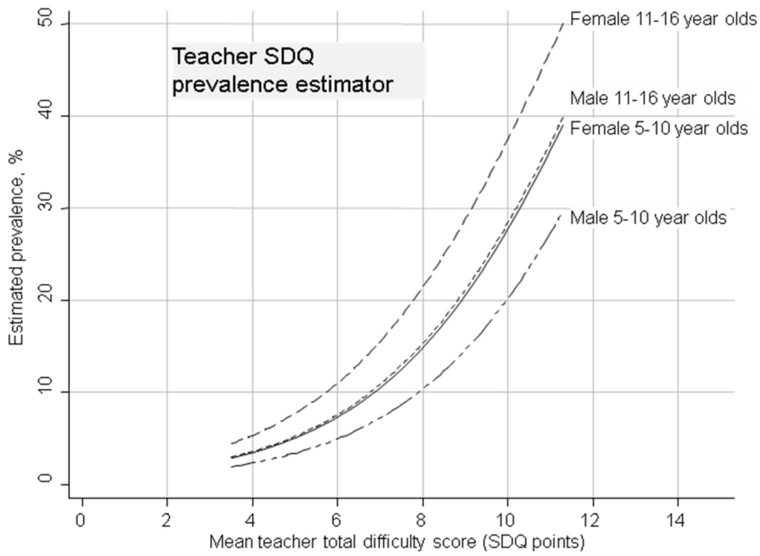

Figure 4.3: Estimated prevalence of disorder based on mean total difficulties scores [22]

4.4.2 Generalised Linear Mixed Models

It is important that attention is given to the distributional assumption of the outcome to have valid model estimates. Firstly, it is common with mental health assessment scores for the distribution of the outcome to be skewed. Most individuals will score at the end of the scale, indicating the absence or low presence of psychopathology [253]. Secondly, the assessment scores may not be continuous, as is assumed in a linear mixed model. Modelling the scores as continuous would mean predicted values could be negative values or fractions.

An alternative approach would be using a Generalised Linear Mixed Model as in the initial model [64]. GLMM is an extension of the linear mixed model that allows alternative distributional assumptions for the response. Instead of the mean of the outcome being a linear combination of explanatory variables, the link function of the expected value of the outcome is a linear combination of explanatory variables:

$$\begin{aligned} g(E(Y_{ij}) &= \eta_{ij} = (\beta_0 + \beta_1 x_{1i} + u_j) \\ E(Y_{ij}) &= g^{-1}(\eta_{ij}) = g^{-1}(\beta_0 + \beta_1 x_{1i} + u_j) \end{aligned} \tag{4.3}$$

The link function g ensures the linear relationship while meeting the criteria of the distribution.

Discrete Distributions

Total difficulties scores are discrete non-negative values which represent the weighted number of likely difficulties a child has in the range of 0-40. The distribution of the ChiME samples scores is shown in Figure 4.4. There were unexplained spikes in the distribution at 0, 2, 7, 12 and 16. The proportion of zero scores in the sample $Pr(Y = 0)$ $= 0.16$. The mean total difficulties (for the positive scores) $E(Y \| Y > 0) = 7.14$ with variance $V(Y \| Y > 0) = 30.31$.

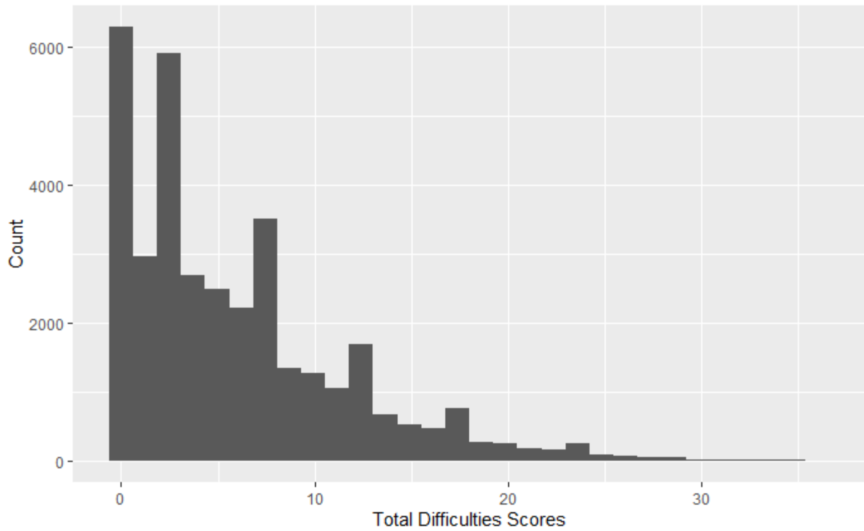

Figure 4.4: Distribution of total difficulties scores (n=35 171)

Poisson and Negative Binomial are discrete distributions for positive integers, typically used for count data. These distributions do not require the data to be symmetrical, as with the normal distribution. In these distributions, the link function (for example the logarithm) ensures some function of the expected value has a linear relationship with the explanatory variables.

Poisson

In a Poisson model, the parameter λ describes the mean number of occurrences of an event or rate. Using the logarithm as the link function changes the interpretation of the coefficients. They are exponentiated and become multiplicative effects that describe the Relative Rate (RR) difference in total scores.

$$
\begin{aligned}
Y_{ij} &\sim Pois(\lambda_{ij}) \\
log(\lambda_{ij}) &= log(E(Y_{ij})) = \eta_{ij} \\
\lambda_{ij} &= (E(Y_i)) = exp(\eta_{ij})
\end{aligned}
\tag{4.4}
$$

The Poisson distribution only depends on λ therefore there is not a separate variance parameter (Equation 4.4). This means the variance must equal the mean. Instances where the residuals have a variance that is greater than expected from the fitted model are known as overdispersion. Overdispersion can lead to a higher chance of type 1 error due to the variance of the parameters being underestimated.

The most appropriate method for dealing with overdispersion may vary by source. Overdispersion can occur due to the exclusion of a predictor, exclusion of a random effect, the presence of outliers or additional heterogeneity.

Negative Binomial

Unlike the Poisson distribution, the Negative Binomial distribution does not have the same requirements for mean and variance equivalence, so the model can accommodate overdispersion. The distribution can be expressed in terms of its mean μ and its size parameter θ (Equation 4.5).

$$
\begin{aligned}
Y_{ij} &\sim NB(\mu_{ij}, \theta) \\
log(\mu_{ij}) &= log(E(Y_{ij})) = \eta_{ij} \\
\mu_{ij} &= (E(Y_i)) = exp(\eta_{ij})
\end{aligned}
\tag{4.5}
$$

Zero Inflated

Assuming a discrete distribution alone may not appropriately model the scores derived from the SDQ [253]. Normative data shows that a proportion of the population will have a total difficulties score of zero [254]. Zeros are thought to represent the absence of difficulties. Non-zeros represent the level of severity among those who have difficulties. The data may exhibit more zeros than the distribution of the model has allowed, resulting in residuals that under-fit the zeros i.e. zero inflation. In which case, it may be important to distinguish the zeros from non-zeros. In discrete distributions, this can be achieved using a zero-inflated model (Equation 4.6).

$$\begin{aligned} Y_{ij} &\sim ZINB(\mu_{ij}, \theta, p) \\ log(\mu_{ij}) = log(E(Y_{ij})) &= (1-p)\eta_{ij} \\ \mu_{ij} &= exp((1-p)\eta_{ij}) \end{aligned} \tag{4.6}$$

The mean of the model is μ_{ij}, p is the zero-inflation parameter i.e. the probability of observing a score of zero and θ is the overdispersion parameter. Therefore, the mean is weighted by the expected proportion of zeros.

Comparing Discrete Distributions

For a given dataset, the chosen distribution might not be a good fit for the total difficulties scores, which can impact parameter estimates. Deviations from the distribution may require the inclusion of a predictor, random effect or use of alternative distributions.

To identify the correct distribution for the ChiME sample, 3 distributions were compared: Poisson, Negative Binomial and Zero-Inflated Negative Binomial. The fixed effects (age group, cohort, deprivation, and sex) and random effects (preschool and ward) were retained from the initial model [64].

$$\begin{aligned} exp(\eta_{ij}) = \exp(\beta_0 + \beta_1 Cohort + \beta_2 AgeGroup + \beta_3 Sex + \beta_4 Deprivation + v_j + \alpha_k) \\ v_j \sim N(0, \sigma_v^2), \frac{1}{\sigma_v^2} \sim \Gamma^{-1}(1, 0.0005) \\ \alpha_k \sim N(0, \sigma_\alpha^2), \frac{1}{\sigma_\alpha^2} \sim \Gamma^{-1}(1, 0.0005) \end{aligned} \tag{4.7}$$

Across the distributions, there was no residual spatial correlation, so instead of the BYM model as used by the initial model [64] here only independent ward effects were included. Models were run in R-INLA using the default, non-informative priors (the priors are reviewed in the next section of the chapter).

The Deviance Information Criterion (DIC) $\bar{D}p_D$ provided a summary of model fit. The posterior mean of the deviance $\bar{D}$ is a measure of goodness of fit, and p_D is the complexity penalty. For fixed effects, the complexity penalty is the number of parameters; for random effects, the complexity is influenced by the extent of heterogeneity within-groups. The more heterogeneous, the more complex the model. As the model improves, the cluster variance reduces and the number of parameters decreases. Smaller values of DIC indicate better model fit.

Five replications from the posterior distribution were compared to the observed data. For the mean and variance in score, adequate model fit was based on similarity between the observed and replicated data.

In Figure 4.5, the red values show the replicated SDQ scores from the distributions and in grey is the observed distribution. The Poisson distribution tends to underestimate the zeros in the data, and overestimate the low scores. The Negative Binomial provides a better fit, though there are still some discrepancies between the observed and expected values. Finally, the zero-inflated negative binomial model shows overfitting of the zeros. These patterns were consistent across the 5 replications.

The difference between the expected and observed values were analysed visually using rootograms [255], generated from 1 of the 5 replications (Figure 4.6). In the rootogram, the grey bars represent the observed counts and the red curve is the expected count, the y axis is the square root of the frequency. Where the bar is above the zero reference line, this means the counts have been over fitted. Where values are below the zero line, this is where counts are under-fitted. A pattern of positive or negative deviations from the reference line mean the model fit could be improved. The Poisson rootogram shows that there is a run of overfitted low scores and underfitted higher difficulties scores, the wave shape shows overdispersion. In the Negative Binomial rootogram, overdispersion has been removed, but there is underfitting of the zero scores (to a smaller extent) and over fitting of the 1–4 scores. Finally, the Zero Inflated Negative Binomial model has slightly overfitted the zeros though there is no evidence of overfitting in positive values.

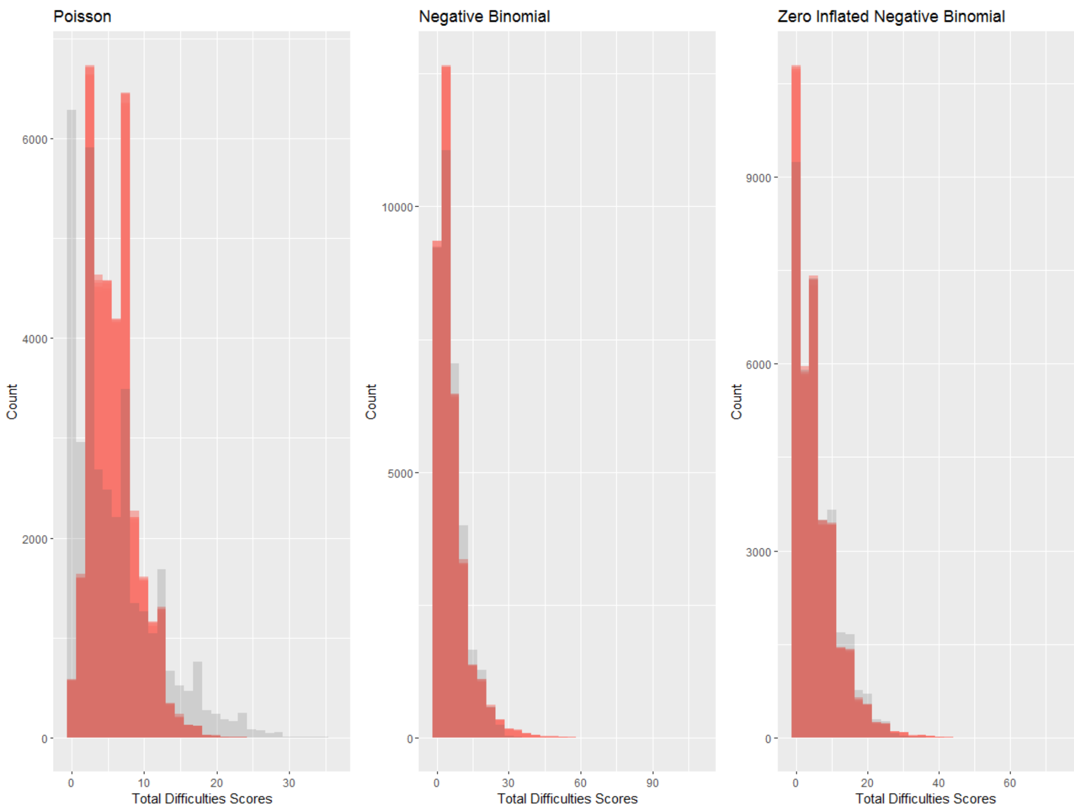

Figure 4.5: Observed scores (grey) versus replicated scores (red)
Five sets of replicated scores (from Equation 4.7) are laid over the observed total difficulties scores from the ChiME sample.

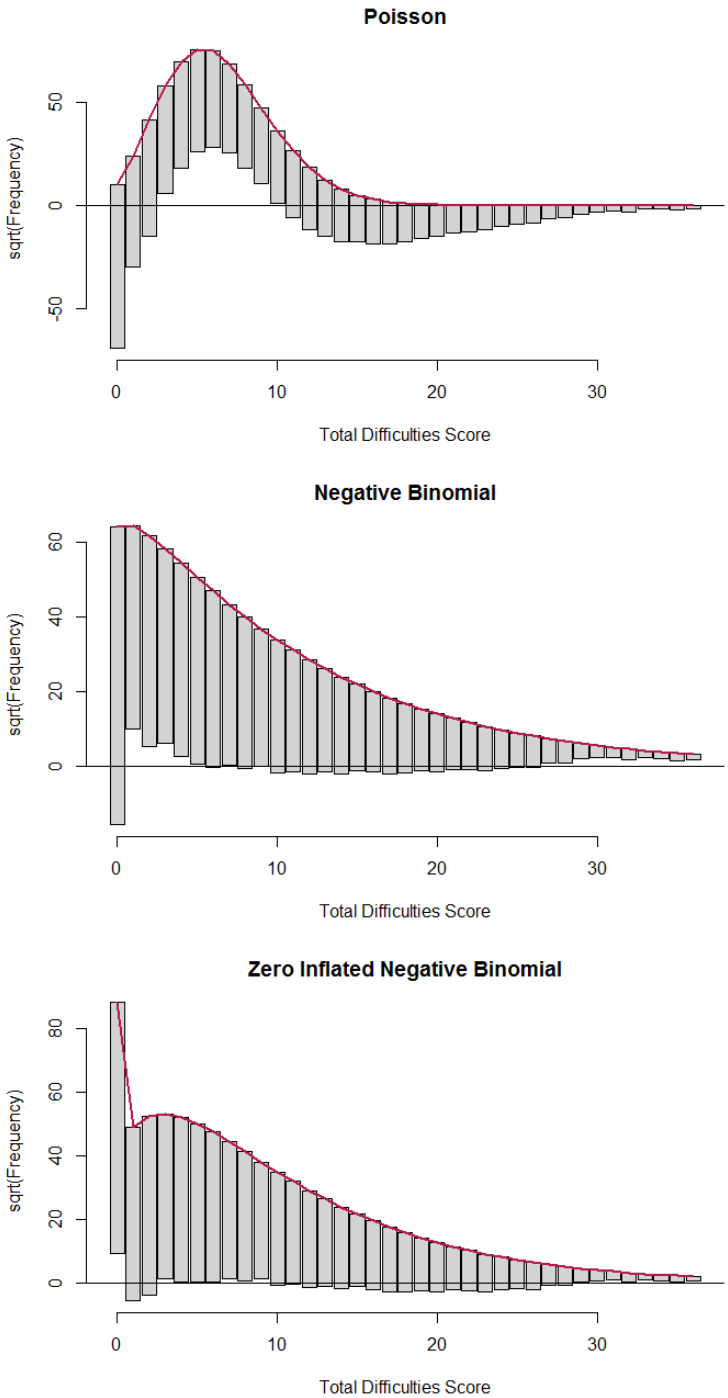

Figure 4.6: Rootograms
Each Rootogram shows the difference between expected and observed values for total difficulties scores replicated from Equation 4.7 following a Poisson (top panel), Negative Binomial (middle) or Zero-Inflated Negative Binomial (bottom) distribution. Grey bars represent the observed counts and the red curve is the expected count.

The summary statistics for observed and expected values shows the impact this has on our model (Table 4.2). Residuals were generated using the R package DHARMa [256] and tested formally for zero inflation and dispersion.

Table 4.2: Model comparison results

	DIC	$Pr(Y=0)$	$E(Y\|Y>0)$	$V(Y\|Y>0)$	ZeroInfl	OverDisp
P	268170	0.03	5.87	10.66	11.02	4.72
NB	195828	0.13	6.77	42.82	1.34	0.74
ZINB	196198	0.23	6.99	32.05	0.78	0.90
	Observed	**0.16**	**7.14**	**30.31**		

P=Poisson, NB=Negative Binomial, ZINB= Zero Inflated Negative Binomial, ZeroInfl= zero-inflation test statistic via comparison to expected zeros with simulation under null hypothesis = fitted model, OverDisp=DHARMa nonparametric dispersion test statistic via standard deviation of residuals fitted vs. simulated

The ZINB model generated the values that were closest to the null value of 1 for zero inflation and dispersion, though it is not a perfect fit to the data. Though a NB distribution was selected for the initial model [64], the ZINB model provided the best fit to the full CHiME sample. This may be due to more zero-inflation in subsequent cohorts compared to 2010-2012. While the best of the models considered, NB and ZINB models may not be accurately explaining the dispersion in the data, resulting in under-dispersion and limiting their ability to fit the zeros appropriately [257].

4.5 True Process

The parameters of the model (fixed and random effects) are selected in Chapter 5.

4.6 Model Parameters

This section focuses specifically on priors of the initial model [64]. The variance terms require a prior distribution that ensures they are greater than zero, such as the (log-) gamma distribution or, for covariance between intercepts and slopes, the Inverse-Wishart distribution. In the Bayesian context, the variance term is parameterised in terms of the precision: $\tau_u = 1/\sigma_u^2$.

Specifying the shape of the variance components can be challenging. Variance terms can tend towards zero while the null hypothesis is that the covariance matrix is equal to zero. Furthermore, in models with multiple precision terms there can be increased sensitivity to the choice of prior as increasing layers of hierarchy are associated with more complex interpretation [258]. There is a lot of literature on how to select priors for the variance terms [259]. Here, three main approaches are described.

- Using prior assumptions about the variance range:
  - Assuming the effect estimate for the variance term σ_u^2 lies between the interval [R1, R2] with a uniform distribution $U(R1, R2)$ [259] this can be used to calculate the distribution of the log precision τ. This was applied in the initial model using WinBUGS [64].
  - Using Student's t distribution for priors. If the prior of the variance follows a gamma distribution, the marginal distribution of the prior can follow a Student's t distribution. Assuming the variance term is likely to lie within the range [R1, R2] , the parameters for the log gamma distribution of $\tau \sim \Gamma(a, b_{MARG})$ where $a = d/2$ and $b = (R^2 d)/(2(t^d_{(1-(1-q)/2)})^2)$, R is the range, q is the quantile of the Student t distribution t and d is the degrees of freedom [260]. For spatial and temporal variance components that are conditional, the shape and scale of the gamma distribution is obtained by selecting the best candidate from random effects simulated from different values of a and b.
- Using a base model (e.g. an intercept only or fixed effects model) to control the fit of the model:
  - The scale parameter of the log-gamma prior (b)is set to the variance of the base model scaled by the shape parameter (a). This allows the b to be the inverse of the variance of the base model.
- Using non-informative priors (e.g. vague or flat priors) that have an equal probability of all possible values using large variance terms or a uniform distribu-

tion. For example, the default INLA prior is vague by using the distribution $\frac{1}{\sigma_u^2} \sim \Gamma^{-1}(1, 0.0005)$

4.6.1 Prior Predictive Checking

Prior choice can impact the posterior distributions in approximate estimations. Prior predictive checking involves selecting different prior distributions and simulating data using those distributions. The process is as follows:

1. Values are drawn from different prior distributions
2. The data from the model equation is simulated using the values
3. The simulated values y_i are reviewed to see if the values are plausible, considering what is already known i.e. prior knowledge
4. If the priors are appropriate, they should produce plausible values of the outcome that visually meet any prior assumptions about the data [261]

For every child in the sample, a total difficulties score was simulated using the random effects determined by each scenario. As there was no residual spatial correlation in the models described in the previous section, only unstructured (independent and identically distributed) variance terms were considered for children i nested in preschool k and ward j:

$$\begin{aligned} Y_{ijk} &\sim ZINB(\mu_{ijk}, \theta, p) \\ exp(\eta_{ijk}) &= \exp(\beta_0 + v_j + \alpha_k) \\ v_j &\sim N(0, \sigma_v^2), \\ \alpha_k &\sim N(0, \sigma_\alpha^2) \end{aligned} \tag{4.8}$$

The intercept β_0 was set to $Normal(\mu = 4, \sigma^2 = 2)$, $\theta = 1.2$ and zero inflation parameter $p = 0.18$ (following a Bayesian workflow, values were taken from previous parameter estimations during model building). The priors were set for random effects σ_v^2 and σ_α^2 to compare default INLA model priors with prior knowledge about the variance terms. Both are represented using σ in the candidate list below.

- Candidate A: Default INLA inverse-gamma prior defined through the precision $\tau : \tau = \frac{1}{\sigma} \sim \Gamma^{-1}(1, 0.0005)$.

- Candidate B: Uniform distribution in line with the values specified in the initial model [64]. These values were not published in the original paper but were obtained by requesting code from the authors: $\sigma \sim U(0, 100)$.

- Candidate C: Assuming that the true value of the variance term σ_u^2 lies between [0,10] gives a marginal density of $\tau = \frac{1}{\sigma} \sim \Gamma(1, 0.286)$ [198, 262].

Figure 4.7 is a visual representation of the candidate prior distributions, in the form of the standard deviation.

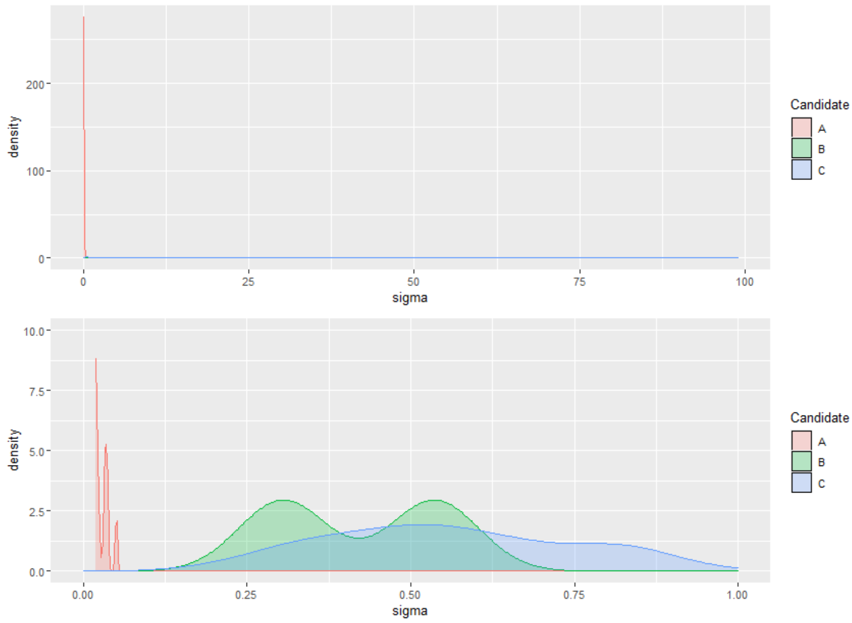

Figure 4.7: Candidate priors
A= Default INLA, B= Uniform, C= Prior Research. The bottom image shows the distributions on a smaller x-axis due to the small values in Candidate B and C.

The distributions of the candidate variance terms are described further in Table 4.3.

Table 4.3: Candidate prior distributions

Candidate	0%	25%	50%	75%	100%
A	0.003	0.007	0.008	0.011	0.050
B	0.305	25.502	55.474	78.637	98.919
C	0.187	0.438	0.582	0.820	5.220

A= Default INLA, B= Uniform, C= Prior Research.

For candidate A, the variance is expected to be very small. with almost all values below 0.5. For candidate B there is a wider range of values between 0 and 99. For candidate C, there is a range of values between 0 and 5. Five values of y_i were simulated for each candidate, selecting a different quantile from the distribution.

The densities of simulated values are plotted against the observed scores in Figure 4.8.

Simulated values for Candidate A were within the range of 0-65. This is consistent with the expectation that the prior distribution should be broader and have more density at extreme values than the data. For Candidates B and C in Figure 4.8, there were very extreme values generated that were implausible, ruling them out as suitable candidates for weakly informative priors. Only the INLA prior (candidate A) provided plausible values across quantiles. Therefore, default INLA priors were selected for random effects. For other model parameters (e.g. fixed effects, hyper-priors), the assumption was made that the same INLA default priors would also be the most suitable candidates.

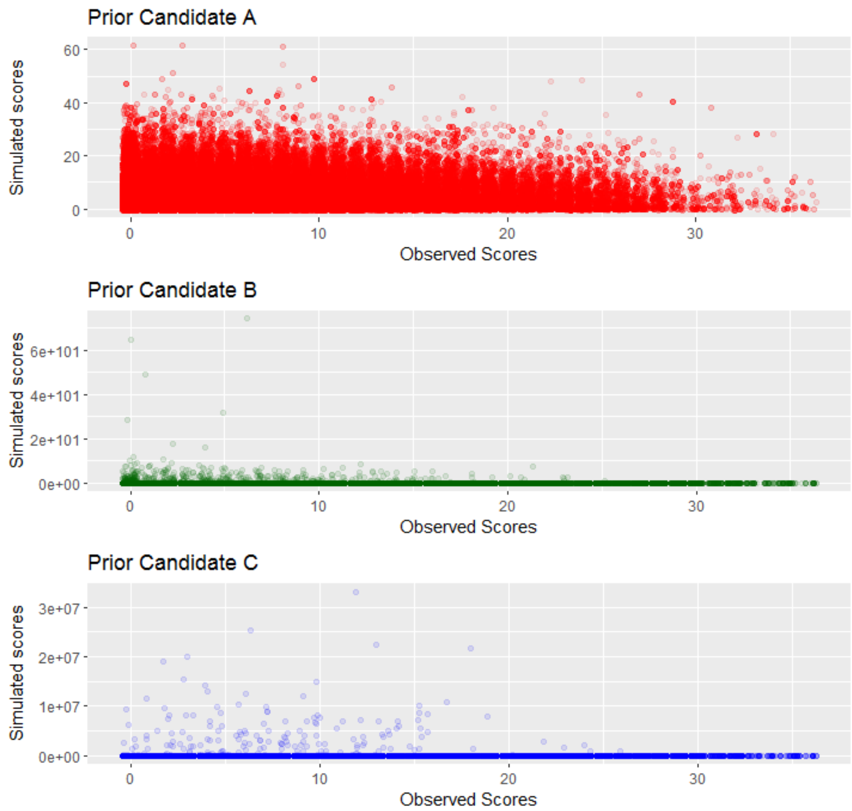

Figure 4.8: Observed data vs simulated data
Data simulated from Equation 4.8. A= Default INLA, B= Uniform, C= Prior Research.

4.7 Discussion

This chapter introduces the Bayesian approach, which is widely used in spatio-temporal modelling. In a Bayesian approach, the distribution of a parameter is estimated through prior information and the likelihood of observing the data. Bayesian hierarchical approaches break down complex modelling into stages (data model, true process and parameters) i.e. the distribution, the regression parameters, the priors and hyper priors. Priors can be used to specify random effect structures.

As a basis for modular construction, the short-term spatial effects model of the ChiME 2010-2012 dataset [64] was considered the initial model. In the initial model, individual scores followed a Negative Binomial distribution and were adjusted for demographics. Individuals were nested in electoral wards and preschools in a cross-classified structure. Ward effects were the sum of spatially structured and unstructured random effects, while preschool effects were unstructured. There have been over 20,000 additional data points since 2012 that need to be incorporated into the data for this current work. This may alter the model components required.

Model building, inference, checking, and improvement can follow a Bayesian workflow [237]. In the workflow, each stage is not a linear process, it is an iterative process where one stage can inform another.

Firstly, the estimation of the model was examined. For the initial model, Markov Chain Monte Carlo (MCMC) was used. MCMC algorithms can be computationally intensive and difficult to evaluate. Due to the additional data that needs to be incorporated and the number of models that will be investigated, it was decided to use faster approximations. Integrated Nested Laplace Approximation (INLA) is robust and closely matches those found in multilevel spatial models using MCMC software [41].

The chapter goes on to review the outcome. The initial model used individual scores, even though the proportion of high scores is used in Scotland's National Performance Framework [110]. Individual scores were considered more informative as they provide information on the population average as well as indicating rates of mental health difficulties in the population [22]. This is discussed in further detail in a publication from this project [251].

When considering the scores in the population, the distribution of the outcome will be skewed, with more children at the low end of the scale indicating no or few difficulties. A discrete distribution is considered appropriate as there are allowances for skewed data and estimated values are integers. There are different types of discrete distributions e.g. Poisson, Negative Binomial which considers over dispersion (which was used in the initial model) and Zero Inflated Negative Binomial which considers the proportion of zeros in the data.

For each candidate distribution, five replications from the posterior distribution were reviewed based on their complexity (using the Deviance Information Criterion), zero-inflation, overdispersion and similarity between the observed and replicated data.

Distributions were assessed visually using rootograms which provide further information on where in the distribution values are over or under fitted. Though it did not address all the issues (there was evidence of overfitting zeros), the Zero Inflated Negative Binomial was considered the best fitting from the candidates.

The final section of the chapter investigated the prior. The prior describes what is already known about the data, to inform the Bayesian posterior distribution. In this case, there is limited knowledge about spatio-temporal variation in early development. Priors can be based on previous studies with similar analyses (e.g. the initial model [64]), a base model or be non-informative (which are given by default in INLA). Prior predictive checking is a process for selecting different prior distributions and simulating data using those distributions. Suitable priors should produce plausible outcome values. Using prior predictive checking, the non-informative priors were considered the best for the data.

In summary, there are some similarities in the modelling decisions when compared to the initial model once the additional data from 2013-2017 is incorporated. There is further support for the use of a discrete distribution and the outcome being the total difficulties score for an individual child. Some alterations to the initial model include the use of approximate estimation, the priors, and the choice of a zero-inflated discrete distribution. Together, these components provide a basis for examining the true process (i.e. individual characteristics, spatial effects and spatio-temporal effects) that relate to variation in total difficulties scores and enable us to ask where and when the neighbourhood is important. This is developed further in the next chapter.

Chapter 5

Modelling Spatial and Spatio-temporal Variation in Social, Emotional and Behavioural Development in Glasgow

This chapter focuses on the contextual effects of preschool, ward and ward-year and if they persist after accounting for demographics. As previously discussed, this expands on the previous research (which only analysed a subset of the data [64]) by examining whether the spatial variation is consistent over a longer time period or is dependent on the time period. Models were built using the whole sample incrementally, before increasing model complexity (Table 5.1). Firstly, a spatial model is built, then adjusted for effects of time and demographics. The model is then expanded to consider spatio-temporal effects.

Table 5.1: Model Building Strategy

Name	Equation	Random Effects	Fixed Effects	Model
Spatial	5.1	Ward	NA	B
Cross Classified Spatial and Preschool	5.3	Ward, Preschool	NA	B
	5.4	Ward, Preschool Preschool:Ward	NA	B
Adjusted Cross Classified Spatial and Preschool	5.5	Ward, Preschool	Cohort	B
	5.6, 5.7	Ward, Preschool	Sex Deprivation, Age, Cohort	B
Adjusted Cross Classified (Spatial, Preschool and) Spatio-temporal	5.9	Ward, Preschool, Spatially varying time trend	Sex Deprivation, Age, Cohort	E
	5.10	Ward, Preschool, Spatio-temporal Interaction	Sex Deprivation, Age, Cohort	D

Model classification based on Schmidt-Catran and Fairbrother [229] (see Chapter 3.3.2).

Model parameters were retained on the basis of five criteria

1. Bayes Factor: Evidence that the random effect variance parameter is equal to zero is Strong or Very Strong [263] (see Table 5.3)
2. Moran's I and Moran's I_{ST}: There is no residual spatial or spatio-temporal correlation in the model
3. Random Effect Variance: The variance term does not include the null value of 0
4. Fixed Effect Relative Rate: The relative rate does not include the null value of 1
5. DIC : Adding the parameters to the model lowered the DIC by ≥ 10 compared to the more simple/previous model

The criteria were considered together, assessing the overall quality of evidence to support the model.

5.1 Spatial Model

The first model aimed to assess whether total difficulties scores vary by ward in 2010-2017. To answer this, a multilevel model is developed to explore whether there is evidence of significant clustering within wards.

Figure 4.1 and Figure 4.2 (in Chapter 4) showed how total scores varied by electoral ward. There does not appear to be much difference between the wards by median score. The number of children in each ward ranged from 860 in Anderston/City to 2485 in North East with a median of 1821 (See Appendix Figure C.1).

The outcome of interest (total difficulties score for an individual child) is assumed to follow a zero-inflated negative binomial distribution, as discussed in Chapter 4.

For i,...,35171 children and j,...,21 electoral wards:

$$\begin{aligned} \eta_{ij} &= \exp(\beta_0 + v_j) \\ v_j &\sim N(0, \sigma_v^2) \\ \frac{1}{\sigma_v^2} &\sim \Gamma^{-1}(1, 0.0005) \end{aligned} \tag{5.1}$$

An unstructured random effect v_j is added to the model for wards. This effect allows separate intercepts for each ward. The variance of the random effect represents the differences between wards compared to the overall city mean. The estimated variance is small, as shown in Table 5.2, suggesting there is not much difference between wards.

Table 5.2: Model estimates for Equation 5.1

Parameter	Estimate	95% Credible Intervals
Intercept	6.61	6.43-6.80
Ward Variance	0.003	0.002-0.007
DIC	198976	

The hypothesis that the ward variance parameter was equal to zero was tested using Bayes Factor [263].

$$B_{AB} = \frac{p(Y|M_A)}{p(Y|M_B)} \tag{5.2}$$

Where B is Bayes Factor, M_B represents the model without the unstructured spatial random effect and therefore assumes the variance is equal to zero and M_A is the model with the random effect and represents the alternative hypothesis and $p(Y|M_k)$ is the marginal likelihood of the model M_k. Kass and Raftery [264] provide interpretation guidelines for Bayes Factor, this is provided in log scale to align with the INLA output (log-marginal likelihood) (Table 5.3). Using this interpretation, there was strong evidence for including the ward random effect ($logBF$=33.5).

Table 5.3: Bayes Factor (BF) interpretation [263]

*log*BF	BF	Evidence
-Inf- 0	0- 1	Negative
0-2	1-3	Weak
2-6	3-20	Positive
6-10	20-150	Strong
10+	150 +	Very Strong

Raw residuals are assessed by simulating values from the distribution and scaled using package DHARMa [256]. For each observation, data simulates a value from the fitted model, and calculates the cumulative distribution function (CDF) based on the simulations. The value of the CDF for each observation is the residual, this means the residual indicates the proportion of simulated values that are less than the observed value [256]. The model assumes there is no relationship between neighbouring wards i.e. spatial dependence. This assumption is tested using the residuals aggregated at ward level. Adjacency is determined through queen adjacency (wards that shared any border). Each ward has at least one neighbour, with one region (Anderston/City) sharing a border with 8 other regions. On average, each ward shared a border with 4.19 other wards.

There is no evidence of correlation between residuals in neighbouring wards (Moran's I=0.02 p=0.29) for Equation 5.1. The p value is above 0.05, so the null hypothesis is supported. Therefore, the independence assumption has been met and there is no evidence to support the inclusion of a spatially structured random effect. Further investigation through localised Moran's I did not identify any individual wards that demonstrated spatial correlation.

5.2 Cross Classified Spatial and Preschool Model

Figure 5.1 shows the box plots of total difficulties scores for each preschool, ordered by median. There is wide variation in total difficulties scores across the preschools, and differences in variability within preschools. For some preschools, there are large differences in scores between children. The median number of children in each preschool was 188. There were three preschools with only one child. The maximum number of children in a preschool was 691 (See Appendix Figure C.1).

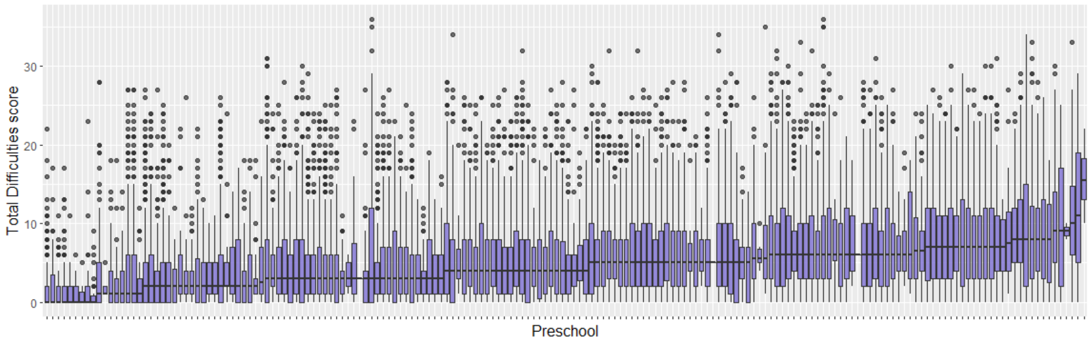

Figure 5.1: Median total difficulties scores by preschool

Random effects α_k are added for preschools k=1,...,180 so that there is an intercept for every preschool (see Equation 5.3). This accounts for any variation in the measurement of SDQ between the preschools and similarities between children within the same preschool. The ward of residence for a child may be different to the ward their preschool is located in; therefore preschool and ward are cross-classified (i.e. they are not hierarchically nested).

$$\begin{aligned} \eta_{ijk} &= \exp(\beta_0 + v_j + \alpha_k) \\ v_j \sim N(0, \sigma_v^2), \frac{1}{\sigma_v^2} &\sim \Gamma^{-1}(1, 0.0005) \\ \alpha_k \sim N(0, \sigma_\alpha^2), \frac{1}{\sigma_\alpha^2} &\sim \Gamma^{-1}(1, 0.0005) \end{aligned} \tag{5.3}$$

There is more variation between preschools from the overall mean than between wards (Table 5.4). The addition of the preschool effect widens the credible interval for ward level variance estimate.

Table 5.4: Model estimates for Equation 5.3

Parameter	Estimate	95% Credible Intervals
Intercept	6.16	5.87-6.46
Ward Variance	0.008	0.003-0.022
Preschool Variance	0.069	0.053-0.071
DIC	197537	

A difference in DIC of at least 10 was considered an improvement to model fit. According to the DIC, adding the preschool random effect improves model fit (from 198976 to 197537). The hypothesis that the preschool variance parameter was equal to zero was tested using Bayes Factor [263]. Using this BF interpretation (Table 5.3) there was very strong evidence of preschool variance (logBF= 568.2).

5.2.1 Contextual Interactions

Do Children Attend Preschool in the Ward They Live In?

The next stage of analysis aimed to explore how preschool and ward may interact. In Australia, greater distance to childcare was associated with reduced developmental vulnerability [265]. This evidence suggests the relationship is complex and may not be clarified through accessibility alone. This means investigating whether the effect of a particular preschool depends on the ward a child lives in or vice versa. Living in a ward and attending a preschool within the same area may amplify the effects of that ward compared to a child who goes to the same preschool but lives in a different ward. Postcode and electoral ward of the participating preschools were identified through the 2013 Childcare Information Services in Glasgow database accessed through the Urban Big Data Centre [95]. The location of the preschool could not be identified for 1333 children. 10 009 attend a preschool outside their ward of residence, while 23 829 remain in their ward.

Children appeared to be more likely to stay in their ward in more central regions of the city. Over 85% of children stay in their ward of residence in Drumchapel/Anniesland, where there are 10 preschools. While in Garscadden/Scotstounhill where there are only 4 preschools, under 40% stay in their ward of residence (Figure 5.2). There was a moderate correlation between the number of preschools in the ward and the proportion who stayed ($r = 0.61$).

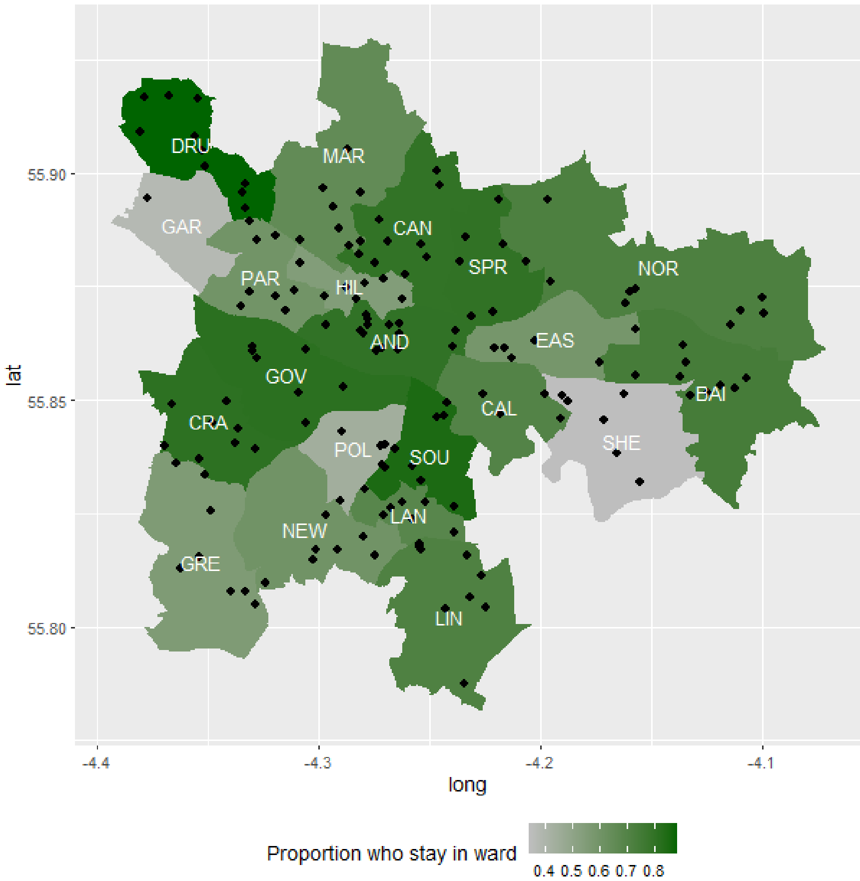

Figure 5.2: Proportion of children who stay in their residential ward for preschool Points indicate the location of preschools. AND Anderston/City 0.79, BAI Baillieston 0.74, CAL Calton 0.69, CAN Canal 0.79, CRA Craigton 0.80, DRU Drumchapel/Anniesland 0.88, EAS East Centre 0.58, GAR Garscadden/Scotstounhill 0.37, GOV Govan 0.81, GRE Greater Pollok 0.55, HIL Hillhead 0.54, LAN Langside 0.68, LIN Linn 0.71, MAR Maryhill/Kelvin 0.65, NEW Newlands/Auldburn 0.60, NOR North East 0.71, PAR Partick West 0.59, POL Pollokshields 0.43, SHE Shettleston 0.34, SOU Southside Central 0.84, SPR Springburn 0.79.

There were 311 routes identified among children who leave their ward. Figure 5.3 and Table 5.5 show the most common routes (taken by more than 100 children each). Many routes are from the residential ward to a neighbouring ward. For example, 991 children left Shettleston to travel to neighbouring wards Bailleston and Calton, this makes up 52 % of the sample that lives in Shettleston.

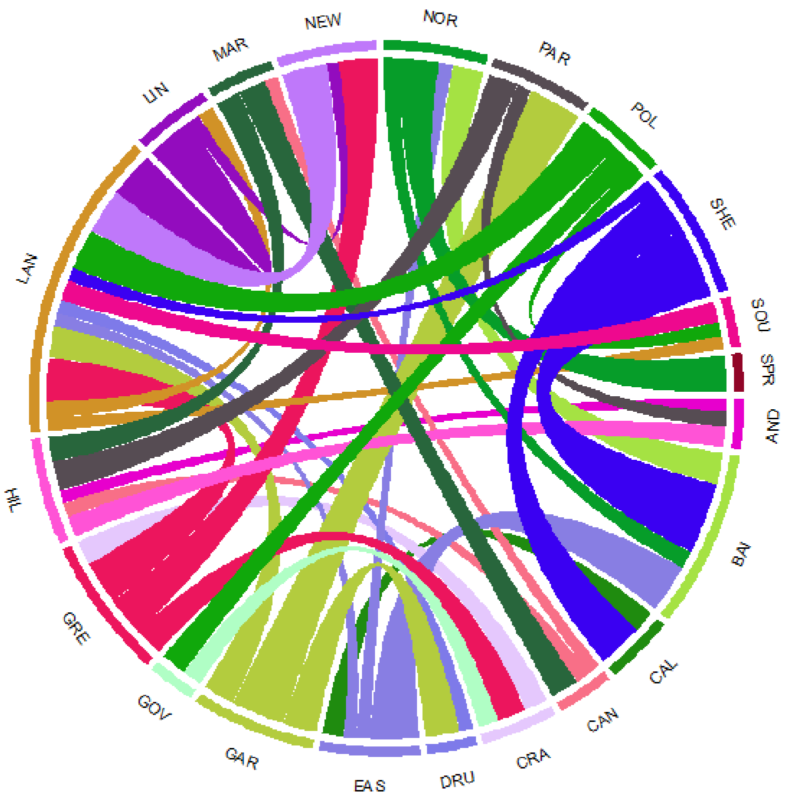

Figure 5.3: Route between the residential ward and preschool ward for children who leave

The outer ring shows the number of children who travel to the ward for preschool, the links show where children from each colour coded ward have travelled from. AND Anderston/City, BAI Baillieston, CAL Calton, CAN Canal, CRA Craigton, DRU Drumchapel/Anniesland EAS East Centre, GAR Garscadden/Scotstounhill, GOV Govan, GRE Greater Pollok, HIL Hillhead, LAN Langside, LIN Linn, MAR Maryhill/Kelvin, NEW Newlands/Auldburn, NOR North East, PAR Partick West, POL Pollokshields, SHE Shettleston, SOU Southside Central, SPR Springburn. Values in Table 5.5 below.

Table 5.5: Most common routes for preschool

Preschool Ward	Residential Ward	Children
AND	HIL	174
AND	PAR	129
BAI	EAS	412
BAI	NOR	150
BAI	SHE	606
CAL	SHE	385
CAN	MAR	237
CRA	GOV	170
CRA	GRE	246
DRU	GAR	288
EAS	CAL	181
GOV	POL	216
GRE	CRA	202
HIL	AND	105
HIL	CAN	124
HIL	MAR	205
HIL	PAR	252
LAN	DRU	116
LAN	EAS	108
LAN	GAR	266
LAN	GRE	370
LAN	LIN	395
LAN	NEW	378
LAN	POL	346
LAN	SHE	113
LAN	SOU	177
LIN	LAN	137
MAR	CAN	108
NEW	GRE	329
NEW	LIN	103
NOR	BAI	261
NOR	EAS	119
PAR	GAR	452
SOU	LAN	112
SOU	POL	123
SPR	NOR	316

AND Anderston/City, BAI Baillieston, CAL Calton, CAN Canal, CRA Craigton, DRU Drumchapel/Anniesland EAS East Centre, GAR Garscadden/Scotstounhill, GOV Govan, GRE Greater Pollok, HIL Hillhead, LAN Langside, LIN Linn, MAR Maryhill/Kelvin, NEW Newlands/Auldburn, NOR North East, PAR Partick West, POL Pollokshields, SHE Shettleston, SOU Southside Central, SPR Springburn.

What Factors Are Associated With Staying in the Ward for Preschool?

On average, the proportion of children who stay in their ward of residence was highest (75.7%) in the most deprived quintile (1) and lowest (47.9%) among children in the least deprived quintile (5).

Do Preschool and Ward Influence Total Difficulties Together?

There was little observed difference between median total difficulties scores in children who left their ward (4, IQR=1-8) compared to those that stayed (4, IQR=1-9). This was assessed formally through a model. The interaction between preschool and ward was estimated through a random effect for each preschool & ward combination. There were 1274 unique combinations. A random sample of preschool total difficulties distributions for children who live in North East (the ward with the largest sample in the study) is shown in Figure 5.4 as an example. For children living in the same ward, there is considerable variation in their total difficulties scores by preschool.

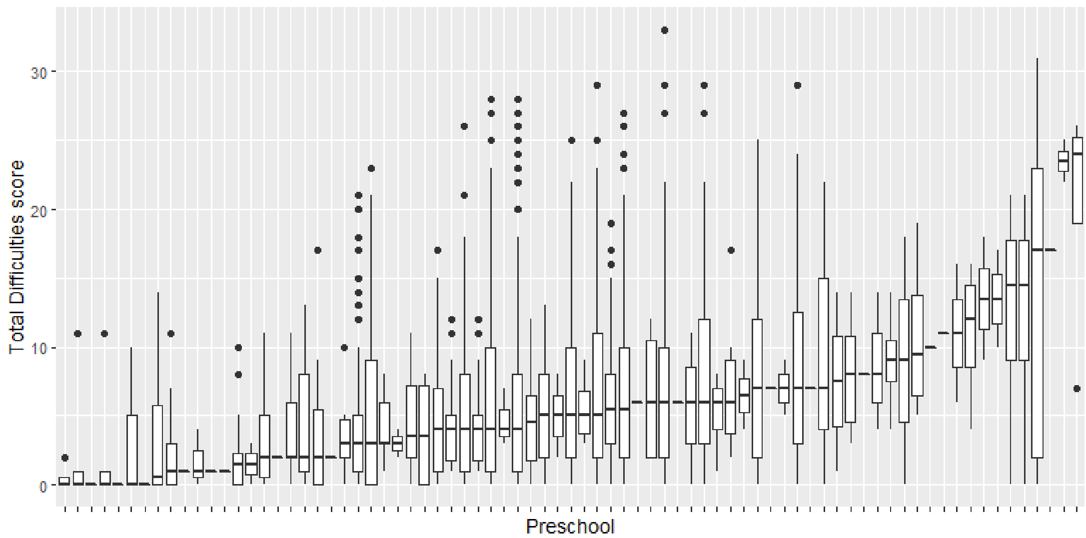

Figure 5.4: Total difficulties scores by preschool for children in North East ward

The interaction was added to the model through a random effect δ_l. Thus, the random effect δ had 1,274 clusters. Clusters represented all the children, across cohorts, who attended the same preschool and lived in the same ward. The size of the clusters ranged from 1 to 655.

$$\begin{aligned} \eta_{ijk} &= \exp(\beta_0 + v_j + \alpha_k + \delta_l) \\ v_j \sim N(0, \sigma_v^2), \frac{1}{\sigma_v^2} &\sim \Gamma^{-1}(1, 0.0005) \\ \alpha_k \sim N(0, \sigma_\alpha^2), \frac{1}{\sigma_\alpha^2} &\sim \Gamma^{-1}(1, 0.0005) \\ \delta_l \sim N(0, \sigma_\delta^2), \frac{1}{\sigma_\delta^2} &\sim \Gamma^{-1}(1, 0.0005) \end{aligned} \tag{5.4}$$

The DIC lowered again from 197537 to 197520, showing improved model fit (Table 5.6). There was strong evidence of variance in the interaction term (logBF= 10.0).

Table 5.6: Model estimates for Equation 5.4

Parameter	Estimate	95% Credible Intervals
Intercept	6.16	5.88-6.44
Ward Variance	0.002	0.001-0.004
Preschool Variance	0.067	0.050-0.088
Preschool:Ward Variance	0.007	0.004-0.011
DIC	197520	

5.3 Adjusted Cross Classified Model

5.3.1 Adjustment for Temporal Trends

Across the years, there was little variation in scores, with children in preschool in 2013, 2014 and 2017 appearing to have slightly lower scores on average. This is consistent for 25th, 50th and 75th quantile (Figure 5.5).

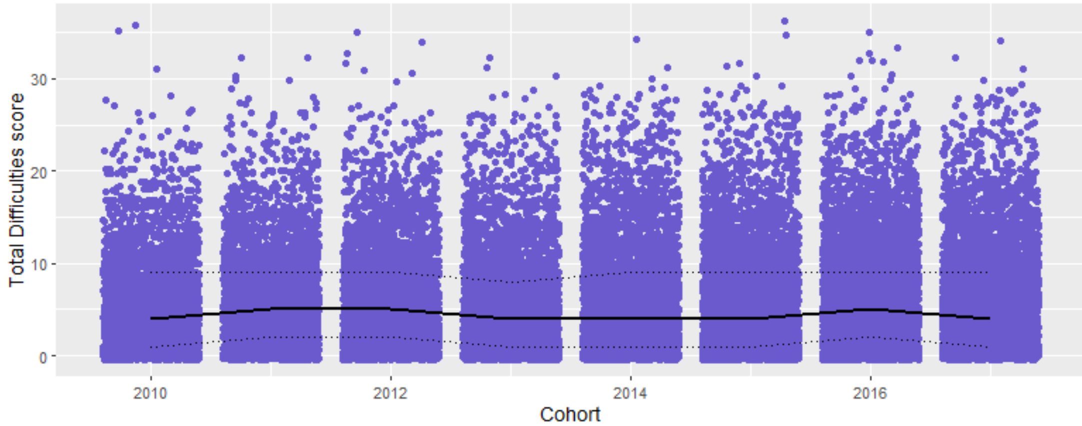

Figure 5.5: Raw total difficulties scores over time
Points represent individual total difficulties scores for the ChiME sample across the cohorts. Lines represent the 25th, 50th (in bold) and 75% quantile.

So far, the models have not included a parameter for cohort effects which may be contributing to the variation in total difficulties scores across preschools and wards. The overall time effect common to all spatial areas is explored. Firstly by defining the time variable t using a categorised variable. As this incorporates dummy variables, the effect of each year relative to 2010 is estimated.

$$\begin{aligned}
\eta_{ijk} &= \exp(\beta_0 + \beta_1 t + v_j + \alpha_k + \delta_l) \\
v_j \sim N(0, \sigma_v^2), \frac{1}{\sigma_v^2} &\sim \Gamma^{-1} \sim (1, 0.0005) \\
\alpha_k \sim N(0, \sigma_\alpha^2), \frac{1}{\sigma_\alpha^2} &\sim \Gamma^{-1} \sim (1, 0.0005) \\
\delta_l \sim N(0, \sigma_\delta^2), \frac{1}{\sigma_\delta^2} &\sim \Gamma^{-1} \sim (1, 0.0005)
\end{aligned} \tag{5.5}$$

Compared to 2010, on average, scores were higher in 2016 and 2017 but the credible intervals included the null value of 1 (Table 5.7). The effect of each cohort is independent of the others. Including a random effect for time did not improve the model fit (DIC= 197535). A limitation of this approach is that power is lost due to the relationship between time periods not being modelled.

Table 5.7: Temporal trend for Equation 5.5

Cohort	Relative Rate	95% Credible Interval
2011	1.01	0.97-1.06
2012	1.01	0.96-1.05
2013	1.03	0.98-1.07
2014	1.03	0.99-1.08
2015	1.02	0.98-1.07
2016	1.05	1.00-1.09
2017	1.05	1.00-1.09

Estimates are in comparison to reference cohort 2010.

The simulated residuals from the posterior were aggregated by year and assessed for residual temporal correlation using the Durbin-Watson test. The results of the test (DW=1.69, p=0.332) support the null hypothesis of no temporal correlation. This ruled out the need for autoregressive temporal trend. Instead, two fixed effects were considered, linear and non-linear.

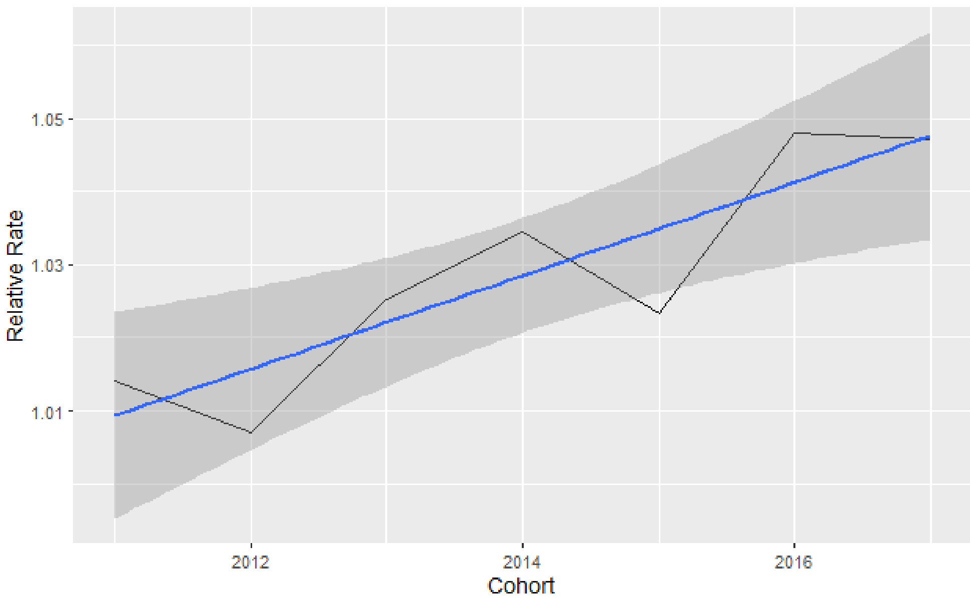

Figure 5.6: Visualising the temporal effects from equation 5.5

The structure of the temporal effects estimated through Equation 5.5 was visually assessed in Figure 5.6 (assuming all other covariates are constant). A fixed effect for the linear trend was added to the plot. The average cohort effects followed a linear trend increasing over time. To allow non-linear changes over time, the model can be extended to include a polynomial t^2 for a more flexible shape. The time variable t is defined using a linear trend and a polynomial term t^2 and its regression coefficient describes the growth rate. Redefining the temporal term in this way improved model fit with DIC (197514 vs 197535). As anticipated, there was no evidence to support non-linear terms in the model, so this was removed from subsequent models. There was evidence of a linear time trend (RR=1.007 (1.001-1.011)). Adding the temporal term impacted the variance parameters, with the interaction term (between ward and preschool) being no longer significant. The interaction was removed from subsequent models so that the overall temporal trend could be included in spatio-temporal modelling.

5.3.2 Adjustment for Individual Covariates

The contextual effects at preschool and ward level may be due to the composition of individual characteristics within a preschool or ward. For example, varying distribution of deprivation across the clusters. Adding individual variables to the model will reveal if contextual effects persist after taking into account these compositional differences. Any remaining variation in the model will be residual.

The distribution of demographics against total difficulties score was explored visually as shown in Figure 5.7. Sample demographics in Table 1.2 shows that the youngest and oldest age groups have higher scores than the middle group. Therefore age is visualised as centered (against the mean age of 59 months) and squared. Median scores were higher in boys, those with the largest squared monthly deviation from the mean age (59 months) and those in the most deprived quintile.

Individual level variables: age, sex and household deprivation (measured by SIMD quintile where 1 is the most deprived quintile) were added to the model. These covariates may indicate whether the preschool and ward variance are due to the composition of individual children's characteristics within the preschools or wards.

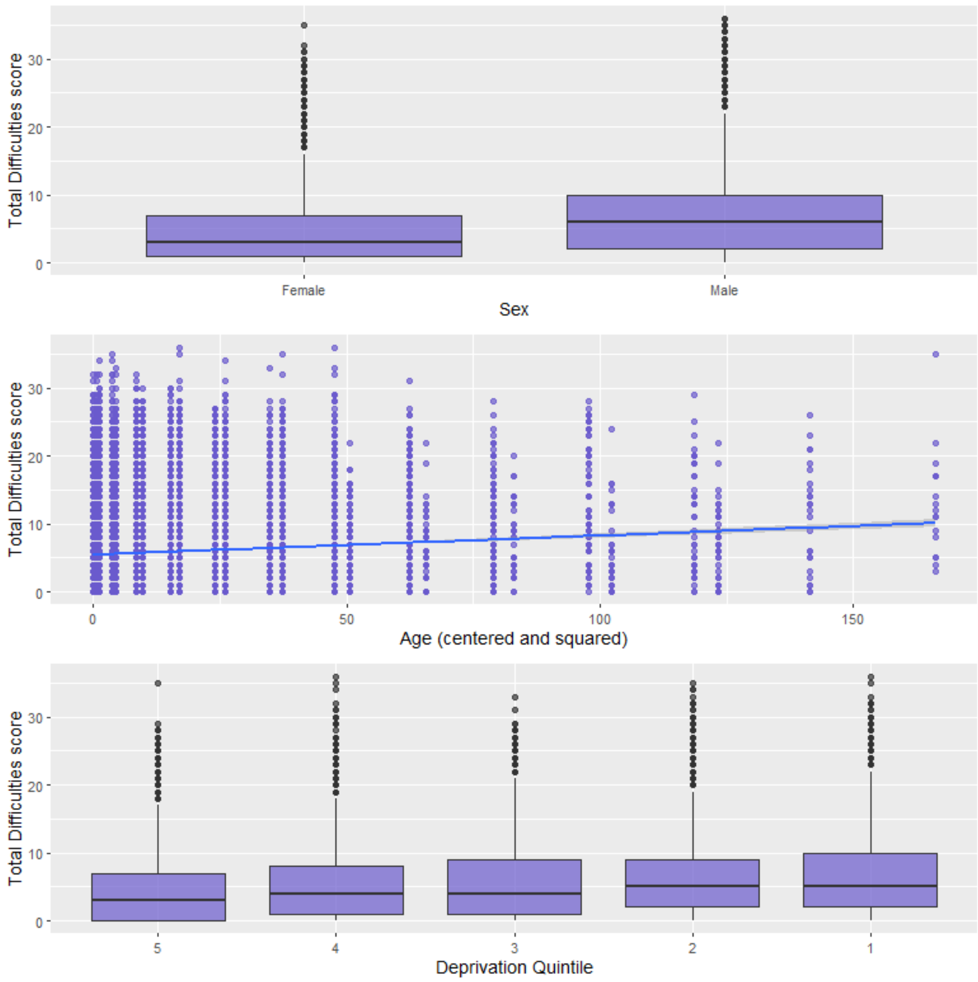

Figure 5.7: SDQ by sex, age and deprivation
Age is shown as difference in months from mean age (59 months)

$$
\begin{aligned}
\eta_{ijk} &= \exp(\beta_0 + \beta_1 \mathrm{t} + \beta_2 \mathrm{age} + \beta_3 \mathrm{sex} + \beta_4 \mathrm{deprivation} + v_j + \alpha_k + \delta_l) \\
v_j &\sim N(0, \sigma_v^2), \frac{1}{\sigma_v^2} \sim \Gamma^{-1}(1, 0.0005) \\
\alpha_k &\sim N(0, \sigma_\alpha^2), \frac{1}{\sigma_\alpha^2} \sim \Gamma^{-1}(1, 0.0005) \\
\delta_l &\sim N(0, \sigma_\delta^2), \frac{1}{\sigma_\delta^2} \sim \Gamma^{-1}(1, 0.0005)
\end{aligned}
\tag{5.6}
$$

As the youngest and oldest children have higher scores than the middle age group, the effect of age is unlikely to be linear. Models with both linear term for age centred and with age centred squared were run. There was improved fit with the non-linear term (DIC=196275) compared to the linear term (DIC=196369). The regression coefficients for the individual covariates estimate the average relationship between each characteristic on total difficulties scores, regardless of where a child lives or goes to preschool. The strength of association is described by the relative rate (RR). The null value is 1 and deviations from 1 mean there is a stronger association. RR = 1.10 would mean there was a 10% higher score in individual children, on average, while RR = 0.90 would mean scores were 10% lower. For dummy variables, the RR is the rate in comparison to the reference group.

Adding covariates to the model clearly improves model fit according to DIC. The rate of difficulties is significantly higher for boys compared to girls at 34-40%. For every unit increase in age from 59 months, the rate of difficulties increased between 0.3-0.4%. Compared to those in the least deprived group (5th quintile), there are increasing rates of difficulties with rising deprivation. The largest difference is found for the most deprived group at 19-29%. The credible intervals for the temporal trend were very close to 1 indicating that each year is a small cumulative increase in rate of total difficulties.

Adding an individual level variable can cause the higher-level variance parameters to change [192]. The variance can increase, if before adjustment, preschools or wards appear to be more similar. The variance can decrease if the individual variables explain part of the preschools or ward variation. The variance can stay the same if levels of the individual variable are the same across all preschools or wards. Changes to the variance parameters were minimal after adjustment. For preschool, the addition of demographics decreased the variance from 0.069 (0.054-0.092) to 0.062, while for ward this decreased from 0.009 (0.003-0.024) to 0.006 (Table 5.8).

Table 5.8: Model estimates for Equation 5.6

Parameter	Relative Rate	95% Credible Intervals
Intercept	4.083	3.840 -4.341
Cohort	1.008	1.003-1.012
Sex (Male)	1.370	1.344-1.397
Deprivation quintile (4th vs 5th)	1.115	1.069-1.156
Deprivation quintile (3rd vs 5th)	1.173	1.128-1.2229
Deprivation quintile (2nd vs 5th)	1.233	1.184-1.283
Deprivation quintile (1st vs 5th)	1.240	1.190-1.2921
Age (centred and squared)	1.003	1.003 -1.004
	Variance	95% Credible Intervals
Ward	0.006	0.003-0.016
Preschool	0.062	0.048-0.083
DIC	196275	

DIC Deviance Information Criterion

Covariate Interactions

With the covariates considered so far, the effect of a covariate on a response is assumed to be independent of the value of other covariates. However, often the effect on one covariate depends on the value of another. This is known as an interaction. Interactions between the covariates were initially examined visually (Figure 5.8).

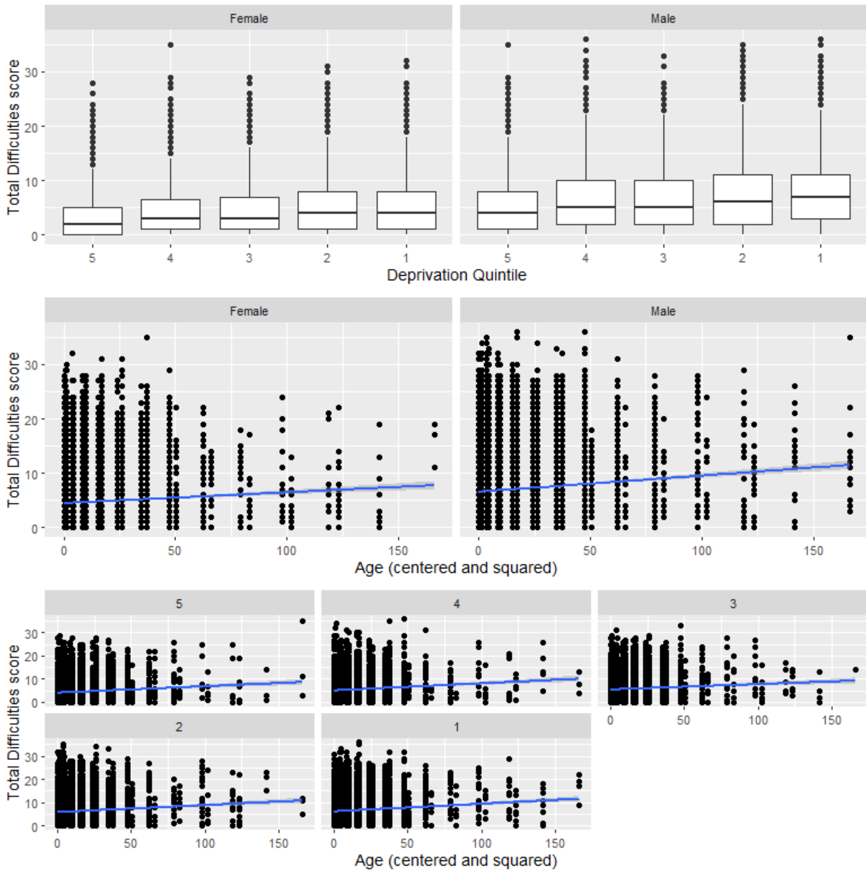

Figure 5.8: Total difficulties by sex & deprivation, sex & age, and age & deprivation quintile

There is no visible difference in the effect of deprivation or age on total difficulties score by sex. Nor did the effect of age on total difficulties score appear to vary by deprivation. This was assessed formally in a model, however all the RR included the null value of 1 as shown in Figure 5.9.

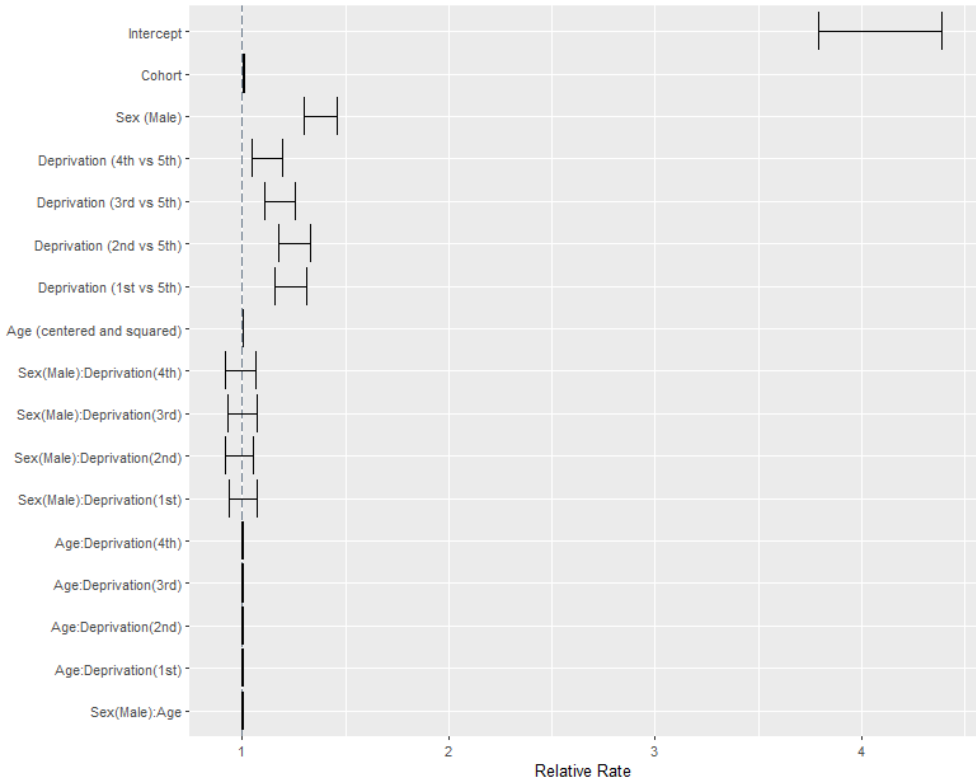

Figure 5.9: Covariate Interaction Effects
Values are the Relative Rate (95% Credible Intervals). The Relative Rate assumes all other covariates are fixed.

Next, the model assessed whether the relationship between an individual characteristic and total difficulties scores depends on the ward a child lives in. First, the covariates for different wards were visually inspected. There are no obvious relationships between total difficulties score and age or sex across wards. There are some differences in the relationship between deprivation and total difficulties across the wards that warranted further exploration (Figure 5.10).

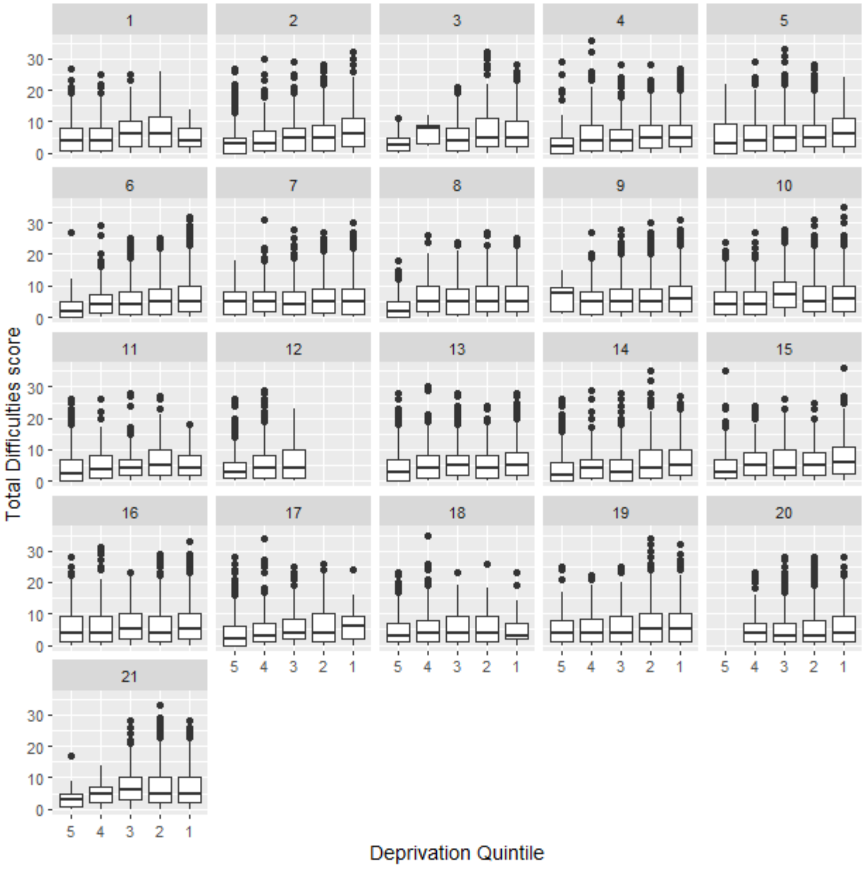

Figure 5.10: SDQ by ward and deprivation quintile
1 Anderston/City, 2 Baillieston, 3 Calton, 4 Canal, 5 Craigton, 6 Drumchapel/Anniesland, 7 East Centre, 8 Garscadden/Scotstounhill, 9 Govan, 10 Greater Pollok, 11 Hillhead, 12 Langside, 13 Linn, 14 Maryhill/Kelvin, 15 Newlands/Auldburn, 16 North East, 17 Partick West, 18 Pollokshields, 19 Shettleston, 20 Southside Central, 21 Springburn. The ward boundaries were obtained from SASPAC (Small Area Statistics PACkage) at `https://saspac.org/` using the boundaries at 2011.

To add this to the model, there is now an intercept v_{0j} and slope v_{1j} for each ward (Equation 5.7). This describes the mean value of total difficulties in a ward (intercept) and the relationship between the total difficulties and deprivation quintile (slope) represented in the equation as $\beta_4 + v_{1j}$. Similar models were run to investigate the interaction between ward and sex, and ward and age.

$$
\begin{aligned}
\eta_{ijk} = \exp(\beta_0 + \beta_1 \mathrm{t} + \beta_2 \mathrm{age} + \beta_3 \mathrm{sex} + (\beta_4 + v_{1j})\mathrm{deprivation} + v_{0j} + \alpha_k + \delta_l) \\
v_{0j} \sim N(0, \sigma^2_{v_0}), \frac{1}{\sigma^2_{v_0}} \sim \Gamma^{-1}(1, 0.0005) \\
\alpha_k \sim N(0, \sigma^2_{\alpha}), \frac{1}{\sigma^2_{\alpha}} \sim \Gamma^{-1}(1, 0.0005) \\
v_{1j} \sim N(0, \sigma^2_{v_1}), \frac{1}{\sigma^2_{v_1}} \sim \Gamma^{-1}(1, 0.0005)
\end{aligned}
\tag{5.7}
$$

While there is a small variation in slopes by deprivation, Bayes Factor suggests that the evidence in support of this term is negative (logBF= -28.72), similarly there is no improvement to the model according to DIC (Table 5.9).

It may be that the intercept and slope are correlated, meaning wards with high total difficulties scores on average also have a stronger association between SDQ scores and deprivation (sex and age). This can be explored by explicitly modelling the correlation between slopes and intercepts. The addition of slopes did not improve model fit, so correlation is not considered further.

Table 5.9: Model estimates for Equation 5.7

Slope	Variance (95% CrI)	DIC
Deprivation	0.006(0.003-0.014)	196280
Sex	0.000 (0.000-0.000)	196280
Age	0.000 (0.000-0.000)	196287

CrI Credible Interval, DIC Deviation Information Criterion

5.3.3 Model Interpretation

Based on the selection criteria introduced at the start of the chapter, the best fitting model so far is the Adjust Cross Classified Spatial and Preschool Model (See Eq 5.6 and Table 5.8). This model accounts for the variation found between wards and preschool, the fixed effect of cohort and demographics that are associated with total difficulties scores. Variance parameters were supported through Bayes Factor and DIC values, there was no residual spatial correlation and model parameters did not include the null values.

In this model, there is a citywide increase over time in children's score, on average. Existing evidence of decreasing temporal trends in teacher-rated total difficulties scores for UK children is largely outside this age group, limiting comparability [266, 267]. Decreasing trends in parent-rated total difficulties in 4-12 year old girls were found in Scotland from 1995-2014 [268]. The contrasting results in this study may point to differences between teacher-raters and parent-raters, our focus on sub-national outcomes, or other factors outside the scope of this study. Whether the temporal trend varies by ward is considered in the next section.

While there is a 0.3-1.2% yearly increase in scores, across all cohorts the population average difficulties of 6.58 (estimated by the spatial model Equation 5.6) is still considered to be within the classification for close to average scores [88]. Taking a dimensional approach [22] discussed in Chapter 4, this rate of increase in average scores is related to increasing rates of likely mental health difficulties in the population (see Figure 4.3). As previously described [64], there is a higher RR in boys, those of increasing deprivation and children outside the average age (Table 5.8).

Preschool effects are shown in Figure 5.11. There is a wide range in the RR associated with each preschool, with one preschool estimated to have scores 98.16% higher than expected based on demographics. There were 72 preschools that had a higher RR than expected based on their demographics. These preschools consist of 17016 children, representing almost half of the sample (48.38%). This further supports the importance of this context in understanding the variation in developmental outcomes.

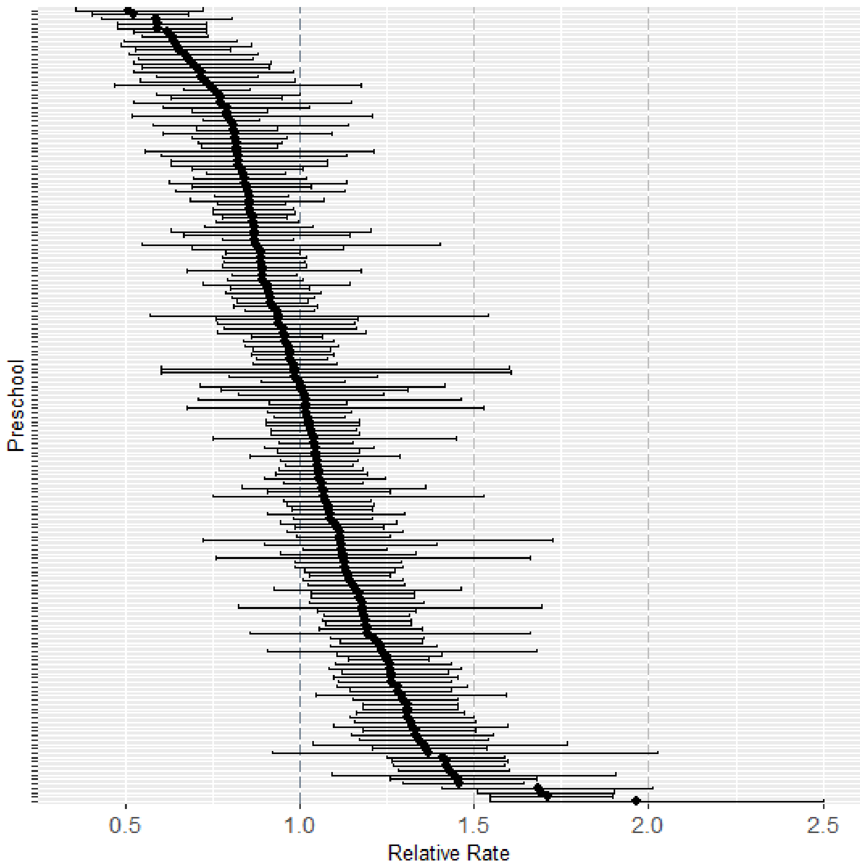

Figure 5.11: Preschool Relative Rate (RR)

At ward level, the range of RRs was 0.934 to 1.053 meaning wards ranged from being 6.6% lower than expected based on demographics (i.e. Southside Central) to being 5.3% higher than expected based on demographics (i.e. Craigton). The highest RRs are dispersed around the city (Figure 5.12). Uncertainty in the ward level RR was represented using the exceedance probability, i.e., the probability that the corresponding RR was greater than 1. Exceedance probability values of 0.8 or above were considered to indicate high certainty in the elevated RR. There is at least 80% probability that the RR is greater than 1 for four wards in city: Anderston/City, Craigton, North East and Pollokshields. In total, 6711 children lived in these wards (19.08% of the sample). There were 3735 children who lived in a ward with a high RR and attended a preschool with a high RR (10.62% of the sample).

The characteristics of the wards that were worse than expected based on their composition were explored. 'On-diagonal' describes when a neighbourhood outcome aligns with our expectations [269]. Differing approaches have been used to quantify whether a neighbourhood is 'on-diagonal' or 'off-diagonal' (the outcome is better or worse than expected, respectively) [269]. For example Kershaw et al., [270] used the residuals from a line of best fit, off-diagonal effects were neighbourhoods that were consistently off diagonal over time (though the model specification was not provided). This approach is useful as it includes multivariable adjustment and the ability to quantify certainty. Similarly, the adjusted RR, represents whether wards are worse than expected after adjustment for demographics.

The percentage of boys, children in the most and second most deprived quintiles and children outside the expected age range was plotted with the ward RR which represented whether the ward was better or worse than expected in Figure 5.13. For easier interpretation, the ward RR is shown as a percentage ($(1 - RR) * 100$). Wards are ordered by their percentage and colour coded by whether they were better (blue) or worse (red) than expected. Of the variation observed, there were some wards with communities of high deprivation e.g. Southside Central, Calton and Govan that were better than expected given their deprivation composition.

The conditions for performing worse than expected (among the 4 that are higher than average which are highlighted using the asterisk) vary. Craigton has a lower percentage of boys. Pollokshields has lower deprivation and children outside the expected age range. Anderston/City has lower deprivation but higher proportion of boys. Therefore, these wards have demographic characteristics that increase and decrease their expected disadvantage. Where neighbourhoods are 'off-diagonal' this presents the possibility of buffering (described by Galster et al., [105]) by another characteristic that has not yet been considered (see Chapter 7).

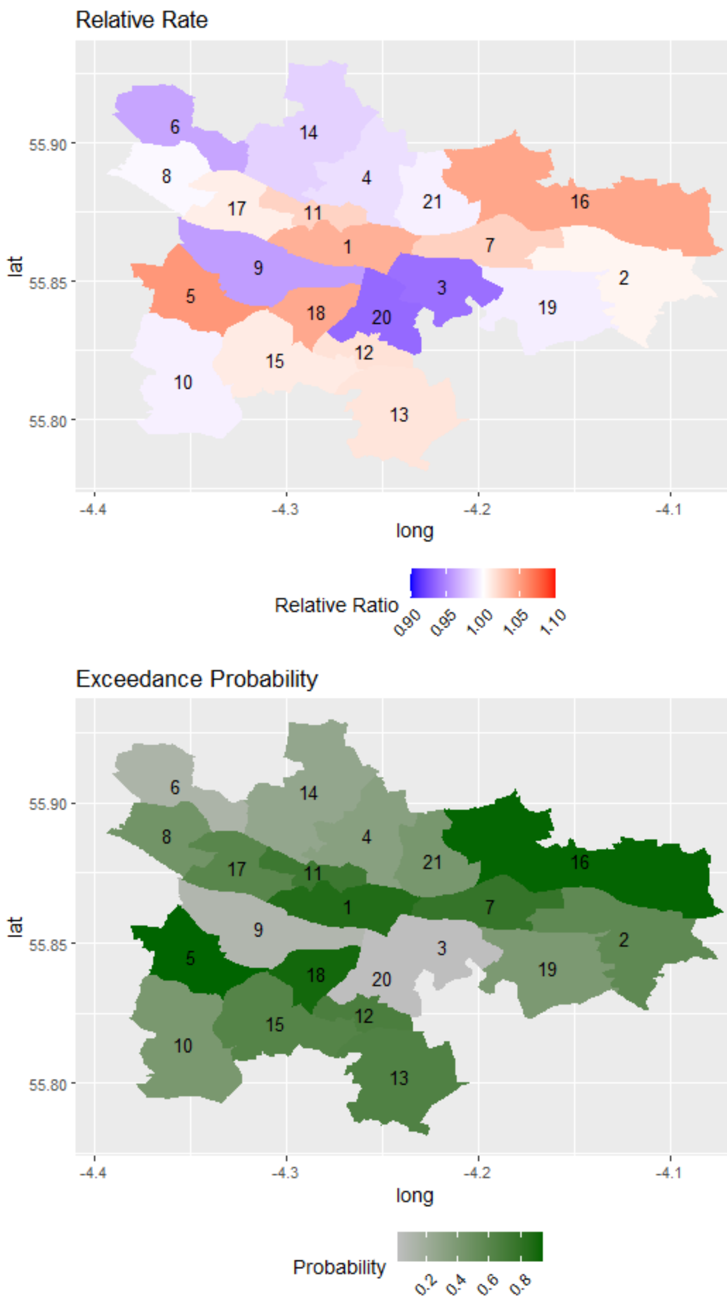

Figure 5.12: Ward Relative Rate (RR)and Exceedance Probability (EP)
1 Anderston/City, 2 Baillieston, 3 Calton, 4 Canal, 5 Craigton, 6 Drumchapel/Anniesland, 7 East Centre, 8 Garscadden/Scotstounhill, 9 Govan, 10 Greater Pollok, 11 Hillhead, 12 Langside, 13 Linn, 14 Maryhill/Kelvin, 15 Newlands/Auldburn, 16 North East, 17 Partick West, 18 Pollokshields, 19 Shettleston, 20 Southside Central, 21 Springburn.

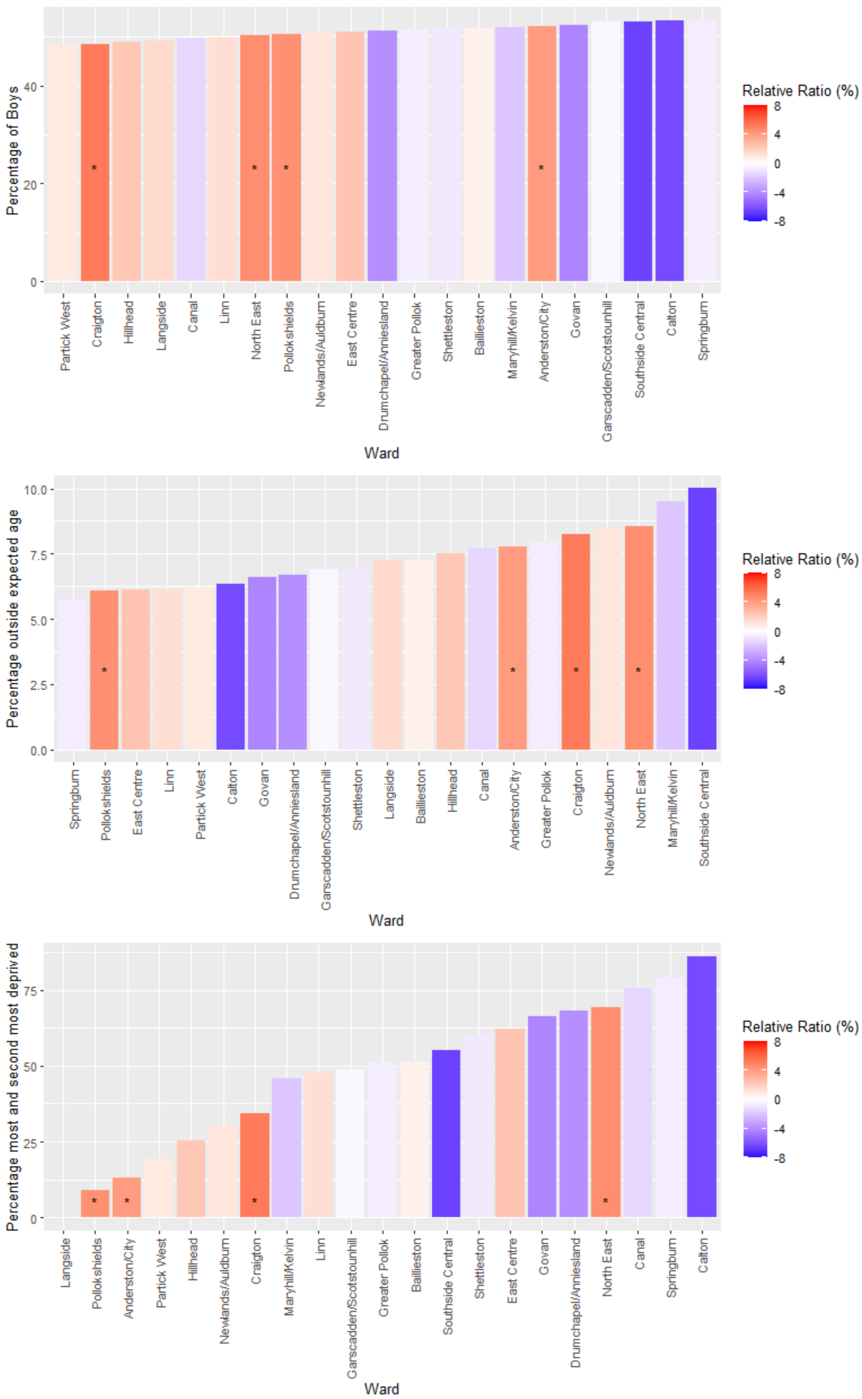

Figure 5.13: Ward level demographic composition and Relative Rate (RR)
Ward level demographics - sex (top), age (middle) and deprivation quintile (bottom panel). * Wards with higher difficulties scores than expected based on the demographics (i.e. exceedance probability > 0.8).

5.4 Adjusted Cross Classified (Spatial, Preschool and) Spatio-temporal Model

The regions identified with relatively higher difficulties than expected (Anderston/City, Craigton, North East and Pollokshields) were different to those originally seen in the initial model of the 2010-2012 ChiME subset [64] (Craigton, North East, East Centre, Baillleston, Shettleston, Langside). One explanation for this is that there are more robust estimates through using several years of data. Alternatively, there may be a spatio-temporal component to variation in difficulties, whereby the effect of an area depends on the point in time. This has implications on model inference. The areas identified in this project have a high relative rate independently of the year, i.e. this is a spatial pattern common across all time points. A spatio-temporal model can identify how time may impact the ward effects. The rest of this chapter considers different spatio-temporal models that can be used to understand how wards may change over time.

5.4.1 Spatially Varying Temporal Trends

The first consideration was whether there any areas with increasing or decreasing trends in total difficulties compared to the overall temporal trend i.e. whether there any areas getting consistently better or worse.

Descriptive plot shows the distribution of difficulties over time by ward (Figure 5.14). Although the previous model found a city-wide increase in difficulties over time, the rate of change varies by ward, in some cases decreasing (Figure 5.14).

The rest of subsection is taken from separate publication which is based on analysis I conducted during this project to explore spatially varying temporal trends [251].

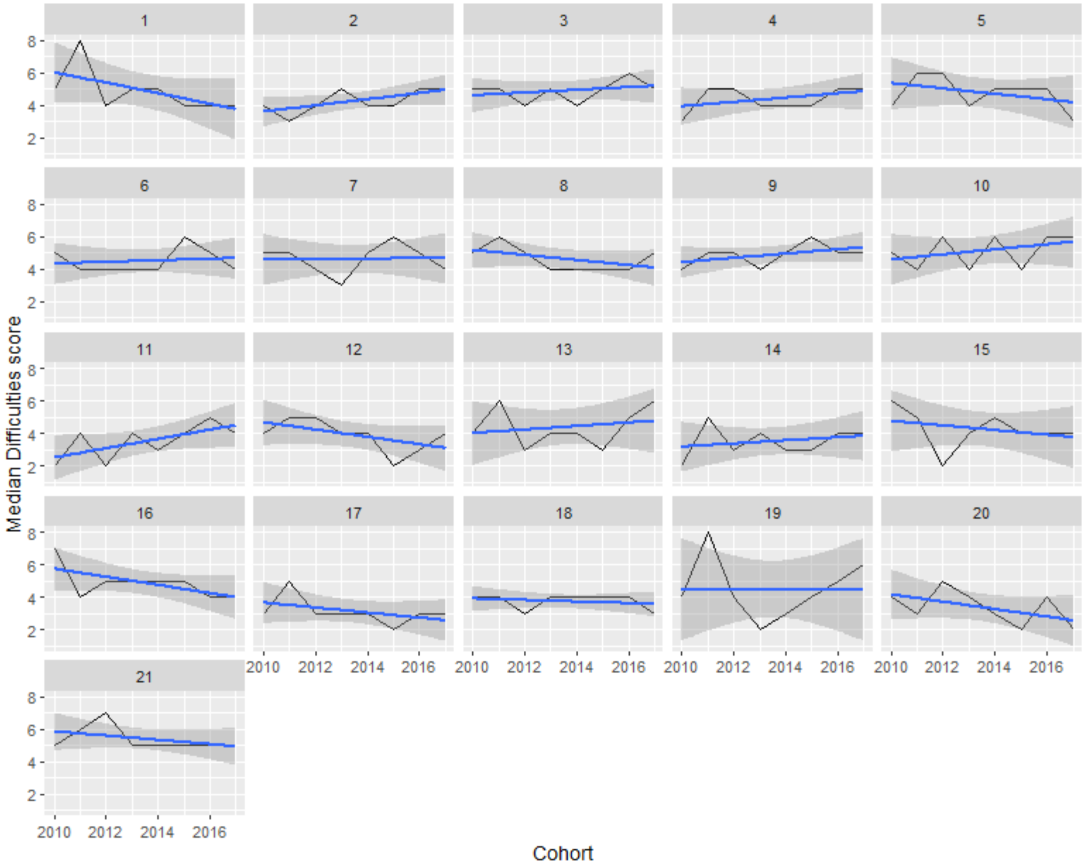

Figure 5.14: Total difficulties scores by ward and year (line)
1 Anderston/City, 2 Baillieston, 3 Calton, 4 Canal, 5 Craigton, 6 Drumchapel/Anniesland, 7 East Centre, 8 Garscadden/Scotstounhill, 9 Govan, 10 Greater Pollok, 11 Hillhead, 12 Langside, 13 Linn, 14 Maryhill/Kelvin, 15 Newlands/Auldburn, 16 North East, 17 Partick West, 18 Pollokshields, 19 Shettleston, 20 Southside Central, 21 Springburn.

Introduction

This paper focuses on geographic patterns in mental health according to where a child lives. Geographic variation in outcomes can be expected as the residential environment influences the day-to-day social and physical experiences of the child and their caregiver. There has been considerable research on how the characteristics of a neighbourhood are associated with child mental health and well-being [24, 25, 34], with deprivation being the most commonly researched factor. Considerable differences in outcomes may point to health inequalities that would benefit from intervention.

There is no common theoretical or methodological framework to investigate geographic differences in child mental health [34] or the effectiveness of place-based interventions [27]. Ebener et al. present a hierarchy of geospatial techniques that support decision making in early childhood [271]: mapping, spatial analysis, and spatial modelling. This process is facilitated by population data, giving an adequate sample size to provide small area estimates (e.g., [33, 42]). Visualising differences between areas through mapping can highlight areas in need of further action. There is increasing literature on the importance of considering time in spatial research [48]. The composition (demographics of the individuals in the neighbourhood) and characteristics of neighbourhoods change over time, affecting the overall spatial pattern. Spatial modelling can be easily extended to consider the effect of time forming spatio-temporal models [228]. Such models estimate the main spatial pattern that is consistent across the time, the temporal trend that is common to all areas, and/or the spatio-temporal interactions that describe how an area changes over time.

Spatial and spatio-temporal techniques typically use aggregated outcomes, e.g., an average or total for an area. Disease mapping [214], a commonly used form of spatial modelling, maps the overall risk of aggregated health outcomes in a region to show small areas that deviate from the region overall and how the relationship between areas is explained by covariates (e.g., [272]). Aggregating the outcome by small area is useful as it can be easily modelled to support local level action. By focusing on an aggregated outcome, however, this approach is limited by ecological fallacy, and we are only able to make inferences about the level at which the outcome is derived (i.e., the area), and thus cannot make conclusions about the individual. A multilevel spatial (or spatio-temporal) temporal approach, in which the outcome of interest is at an individual level and the variation between areas can be estimated (e.g., [64, 273]). In this case, information is retained about each child and their neighbourhood, avoiding loss of information. Considering individual, spatial, and spatio-temporal effects adds further complexity to the model [230].

The approach chosen to evaluate child mental health trends can influence decision-making. We are interested in looking at the impact of methodology in identifying geographic variation in early child mental health in the United Kingdom. The current study aims to compare disease mapping and multilevel approaches in their ability to:

1. Map the overall risk of preschool children's social and emotional difficulties in an entire city from 2010–2017;
2. Analyse the relationship between preschool children's social, emotional, and behavioural difficulties in neighbouring areas across a whole city from 2010–2017;
3. Investigate the extent to which the relationship between geography and preschool children's social, emotional, and behavioural difficulties is explained by demographics;
4. Explore the temporal and spatio-temporal trends in preschool children's social, emotional, and behavioural difficulties across an entire city from 2010–2017.

Methodology

Both models followed the spatio-temporal formulation which assumed separable spatial and temporal effects e.g. Model E (for full model specification, see [274] and Eq 5.8). According to this formulation, we included a linear time trend common to all wards in the city and an overall spatial random intercept (describing how wards deviate from the city-wide average). Spatial correlation of residuals aggregated by ward can be measured through Moran's I statistic [202]. For the multilevel model, we generated residuals by simulating values from the distribution and scaling them using R package DHARMa [256].

The Disease Mapping outcome of interest was the number of children with or at high risk of psychopathology in an area. The outcome was defined as the number of children in each ward and year with a high total difficulties score ($\geq$15). We assumed a Poisson distribution for the outcome, as high scores are discrete and relatively rare. The model was specified as follows:

$$\begin{aligned} Y_j &\sim Pois(E_j\Theta_j) \\ \Theta_j &= exp(\beta_0 + (\beta_1 + u_{1j})Cohort + u_{oj} + \beta_k x_j \\ u_{0j} &\sim N(0, \sigma^2_{u0}) \text{ where } \frac{1}{\sigma^2_{u0}} \sim \Gamma^{-1}(1, 0.0005) \\ u_{1j} &\sim N(0, \sigma^2_{u1}) \text{ where } \frac{1}{\sigma^2_{u1}} \sim \Gamma^{-1}(1, 0.0005) \end{aligned} \tag{5.8}$$

where Y_j was the number of high scoring children in ward j = 1,. . . , 21, E_j was the population of the ward (used as an offset), and Θ_j was the probability of having a high score. In the model, β_0 was the intercept, β_1 was the main linear trend across the eight yearly cohorts, and u_{0j} the ward-level spatial intercept. There was no evidence of a spatial correlation in the model; therefore, the spatial effect was unstructured to model spatial heterogeneity. The random slope u_{1j} allowed for separating linear trends for each ward. Although shown here to be independent of random intercepts for simplicity, correlated intercepts and slopes were assessed during model building. Coefficient β_k was associated with ward characteristic k. Ward characteristics were the proportion of children outside the expected age for school start (under 4.5 years or over 5.5 years), the proportion of children in the most deprived quintile, and the proportion of boys. The parameters were added to the model in the order described and were retained based on the Deviance Information Criterion (DIC) [275], with lower values indicating better fit. The disease mapping approach was repeated using the median difficulties per ward as the outcome. When the disease mapping model was run using median difficulties scores, the variation between wards was estimated at zero (0.000 (0.000–0.074)), meaning there was no heterogeneity in the median difficulties per ward.

The Multilevel model of interest was the total difficulties score for an individual child, which was modelled using a multilevel model. We assumed a zero-inflated negative binomial distribution [253, 276]. The mean of the model is λ, ρ is the zero-inflation parameter, and r is the overdispersion parameter.

$$
\begin{aligned}
Y_{ijk} &\sim NB(\lambda, \rho, r) \\
\lambda_{ijk} &= exp(\beta_0 + (\beta_1 + v_{1j})Cohort + \alpha_k + v_{oj} + \beta_\phi x_i \\
v_{0j} &\sim N(0, \sigma^2_{v0}) \text{ where } \frac{1}{\sigma^2_{v0}} \sim \Gamma^{-1}(1, 0.0005) \\
v_{1j} &\sim N(0, \sigma^2_{v1}) \text{ where } \frac{1}{\sigma^2_{v1}} \sim \Gamma^{-1}(1, 0.0005) \\
\alpha_k &\sim N(0, \sigma^2_{\alpha 0}) \text{ where } \frac{1}{\sigma^2_{\alpha 0}} \sim \Gamma^{-1}(1, 0.0005)
\end{aligned}
\tag{5.9}
$$

Here, child i = 1,. . . , N was nested within ward j = 1,. . . , 21 and preschools k = 1,. . . , 180. In the model, β_0 was the intercept, β_1 the coefficient for the overall time trend, v_{oj} the ward-level spatial intercept, and α_k a preschool effect. There was no evidence of a residual spatial correlation of ward level residuals in the model; therefore, the spatial effect was unstructured. The preschool effect and ward were cross-classified (i.e., they were not hierarchically nested). The random slope u_{1j} allowed for separating linear trends for each ward. Coefficient β_ϕ was associated with individual-level variables ϕ —age (centred on mean age of 59 months and squared), sex, and deprivation quintile. The parameters were added to the model in the order described and were retained based on the Deviance Information Criterion (DIC) [275].

The full methodology and results are in the paper [251].

Findings

There was an overall increase in the number of high scoring children (i.e., children with likely mental health difficulties) in each ward over time from the disease mapping model (Table 5.10).

We also identified a citywide increase over time in the child score, on average, through the multilevel modelling approach. The rate of increase in the average score was lower than that of the proportion of high scores (Table 5.11).

Table 5.10: Model estimates for Disease Mapping Model (Equation 5.8)

	Unadjusted	Adjusted
	RR (95% CrI)	RR (95% CrI)
Intercept	0.077 (0.069–0.087)	0.033 (0.017–0.066)
Proportion > 5.5 AND <4.5 years	-	1.467 (0.500–4.283)
Proportion boys	-	3.462 (1.157–10.308)
Proportion most deprived quintile	-	1.326 (0.934–1.839)
Cohort	1.026 (1.009–1.043)	1.033 (1.015–1.050)
	Variance (95% CrI)	Variance (95% CrI)
Ward	0.026 (0.011–0.054)	0.018 (0.006–0.041)
Differential Time Trend	0.000 (0.000-0.000)	-
DIC	1022	1025

RR- Relative Rate; CrI—credible interval; DIC—deviance information criterion.

Table 5.11: Model estimates for Multilevel Model (Equation 5.9)

	Unadjusted	Adjusted
	RR (95% CrI)	RR (95% CrI)
Intercept	5.963 (5.647–6.297)	4.079 (3.886–4.350)
Boys vs. Girls	-	1.370 (1.344–1.396)
Age (centred and squared)	-	1.003 (1.003–1.004)
2nd least deprived quintile vs. least	-	1.115 (1.073–1.159)
middle deprived quintile vs. least	-	1.174 (1.128–1.222)
2nd most deprived quintile vs. least	-	1.234 (1.186–1.284)
Most deprived quintile vs. least	-	1.243 (1.193–1.293)
Cohort	1.007 (1.002–1.011)	1.008 (1.003–1.012)
	Variance (95% CrI)	Variance (95% CrI)
Preschool	0.071 (0.054–0.092)	0.062 (0.045–0.082)
Ward	0.011 (0.004–0.021)	0.013 (0.008–0.020)
Differential Time Trend	0.001 (0.000-0.001)	-
DIC	197,533	196,273

RR — Relative Rate; CrI—credible interval; DIC—deviance information criterion.

Both approaches found minimal variation between wards, as shown by the small variance terms.

The geographic pattern differed between the approaches (Figures 5.15 and 5.16). For example, ward 18 (Pollokshields) (which has low levels of deprivation) was associated with increased average SDQ score in the multilevel model and a low rate of high scoring children in the disease mapping model. The opposite effect was found in ward 9 (Govan), where there were high levels of deprivation.

A single ward was identified with certainty in both modelling approaches as having a level of difficulties in excess of the city as a whole (ward 5, Craigton, where most children are in the middle quintile for deprivation). There may be unmeasured covariates that would help explain this pattern [38].

A limitation of the disease mapping model is the fact that characteristics were aggregated by ward. Defining the variables in this way is likely to dilute any existing variations, giving less power to find an effect (Table 5.10). In line with prior knowledge, biological sex was identified as important in both approaches. This may reflect differences in how teachers perceive social, emotional, and behavioural problems in young girls and boys [91]. The multilevel model found an association with age and socioeconomic deprivation (Table 5.11). This demographic trend is consistent with other settings [64, 273, 277].

We did not find evidence to support the use of random slopes, meaning the linear temporal trends were consistent across all wards in the city.

Although the outcomes in each approach are not directly comparable, they both relate to clinical disorder rates at a population [22]. There may be different mechanisms at play for average scoring children compared with those in the high score category, which likely contributed to the difference between trends in our approaches [252].

Conclusion

Our interpretation of the results is that, on average, children's scores have increased marginally over time, while, at the same time and partly as a result, more children are reaching the high score cut-off. Both effects are consistent across electoral wards, supporting a citywide intervention.

The current approach to policy, such as the Scottish National Performance Framework, focuses on excessive rates of high scores [278]. According to the framework, if parent-rated scores increase by more than 1% for 3 years, performance is worsening at a local level. An alternative explanation may be that there is increased reporting of mental health problems [279]. Using the Scottish Government's guideline, the current study found a worsening performance in the number of high scoring children across 8 years, prompting the need for further action, especially (but not exclusively) in neighbourhoods with high socioeconomic deprivation. Off-diagonal effects show, however, that focusing entirely on deprivation may not always lead to effective place-based interventions [27], which should be directed towards children with the greatest difficulties and should be delivered at pre-school-level.

We argue that multilevel modelling of individual scores may be beneficial in identifying priority preschools and areas, warranting further investigation as rising scores transition over the high score cut-off. Therefore, using both approaches together gives deeper insight into the trends in early childhood mental health, which are potentially useful in supporting decision-making.

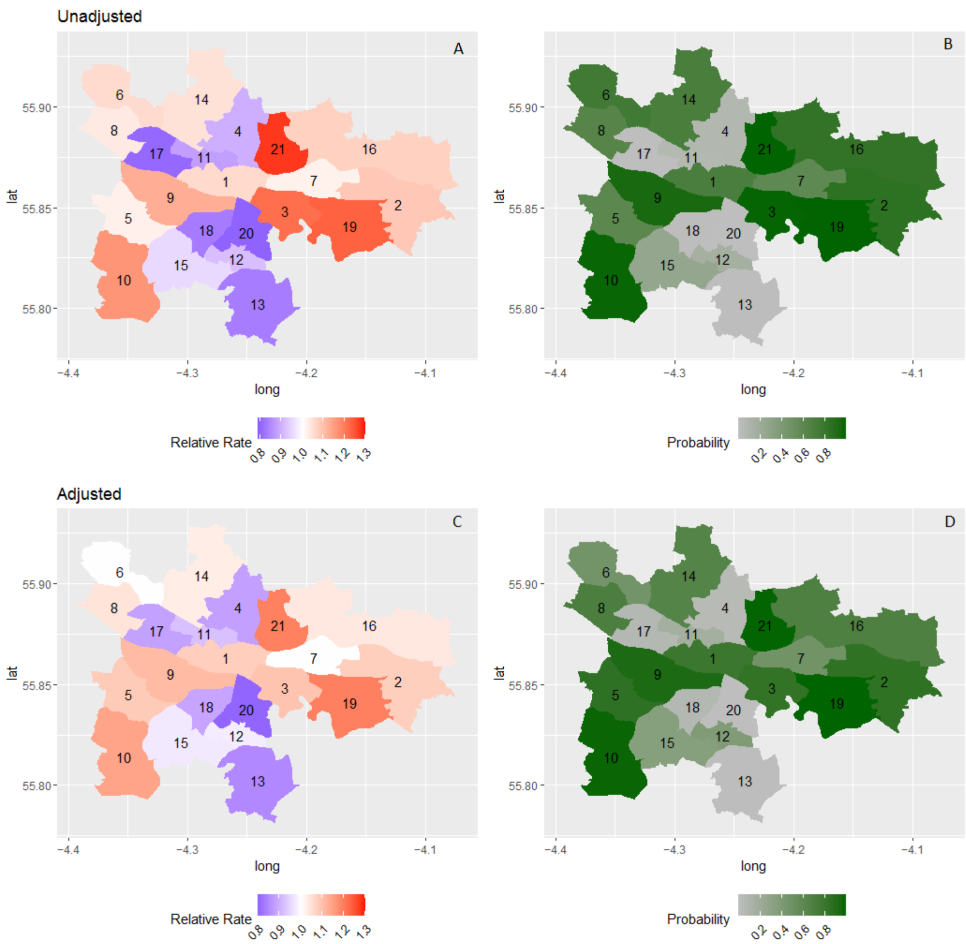

Figure 5.15: Disease Mapping Model: Relative rate increase in number of children with high total SDQ scores before (a) and after (c) and adjustment and exceedance probability before (b) and after (d) and adjustment for sex, age, cohort, and deprivation 1 Anderston/City, 2 Baillieston, 3 Calton, 4 Canal, 5 Craigton, 6 Drumchapel/Anniesland, 7 East Centre, 8 Garscadden/Scotstounhill, 9 Govan, 10 Greater Pollok, 11 Hillhead, 12 Langside, 13 Linn, 14 Maryhill/Kelvin, 15 Newlands/Auldburn, 16 North East, 17 Partick West, 18 Pollokshields, 19 Shettleston, 20 Southside Central, 21 Springburn

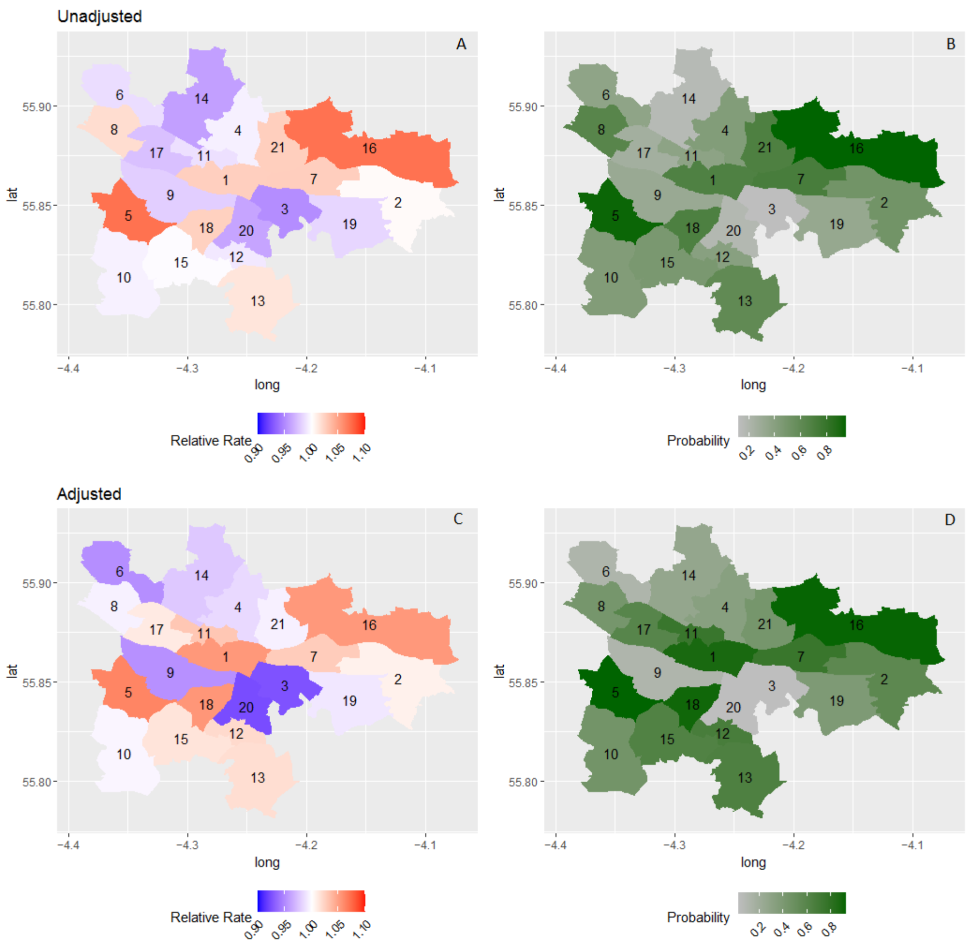

Figure 5.16: Multilevel Model: Relative rate increase in average total difficulties scores before (a) and after (c) and adjustment and exceedance probability before (b) and after (d) and adjustment for sex, age, cohort, and deprivation.
1 Anderston/City, 2 Baillieston, 3 Calton, 4 Canal, 5 Craigton, 6 Drumchapel/Anniesland, 7 East Centre, 8 Garscadden/Scotstounhill, 9 Govan, 10 Greater Pollok, 11 Hillhead, 12 Langside, 13 Linn, 14 Maryhill/Kelvin, 15 Newlands/Auldburn, 16 North East, 17 Partick West, 18 Pollokshields, 19 Shettleston, 20 Southside Central, 21 Springburn

5.4.2 Spatio-temporal Interaction

The analysis so far has shown there was limited evidence of wards getting consistently better or worse over time. This does not rule out the possibility of other spatio-temporal effects. Following the structures proposed by Knorr-held [227] it is still possible that spatio-temporal effects are completely unstructured, follow a non-linear temporal structure or vary in both space and time (see Chapter 3.3.2).

Adding spatio-temporal interaction is of interest as it can be used to identify whether areas deviate from the overall spatial effect observed after adjustment for demographics. The yearly distribution of scores appears to vary by ward (Figure 5.17).

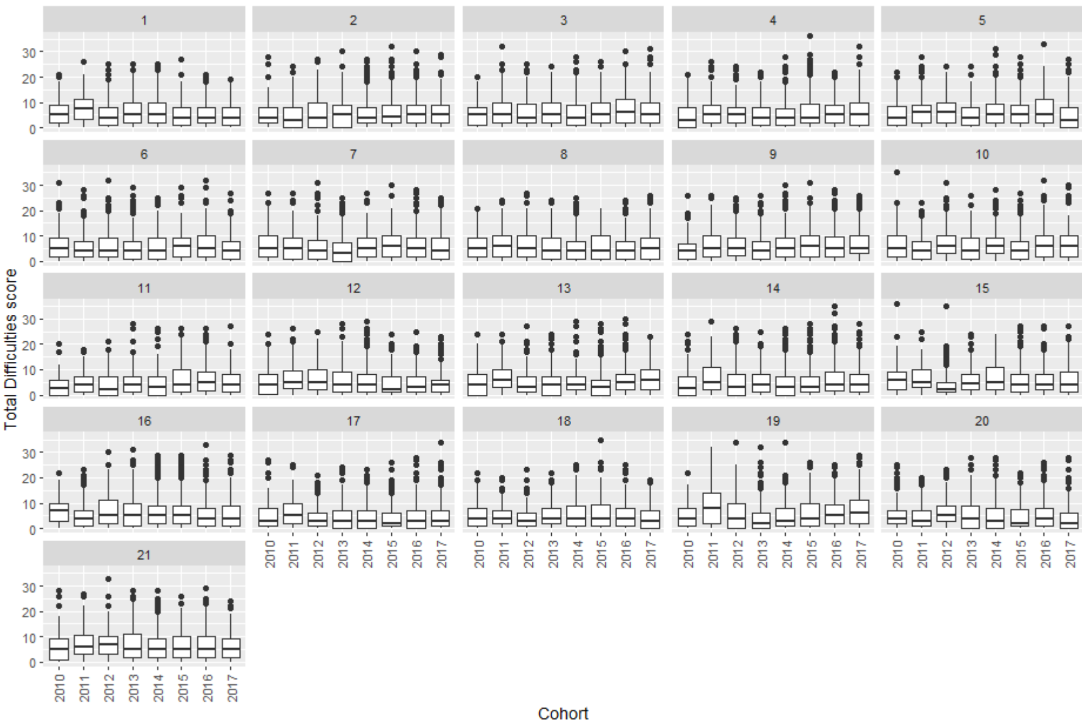

Figure 5.17: Total difficulties scores by ward and year (box plot)
1 Anderston/City, 2 Baillieston, 3 Calton, 4 Canal, 5 Craigton, 6 Drumchapel/Anniesland, 7 East Centre, 8 Garscadden/Scotstounhill, 9 Govan, 10 Greater Pollok, 11 Hillhead, 12 Langside, 13 Linn, 14 Maryhill/Kelvin, 15 Newlands/Auldburn, 16 North East, 17 Partick West, 18 Pollokshields, 19 Shettleston, 20 Southside Central, 21 Springburn.

Residual spatio-temporal correlation in the final spatial model was assessed using Moran's I- weights which were assigned to proximal years. For example, 2010 was assigned the following weights [0,1,0,0,0,0,0] while 2011 was given [1,0,1,0,0,0,0,0]. A multiplicative spatio-temporal matrix was created through the Kronecker product of the ward weights and the temporal weights. Spatio-temporal Moran's I_{ST} was close to 0 at (I_{ST}=-0.069, p=0.949) confirming there was no spatio-temporal dependence.

The next spatio-temporal model used the unstructured spatio-temporal models described by Schmidt-Catran and Fairbrother, [229] discussed in the methodology chapter. The recommended approach is the fullest model (spatial, temporal and spatiotemporal effects). Where there is a risk of over parameterising the model, they suggest a simplification to Model D (See Figure 3.6) where individuals are nested in spatial and spatio-temporal structures. This is fitting to this case where time has already been specified through the linear trend, with limited evidence for a temporal random effect.

Therefore, the model accounts for clustering at the ward and preschool level and for children living in the same ward in the same year. There is an unstructured spatial main effect and an unstructured spatio-temporal interaction, whereby the interaction describes deviations from the main effect. The median number of children in a ward for a specific year was 204. The minimum was 46, and the maximum was 408 (See Appendix Figure C.1).

$$\begin{aligned} \eta_{ijk} = \exp(\beta_0 + \beta_1 \mathrm{t} + \beta_2 \mathrm{age} + \beta_3 \mathrm{sex} + \beta_4 \mathrm{deprivation} + v_{0j} + \alpha_k + \phi \\ v_{0j} \sim N(0, \sigma^2_{v0}), \frac{1}{\sigma^2_{v0}} \sim \Gamma^{-1}(1, 0.0005) \\ \alpha_k \sim N(0, \sigma^2_{\alpha}), \frac{1}{\sigma^2_{\alpha}} \sim \Gamma^{-1}(1, 0.0005) \\ \phi \sim N(0, \sigma^2_{\phi}), \frac{1}{\sigma^2_{\phi}} \sim \Gamma^{-1}(1, 0.0005) \end{aligned} \tag{5.10}$$

Adding the spatio-temporal term reduced the DIC further to 196173 and was supported by Bayes Factor (logBF=24.07).

Model Interpretation

Based on the selection criteria introduced at the start of this chapter, the best fitting spatio-temporal model is Eq 5.10 (results shown in Table 5.12). This model accounts

Table 5.12: Model estimates for Equation 5.10

Parameter	Relative Rate	95% Credible Intervals
Intercept	4.056	3.777-4.356
Cohort	1.009	1.002-1.015
Sex (Male)	1.370	1.344-1.397
Deprivation quintile (4th vs 5th)	1.115	1.072-1.159
Deprivation quintile (3rd vs 5th)	1.176	1.130-1.224
Deprivation quintile (2nd vs 5th)	1.235	1.187-1.285
Deprivation quintile (1st vs 5th)	1.245	1.195-1.296
Age (centered and squared)	1.003	1.003-1.004
	Variance	95% Credible Intervals
Ward	0.011	0.007-0.018
Preschool	0.059	0.046-0.084
Spatio-temporal interaction	0.006	0.004-0.009
DIC	196173	

for the non linear, independent temporal effects that exist at a ward level. The spatio-temporal variance parameters were supported through Bayes Factor, a reduction in DIC, and no residual spatio-temporal correlation.

After consideration of demographics, there are independent spatio-temporal patterns in total difficulties that exist in addition to the overall spatial effect seen in the previous model. The spatio-temporal variance (0.006 (0.004-0.009)) was estimated to be less than the ward and preschool variance (Table 5.12). This is more formally assessed in the next chapter.

Figure 5.18 shows the spatio-temporal deviation from the overall spatial effect each year. Each year highlights different areas. The largest deviations were in Newlands/Auldburn in 2012 where the RR was 0.838 therefore scores were 16% lower and in Shettleston in 2011 where the RR was 1.198 therefore scores were 19.8% higher.

Figure 5.19 shows the exceedance probability for the spatio-temporal RR. The greatest range in RR was in 2011 where there were 6 wards with increased RR with high certainty. The ward with the most spatio-temporal deviations was Newlands/Auldburn where RR>1 in 2010, 2012, 2013 and 2014. Among the wards with relatively high SDQ (Anderston/City, Craigton, North East and Pollokshields) according to the overall spatial effect, there were still spatio-temporal deviations among these wards.

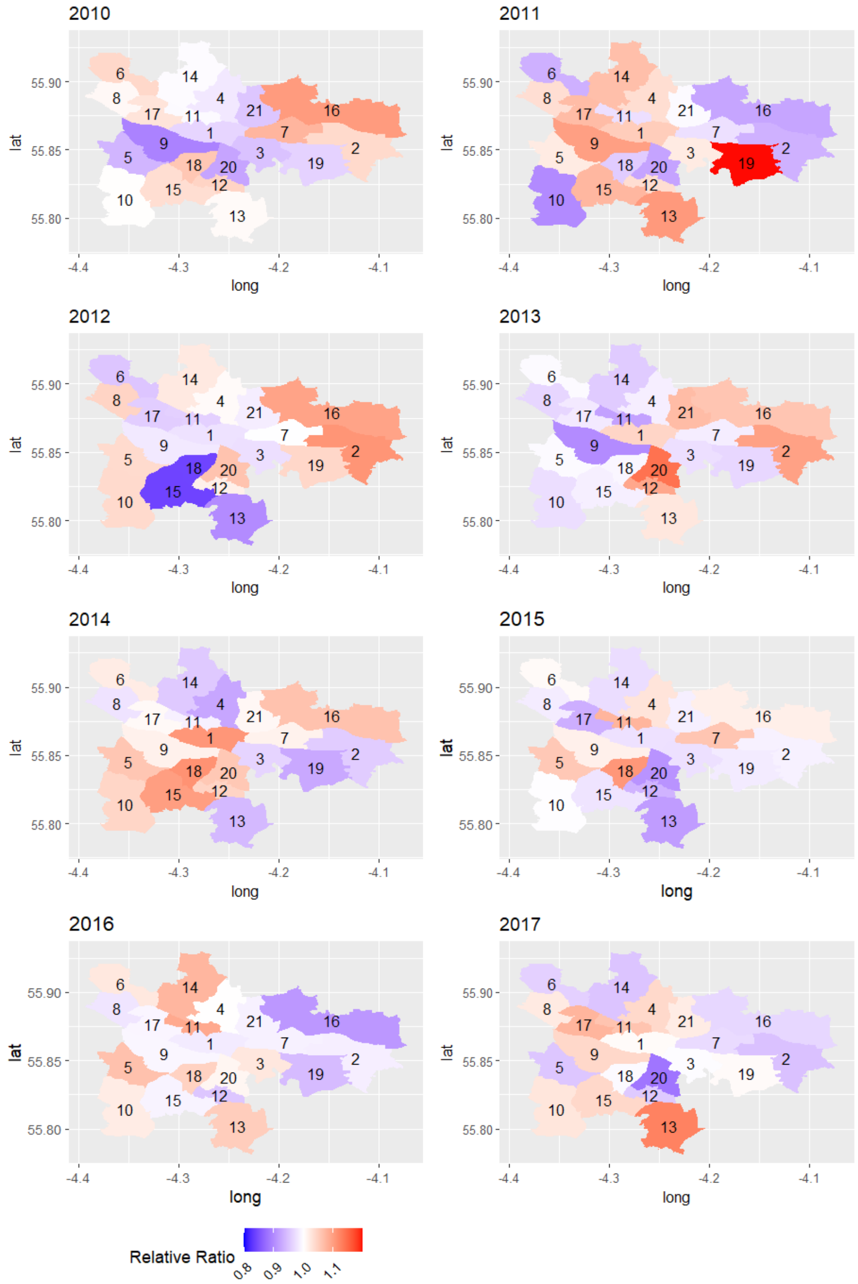

Figure 5.18: Spatio-temporal Relative Rate (RR) at ward level
1 Anderston/City, 2 Baillieston, 3 Calton, 4 Canal, 5 Craigton, 6 Drumchapel/Anniesland, 7 East Centre, 8 Garscadden/Scotstounhill, 9 Govan, 10 Greater Pollok, 11 Hillhead, 12 Langside, 13 Linn, 14 Maryhill/Kelvin, 15 Newlands/Auldburn, 16 North East, 17 Partick West, 18 Pollokshields, 19 Shettleston, 20 Southside Central, 21 Springburn

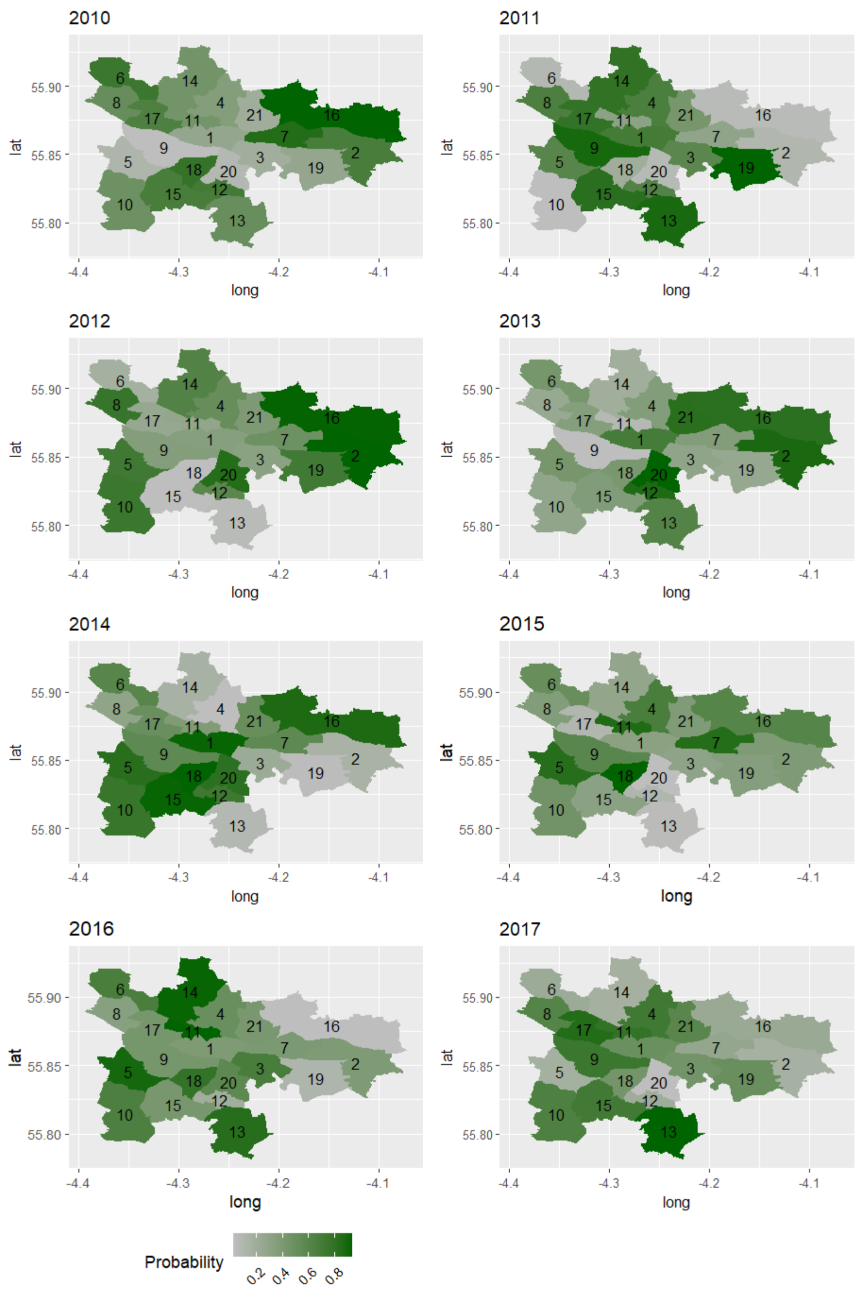

Figure 5.19: Spatio-temporal Exceedance Probability (EP) at ward level
1 Anderston/City, 2 Baillieston, 3 Calton, 4 Canal, 5 Craigton, 6 Drumchapel/Anniesland, 7 East Centre, 8 Garscadden/Scotstounhill, 9 Govan, 10 Greater Pollok, 11 Hillhead, 12 Langside, 13 Linn, 14 Maryhill/Kelvin, 15 Newlands/Auldburn, 16 North East, 17 Partick West, 18 Pollokshields, 19 Shettleston, 20 Southside Central, 21 Springburn

Examining the spatio-temporal relative rate alone does not give a full picture of the spatio-temporal variation. It is more informative to examine how the spatio-temporal effects deviate from the overall spatial effect. Figure 5.20 shows the overall spatial effect (u_j) and the spatio-temporal deviation (v_j) combined for Anderston/City, Craigton, North East and Pollokshields (where zero is the null value and deviations from null shows whether the higher RR depends on the cohort).

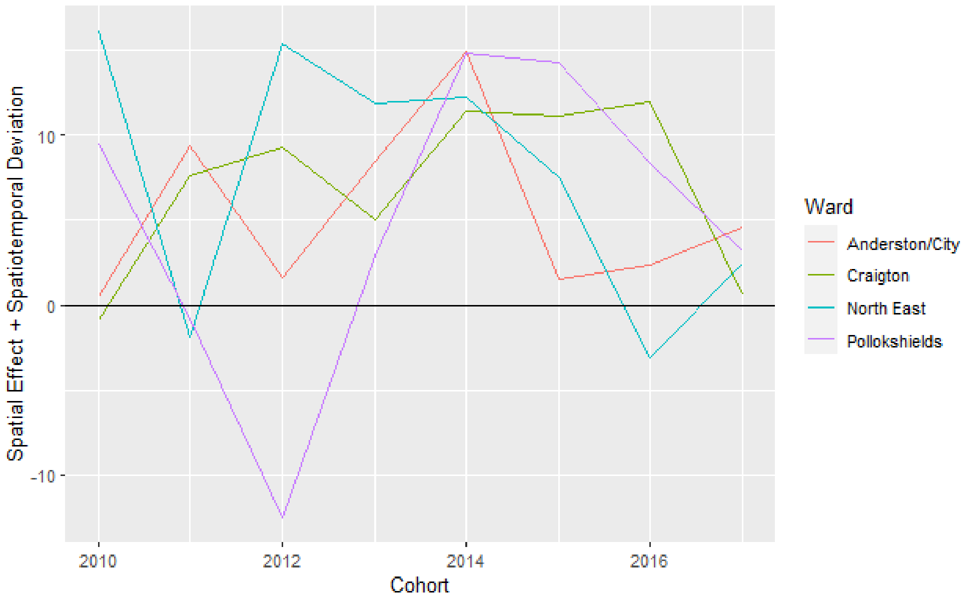

Figure 5.20: Overall spatial and spatio-temporal deviation effect at ward level

Despite being worse than expected overall, in 2012, Pollokshields is considerably better than expected. After adding the spatio-temporal term, the overall spatial effect of Pollokshield fell below the exceedance probability (EP) threshold for certainty (EP > 0.8) to 0.78. This means now only North East, Anderston/City and Craigton have an overall spatial effect.

This spatio-temporal pattern is likely to reflect the short-term ward changes. For example, populations within North East and Anderston have been highlighted for their considerable changes in recent years as a result of renewal and regeneration [77].

5.4.3 Sensitivity Analysis: Preschool Samples

The spatio-temporal variation could be due to the changing characteristics of included preschools over the years of the study (shown in Table 5.13). Preschools that collected data in every cohort are referred to as returning preschools. There were 16 preschools (with 125 children) that were only in the ChiME study for 1 cohort and 60 returning preschools, with a total of 19 017 children participating across the years. The median difficulties scores varied across the years of involvement in ChiME. Preschools that were only partially involved in the study (for example, took part in 4 or 5 cohorts) had slightly lower SDQ scores. This was formally assessed as part of the evaluation of the Triple P programme and there were no considerable differences in the SDQ scores at a population level between the preschools that remained in the study during every cohort and those that did not [63]. The proportion of boys ranged from 48-56%, and children outside the expected age ranged from 7-11%. The 6 preschools that were only in 2 cohorts had the highest proportion of boys and children outside the expected age range. Deprivation varied the most across involvement in the study from 5% to 30% of children in the most deprived quintile. Adjustment for demographics means the preschool variation found in the models, is after accounting for these differences. But there may be additional characteristics of the sample, that are non-random and have not been accounted for.

Table 5.13: Preschool demographics by years of involvement in ChiME

Years in study	Number of preschools	Children in preschools	Median SDQ (IQR)	% Most deprived	% Boys	Outside % expected age
1	16	125	5(2-9)	11 (8.8%)	61 (48.8%)	11 (8.8%)
2	6	262	5(2-9)	39 (14.9%)	148 (56.5%)	30 (11.4%)
3	7	340	4(1-9)	18 (5.29%)	165 (48.5%)	25 (7.4%)
4	21	1114	3(0-6)	122(11.3%)	528 (47.4%)	85 (7.6%)
5	24	2117	3(0-7)	406(19.2%)	1073 (50.7%)	130 (6.1%)
6	18	4342	5(2-9)	1209 (27.8%)	2255 (51.9%)	333 (7.7%)
7	28	7854	4(1-8)	1941 (24.7%)	4069 (51.8%)	604 (7.7%)
8	60	19 017	5(2-9)	5869 (30.9%)	9660 (50.8%)	1393 (7.3%)

Changing preschool samples may affect the representativeness of a ward sample, as each preschool will have a different geographic reach (demonstrated in Figure 5.2). Table 5.14 shows the percentage of children, by year and ward, that were from a returning preschool. There was a wide variation by ward. For example, in 2011 only 14.6% of the sample living in Baillieston were from returning preschools, compared to 100% of the sample living in Partick West.

Table 5.14: Ward reach (%) of returning preschools

Ward	2010	2011	2012	2013	2014	2015	2016	2017
Anderston/City	48.1	87.0	59	58.9	50.7	52.0	51.6	46.1
Baillieston	33.3	14.6	28.4	30.8	18.0	27.3	19.3	28.4
Calton	95.3	76.7	81.1	78.7	75.3	73.7	66.4	71.5
Canal	69.3	62.8	56.3	63.6	45.4	39.9	47.0	47.8
Craigton	70	61.2	61.7	59.2	50	53.2	50.7	49.8
Drumchapel/Anniesland	85.7	79.2	78.3	93.5	69.9	74.4	79.5	77.3
East Centre	87.9	51.8	48.5	58.7	42.1	52.1	48.3	44.3
Garscadden/Scotstounhill	80.3	88.5	90.5	93.8	77.9	83.8	77.4	78.4
Govan	39.2	33.7	29.0	36.6	25.9	28.3	23.7	30
Greater Pollok	76.0	65.8	56.3	83.6	63.6	56.8	51.3	53.5
Hillhead	52.2	31.7	56.2	51.7	39.4	37.0	43.7	43.6
Langside	41.1	42.4	38.0	38.0	37.7	35.0	34.5	36.8
Linn	48.9	68.0	64	45.9	43.9	42.7	45.5	43.5
Maryhill/Kelvin	72.6	86.6	70.5	70.1	50.5	56.7	56.3	61.6
Newlands/Auldburn	48.6	50	93.1	90.4	70.9	75.4	80.3	76.6
North East	71.1	60.8	63.2	66.1	49.9	55.0	51.0	69.9
Partick West	51.9	100	89.2	87.4	61.2	64.6	66.5	65.2
Pollokshields	71.6	88.2	90.3	95.4	60.3	61.1	67.2	72.5
Shettleston	73.2	17.6	52.4	33.2	23.6	27.9	29.9	32.6
Southside Central	55.2	31.6	29.6	35.9	26.3	27.6	26.3	28.9
Springburn	51.5	47.4	37.2	46.7	35.1	42.6	46.3	42.6

A sensitivity analysis was conducted to investigate whether the spatial and spatio-temporal variation held for the 60 preschools that took part in the study every year – this was a sample of 19017 children (Table 5.15).

The fixed effects estimates were similar across the two samples. Variance parameters were smaller. The mean parameter estimates do not fall inside the credible intervals from the full sample. There appears to be slightly less spatial and spatio-temporal variability, this may be due to the small sample.

The spatio-temporal RR was similar at 0.87-1.10 (compared to 0.87-1.16 in the full

Table 5.15: Sensitivity analysis for Equation 5.10 based on preschool sample

Parameter	All Preschools	Returner Preschools
	Relative Rate (95% CrI)	Relative Rate (95% CrI)
Intercept	4.056(3.777-4.356)	4.315 (3.986-4.670)
Cohort	1.009 (1.002-1.015)	1.014 (1.007-1.021)
Sex (Male)	1.370 (1.344-1.397)	1.360 (1.327-1.395)
Deprivation (4th vs 5th)	1.115 (1.072-1.159)	1.113 (1.058-1.172)
Deprivation (3rd vs 5th)	1.176 (1.130-1.224)	1.175 (1.115-1.239)
Deprivation (2nd vs 5th)	1.235 (1.187-1.285)	1.226 (1.163-1.291)
Deprivation (1st vs 5th)	1.245 (1.195-1.296)	1.263 (1.199-1.331)
Age (centered and squared)	1.003 (1.003-1.004)	1.003 (1.003-1.004)
	Variance (95% CrI)	Variance (95% CrI)
Ward	0.011 (0.007-0.018)	0.004 (0.002-0.009)
Preschool	0.059 (0.046-0.084)	0.040 (0.026-0.063)
Spatio-temporal	0.006 (0.004-0.009)	0.003 (0.002-0.006)

CrI- Credible Interval

sample). There was still support for spatio-temporal interaction according to Bayes Factor (logBF=11.58).

For the overall spatial effect, the ward RR range was similar (0.91-1.06 vs 0.92-1.06 in the full sample), however the wards identified as high risk with certainty changed to East Centre, Langside, and North East. Only the North East was also identified in the full sample. All three wards were among those identified as high risk in 2010-2012 subset of the data [64]. This suggests that the additional preschools for the later cohorts have impacted the spatial distribution of the outcome. However, it is worth noting that the characteristics of the returning preschool sample differ from expected in the overall population, as local authority schools were early adopters. No partnership schools (i.e. those from the voluntary sector and private business) were returning preschools. There may be a bias in years of involvement in the ChiME study towards preschools with greater capacity for SDQ assessment or preschools with greater need for assessment. Using a whole study sample increases the geographic reach of the study and is assumed to be more representative, as the preschools involved in early years only reached 54% of the target sample (Table 1.3).

5.5 Discussion

There are several inequalities in total difficulties scores found using the long term (2010-2017) ChiME data. Demographic factors such as age, sex, and deprivation were all associated with total difficulties scores. Children outside the expected age of school start, boys and those in higher deprivation quintiles than the least deprived group had more total difficulties on average. These demographic patterns in social, emotional and behavioural scores are consistent with the literature [8, 91, 92].

There was an increasing temporal trend, meaning there was a small, cumulative increase in population average over the study period. This may be due to worsening mental well-being in this age group or increased reporting over time (e.g. due to policy changes). In a review of representative population studies between 2000 and 2014, few were found to examine long-term changes in emotional and conduct problems in young children [279]. Among the identified studies, temporal trends varied between the Netherlands, Brazil, Germany and the UK – though this may reflect differences in study methodology [279].

Model building showed there is evidence to support several contexts in the role of the individual variation in total difficulties. Both the preschool and ward contexts were important to understanding variation in total difficulties according to the models. Children in the same ward (or preschool) are more alike than children in different wards (or preschools). This provides further support to the proposed pathway in the literature review which showed the role of multiple contexts on child development (See Figure 2.1).

The model was improved by the cross-classified structure, therefore, focusing on one context does not provide the complete picture. Most children stayed in their ward for preschool, but this varied depending on the ward and the deprivation quintile. This differs from a preschool sample in Massachusetts, US where most children were found to leave their residential neighbourhood to attend preschool, regardless of socioeconomic status [280]. The cross-classified data structure means there is an additive effect from the preschool and ward contexts. A child in a ward and preschool that are both worse than expected is at even higher risk. This represented roughly 10% of the total sample. The preschool effects could be due to similarities in preschool choice according to developmental outcomes, preschool processes that influence development outcomes or differences in how the staff measure developmental outcomes. It may be that further work is needed to standardise the process of SDQ assessments.

There was limited explanatory power associated with the covariates, i.e. how much the contextual variation is explained by the demographics. This means that the proxy for household deprivation is not a distinguishing factor in the variation in wards. This suggests there is a need to consider factors beyond deprivation to reduce area level inequalities. The map of the ward RR shows areas of priority in comparison to the city average, based on demographics. The exceedance probability gives an idea of the uncertainty (with a cut point of 0.8%).

Some wards with high RR were already noted in Chapter 1 for being sites of place-based activity (e.g. North East (Table 1.4)). Though found to be worse than expected, initiatives in the North East ward may yet to lead to meaningful differences in total difficulties at the point of data collection. There were limited similarities between the wards that were worse than expected at an individual level (supporting the lack of explanatory power in the covariates). However, the North East ward had the highest level of deprivation, which explains why it is already considered an area of interest for policymakers.

The cross classified model was extended to allow spatio-temporal variation to be captured. Firstly, a model was built to review if the temporal trend is consistent across all wards. A comparison of disease mapping and multilevel approaches showed both have utility in identifying and predicting changes in children's difficulties over time, and therefore can make important contributions to policy development and resource allocation. The multilevel model provided more information on contextual and demographic effects. There was no evidence in either approach to support wards having increasing or decreasing difficulties consistently over time. Areas with increasing and decreasing trends have been examined in related outcomes such as child malnutrition

[281], mortality [282] and maltreatment [51]. At the time of writing, we were unable to find similar studies in social, emotional and behavioural development.

Instead, the best model allowed independent spatio-temporal interactions. When observing only an overall spatial effect, this can attenuate contrasting spatio-temporal deviations. Spatio-temporal deviations should be considered along side their overall spatial effect for a true picture of the contextual effect. A deviation from an overall spatial effect does not necessarily mean there is a meaningful difference in average scores (Figure 5.20)

Purely spatial models are used with the justification that aggregating several years provides more stability in the estimates, but aggregating many years may bias our understanding of neighbourhoods that are worse than expected. Neighbourhood variation is not solely due to consistently poor performing areas. Instead, there is evidence of yearly variations in total difficulties across wards. Spatial analysis using only a single or few years may lead to misleading conclusions about area level variability.

The spatial and spatio-temporal profile of total difficulties scores here at preschool differ from those identified from the health review at 27-30 months (See Figure 1.2). This may be in part due to the difference in the geographic boundaries used. The health review used Intermediate zones, while this analysis was conducted at electoral ward level. This is discussed in the next chapter.

Sensitivity analysis was conducted to understand the impact of selection bias on model estimates. This was conducted by comparing the estimates in the full sample with the preschools that collected data in every cohort (returners). Returning preschools had smaller variance estimates for all random effects. There was a difference in the areas identified as high risk. The profile of preschools that responded to the invitation for data collection affected the geographic reach of the sample each year and, consequently, which wards were considered better or worse than expected.

Chapter 6

Estimating the Role of the Neighbourhood Context on Social, Emotional and Behavioural Development in Glasgow at Multiple Scales

This chapter discusses how consistent the spatial distribution of total difficulties is across multiple geographic scales. There may be additional spatial patterns within a ward that could benefit from targeted intervention. Or, it may be that the ward boundary does not accurately reflect the neighbourhood context and that there are hidden neighbourhood effects that would only be revealed through another boundary. In this chapter, differences between model inference according to the geographic scale are a source of bias in the analysis. The impact of the geographic scale was compared based on:

- The location of the areas identified as being worse than expected.
- The relationship between individuals within a neighbourhood (i.e. their correlation within an area) and the relationship between neighbouring areas (i.e. their

spatial correlation).

- The relative importance of the neighbourhood compared to other contexts.

6.1 Alternative Neighbourhood Boundaries

Previous studies have demonstrated the impact that geographic scale has on the relationship between neighbourhood and early development. In the United States [47] and Canada, [273], clustering of child social, emotional and behavioural problems was found at the smaller area level which supported place-based approaches, while at a larger scale, there was less variation, supporting a more universal approach.

In this project, there were two main considerations when selecting the lower level geographies for analysis:

- Relevance: The scale should focus on the geographic level that policy and interventions are most likely to apply so that the analysis is relevant to decision-makers. The scale should consider whether the boundary was meaningful to the residents in the neighbourhood and if the boundary definition was generalisable for research.

- Consistency: When data at an area level are collected over time, a new challenge introduced is ensuring the consistency of these areas over time. For areal data, typically administrative or statistical boundaries are used. But these can change for many reasons, including population dynamics, housing developments and demolitions. This particularly affects smaller area geographies that are thought to be more representative of a neighbourhood. Individuals with a certain postcode may no longer be considered members of an area, or a geographic space may no longer be within a border. This not only affects how we conceptually think of an area but also how the characteristics of that area are defined, such as the level of employment or the proportion of greenspace.

I considered three alternative boundaries: Community Planning Partnership (CPP) Localities, Intermediate Zones and Consistent Areas Through Time (CATTs). Each boundary was applied to the adjusted (cross-classified) spatio-temporal model in Chapter 5 (Equation 5.10):

$$
\begin{aligned}
\eta_{ijk} = \exp(\beta_0 + \beta_1 \mathrm{t} + \beta_2 \mathrm{age} + \beta_3 \mathrm{sex} + \beta_4 \mathrm{deprivation} + v_{0j} + \alpha_k + \phi \\
v_{0j} \sim N(0, \sigma^2_{v0}), \frac{1}{\sigma^2_{v0}} \sim \Gamma^{-1}(1, 0.0005) \\
\alpha_k \sim N(0, \sigma^2_{\alpha}), \frac{1}{\sigma^2_{\alpha}} \sim \Gamma^{-1}(1, 0.0005) \\
\phi \sim N(0, \sigma^2_{\phi}), \frac{1}{\sigma^2_{\phi}} \sim \Gamma^{-1}(1, 0.0005)
\end{aligned}
\tag{5.10 revisited}
$$

Random effects α_k are added for preschools k=1,...,180 so that there is an intercept for every preschool (see Equation 5.3). This accounts for any variation in the measurement of SDQ between the preschools and similarities between children within the same preschool. There is an unstructured spatial main effect v_{0j} and an unstructured spatio-temporal interaction ϕ, whereby the interaction describes deviations from the main effect. Random effects account for individual level variables: age, sex and household deprivation (measured by SIMD quintile where 1 is the most deprived quintile).

6.1.1 Community Planning Partnerships (CPP) Localities

The localities were introduced in Chapter 1. Boundaries for localities were obtained by request from Glasgow City Council. ChiME postcodes were plotted against the locality boundaries to assign each child to a locality.

There were 5 postcodes that did not fall within the locality boundaries provided. These were assigned to the closest locality (Easterhouse in the North East and Baillieston/Garrowhill in the East). For the remaining unmatched postcodes in the South, as they bordered multiple localities, localities were assigned based on their electoral ward (Southside Central) placing them in Toryglen. On average, there were 628 children in each locality. The most populated was Drumchapel with 1380 children and the least was Carmunnock with 38.

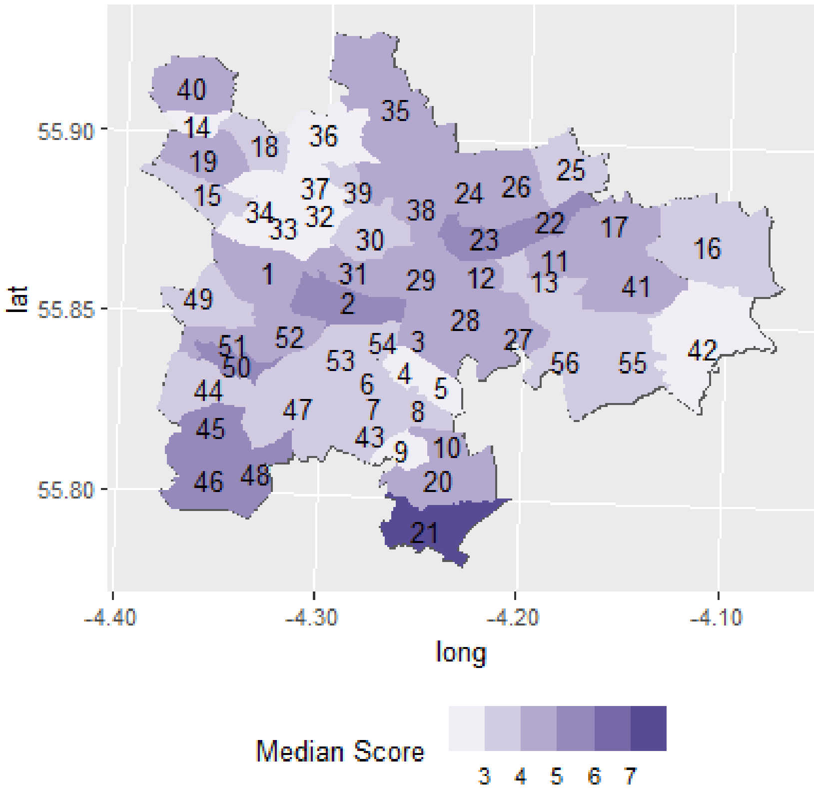

Figure 6.1: Median difficulties score by locality
1.Greater Govan, 2.Ibrox / Kingston, 3.Greater Gorbals, 4.Govanhill, 5.Toryglen, 6.Shawlands / Strathbungo, 7.Langside / Battlefield, 8.King's Park / Mount Florida, 9.Cathcart / Simshill, 10.Croftfoot, 11.Riddrie / Cranhill, 12.Dennistoun, 13.Haghill / Carntyne, 14.Blairdardie, 15.Yoker / Scotstoun, 16.Easterhouse, 17.Ruchazie / Garthamlock, 18.Temple / Anniesland, 19.Knightswood, 20.Castlemilk, 21.Carmunnock, 22.Blackhill / Hogganfield, 23.Sighthill / Roystonhill / Germiston, 24.Springburn, 25.Robroyston / Millerston, 26.Balornock/ Barmulloch, 27.Parkhead / Dalmarnock, 28.Calton / Bridgeton, 29.City Centre / Merchant City, 30.Hillhead / Woodlands, 31.Yorkhill / Anderston, 32.Hyndland / Dowanhill / Partick East, 33.Broomhill / Partick West, 34.Anniesland / Jordanhill / Whiteinch, 35.Lambhill / Milton, 36.North Maryhill / Summerston, 37.Kelvindale / Kelvinside, 38.Ruchill / Possilpark, 39.Maryhill Road Corridor, 40.Drumchapel, 41.Springboig / Barlanark, 42.Baillieston / Garrowhill, 43.Newlands / Cathcart, 44.Pollok, 45.Priesthill / Househillwood, 46.South Nitshill / Darnley, 47.Pollokshaws / Mansewood, 48.Arden / Carnwadric, 49.North Cardonald / Penilee, 50.Corkerhill / North Pollok, 51.Crookston /South Cardonald, 52.Bellahouston / Craigton / Mosspark, 53.Pollokshields West, 54.Pollokshields East, 55.Mount Vernon / East Shettleston, 56.Tollcross / West Shettleston

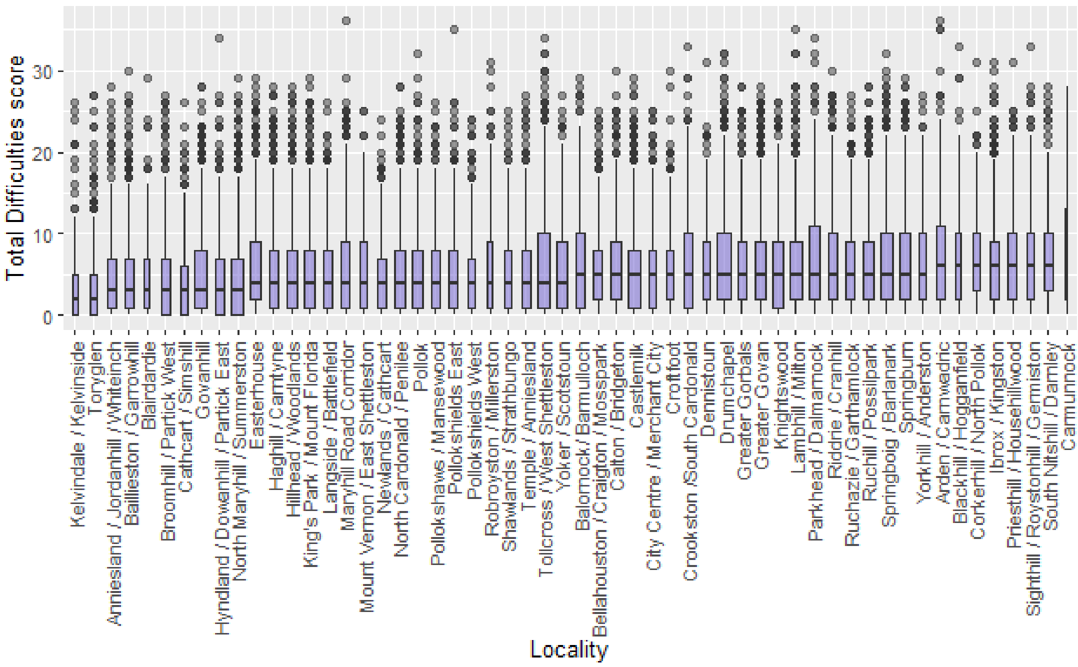

Figure 6.2: Total difficulties score by locality

Figure 6.2 shows the distribution of total difficulties scores across the localities. Median scores ranged from 2 in Toryglen and Kelvindale/ Kelvinside to 7.5 in Carmunnock. A map of the median scores in Figure 6.1 shows there are some clusters of lower scores in the North West. Otherwise, there is no discernible pattern.

To model the scores by locality, the adjusted spatio-temporal model (Equation 5.10) was applied. Now the random effect u_j allows 56 intercepts for each locality and ϕ allows 448 intercepts for each locality and cohort interaction.

The residuals of the model were assessed for spatial correlation, this time at the level of locality. Moran's I = 0.19 (p=0.004) indicating there is weak dependence between the neighbouring localities. There was no evidence of spatio-temporal dependence (I=-0.04, p=0.93) or temporal dependence (DW = 1.81, p = 0.39) in the residuals. To account for the spatial dependence, three structures (see Chapter 4.4.1) were compared to find the best fit for the data.

- First, using two parameters to describe the spatial structure: a spatial convolution (or BYM) where there is the unstructured spatial effect u_j and a spatially structured random effect u_{ICAR} with an Intrinsic CAR (ICAR) prior (see in Equation 3.11) with default INLA hyper-priors.

- Secondly, random effects at locality level are only described using the spatial structured u_{ICAR} with an Intrinsic CAR (ICAR) prior.

- And finally a Leroux CAR where there is one spatially structured random effect u_{LEROUX} which includes parameter ρ to indicate the degree of spatial correlation with default INLA priors.

Table 6.1: Locality spatial variance estimates

Structure	Unstructured Variance (95% CrI)	Spatially Structured Variance (95% CrI)	DIC	Spatial Dependence (95% CrI)	BF
u_j	0.002 (0.001-0.004)		196131		
$u_j + u_{ICAR}$	0.000 (0.000-0.001)	0.000(0.000-0.001)	196133		-8.16
u_{ICAR}		0.008 (0.006-0.011)	196132		12.76
u_{LEROUX}		0.014 (0.010-0.020)	196121	0.82(0.61-0.91)	-10.38

DIC Deviance Information Criterion. CAR Conditional Autoregressive random effect. BF Bayes Factor in each case is in comparison to the model above

Selecting spatially structured models on the basis of goodness-of-fit alone (such as DIC) is discouraged [283]. The DIC tends to favour under smoothing in disease mapping models [283]. Instead, goodness-of-smoothing should be considered, although guidelines for what is considered appropriate level smoothing are still to be determined [283]. Table 6.1 shows that adding the ICAR effect reduced both variance terms to zero. This is likely due to over parameterisation [216]. There was negative evidence to support the use of a BYM model (structured CAR term with an unstructured term) according to Bayes Factor (logBF=-8.16). Simplifying the model to ICAR meant the variance could be estimated. However, a limitation of this model is that it has not accounted for the within locality variation. Bayes Factor showed there was still strong evidence of including the unstructured variation term (logBF=12.76).

In the Leroux model, the spatial dependence parameter $\rho = 0.82(0.61 - 0.91)$ was close to 1 indicating strong spatial dependence is accounted for in the model but also that there is the presence of some independent variation. The evidence supporting the ρ term was limited according to Bayes Factor (logBF=-10.38) when compared to the simplified ICAR model. Taking the evidence altogether, the Leroux model is considered a moderate approach between an under-smoothed model (using only the unstructured effect) and a potentially over-smoothed model (with solely an ICAR).

Table 6.2: Model estimates for Equation 5.10 at locality level

Parameter	Relative Rate	95 % Credible Intervals
Intercept	4.096	3.720-4.510
Cohort	1.008	1.002-1.014
Sex (Male)	1.371	1.345-1.398
Deprivation (4th vs 5th)	1.106	1.063-1.150
Deprivation (3rd vs 5th)	1.161	1.114-1.210
Deprivation (2nd vs 5th)	1.219	1.169-1.270
Deprivation (1st vs 5th)	1.230	1.179-1.284
Age	1.003	1.003-1.004
	Variance	95 % Credible Intervals
Locality	0.014	0.010-0.020
Preschool	0.064	0.042-0.090
Spatio-temporal	0.007	0.004-0.011
DIC	196121	

Using the Leroux model, Figure 6.3 shows the relative rate of difficulties after accounting for demographics (shown in Table 6.2) and the exceedance probability that the rate is greater than one. The outlines show the electoral ward boundaries. The relative rate ranged from 0.90-1.10. Only 2 areas had an exceedance probability above the cut-off of 0.8: Easterhouse (16) & Robroyston / Millerston (25) both located in the North East ward. Therefore, as in the ward model, North East is worse than expected based on its demographics. However, only focusing on the locality misses some effects that apply to the ward (for example, the elevated RR in Anderston/City and Craigton). For these other wards, it appears that the elevated RR was not explained by any further clustering at the locality level.

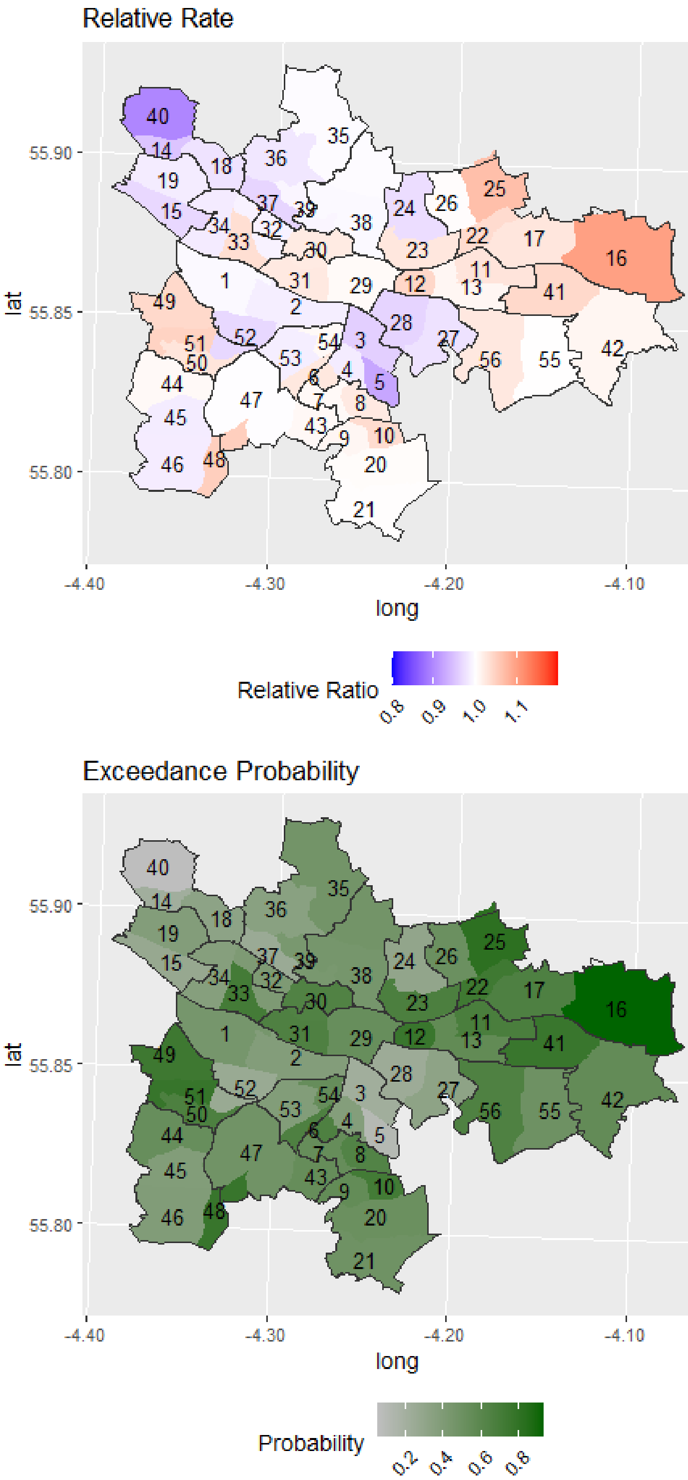

Figure 6.3: Spatial Relative Rate (RR) and exceedance probability at locality level
For Key, see Figure 6.1.

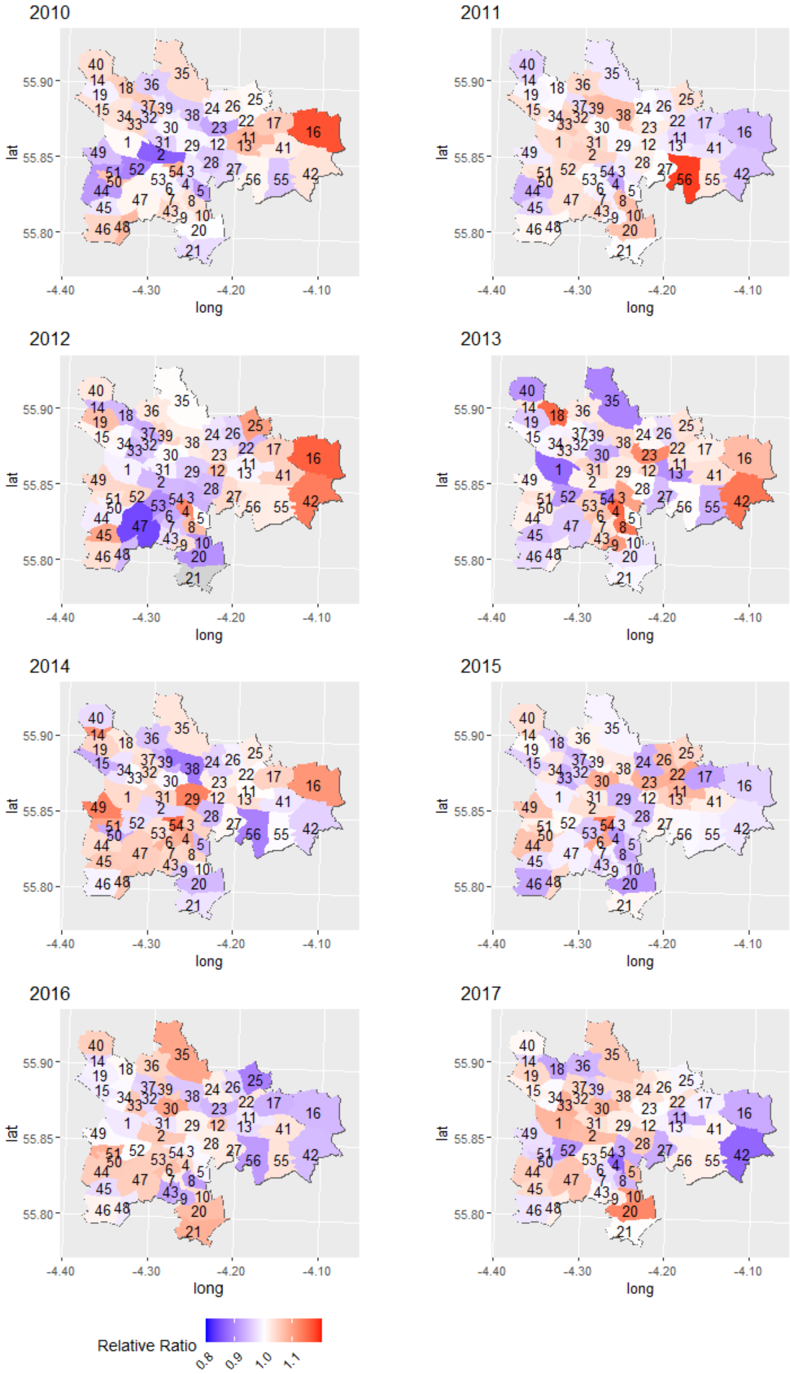

Figure 6.4: Spatio-temporal Relative Rate (RR) at locality level
For Key, see Figure 6.1. Note there were no children in locality 21 in 2012.

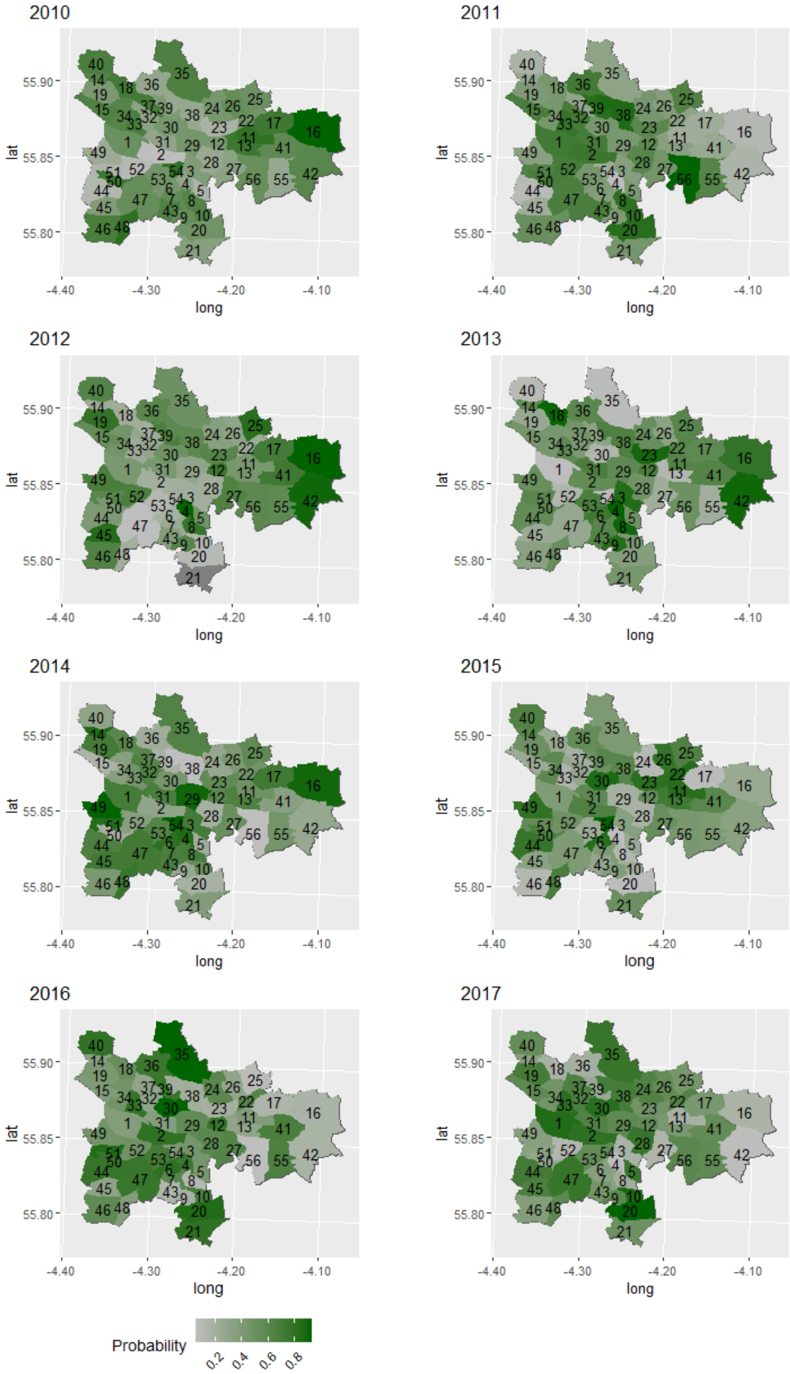

Figure 6.5: Spatio-temporal exceedance probability at locality level
For Key, see Figure 6.1. Note there were no children in locality 21 in 2012.

Localities 16 and 25 (Easterhouse & Robroyston / Millerston) were identified for the overall spatial effect (Figure 6.3), and their spatio-temporal deviation (Figure 6.4) showed there were even higher scores in the earlier cohorts. Other localities alternate between high and low RR across the cohorts.

6.1.2 Intermediate Zones

Data zones (described in Chapter 2) can be aggregated into Intermediate Zones (IZ) which each represent a population of 2,500 to 6,000 people who live within a geographical boundary and share social characteristics. Intermediate Zones have been suggested for use as part of the Scottish government's new action plan to provide more data at the small area level [284]. Intermediate Zones are the boundary used for 27-30 month child review reviews (See Figure 1.2).

As with data zones, there were 2 separate Intermediate Zone boundaries used for the study, based on the 2001 and 2011 censuses. The 2011 boundaries were released in 2014. Cohorts 2010–2013 use the 2001 boundaries and cohorts 2014–2017 use the 2011 boundaries. Figure 6.6 shows the different boundaries for 2001 and 2011 in the top panel and how they overlap in the bottom panel. There were 133 IZs for 2001 IZs and 136 for 2011 IZs. The corresponding names and codes for each IZ are shown in the Appendix D.1 and D.2.

There were two main impacts of the changes in boundaries: area changes and population changes. Area changes are the extent that the physical boundaries match as shown in Figure 6.6. For data zones, which are aggregated into Intermediate Zones, only 399 out of 6976 (5.7%) directly cover the same geographic area in 2001 as in 2011. Population changes are whether the individuals (based on postcodes) are in the same data zone. There were 3,499 out of 6,976 (50.2%) data zones in Scotland that include the same postcodes in 2001 as in 2011.

Intermediate Zones are advantageous as they represent contemporaneous communities, but this inhibits the ability to make comparisons about long term spatial trends. Scottish Government advises against applying analysis to incongruous boundaries for temporal analysis.

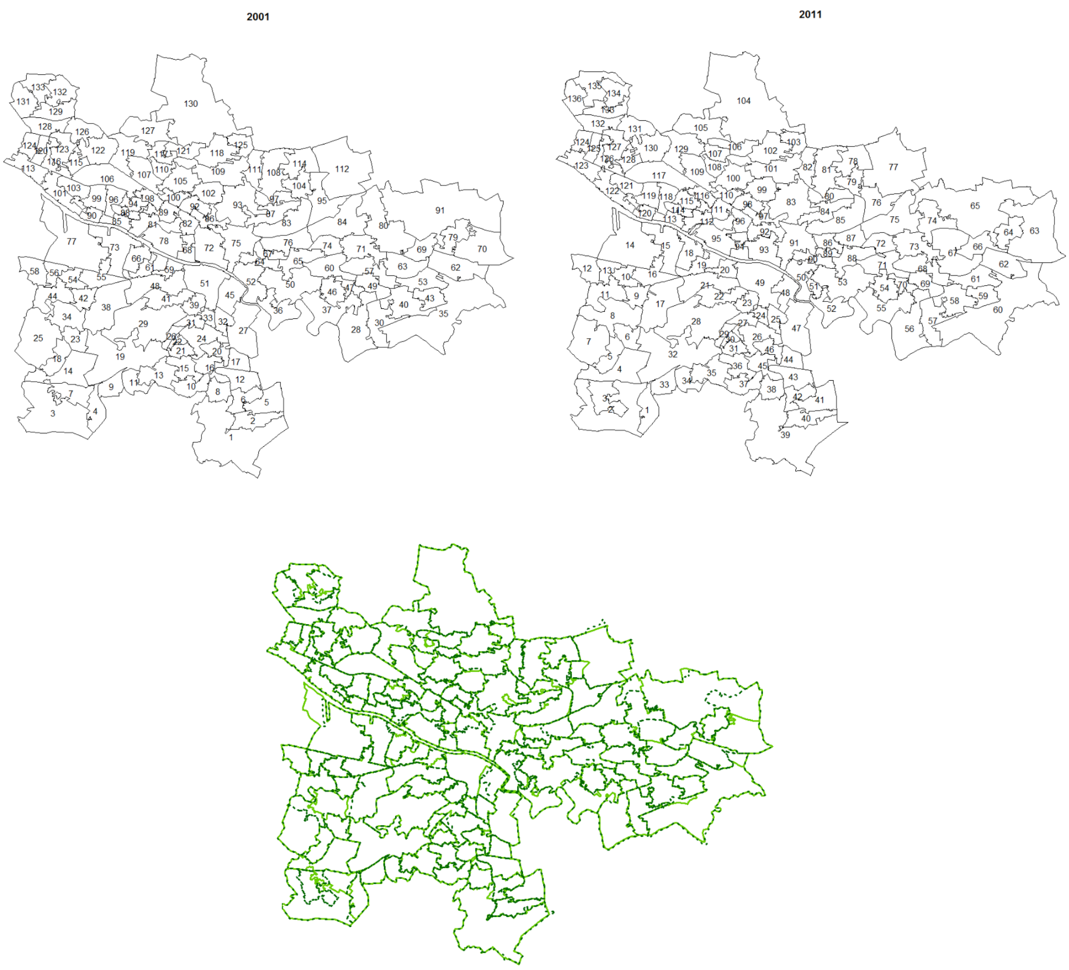

Figure 6.6: Intermediate Zones - 2001 and 2011 boundaries
Boundaries for 2001 and 2011 in the top panel and how they overlap in the bottom panel. 2001 is light green, 2011 is dark green.

The analysis at the IZ level is not directly comparable to the results of the previous sections. Intermediate Zones do not nest into the electoral wards or localities (Figure 6.7). Moreover, IZ analysis deals with two subsets of the data: 2010-2013 (i.e. those within 2001 IZ (n=14 199)) and 2014-2017 (i.e. those within 2011 IZ (n=20 972)).

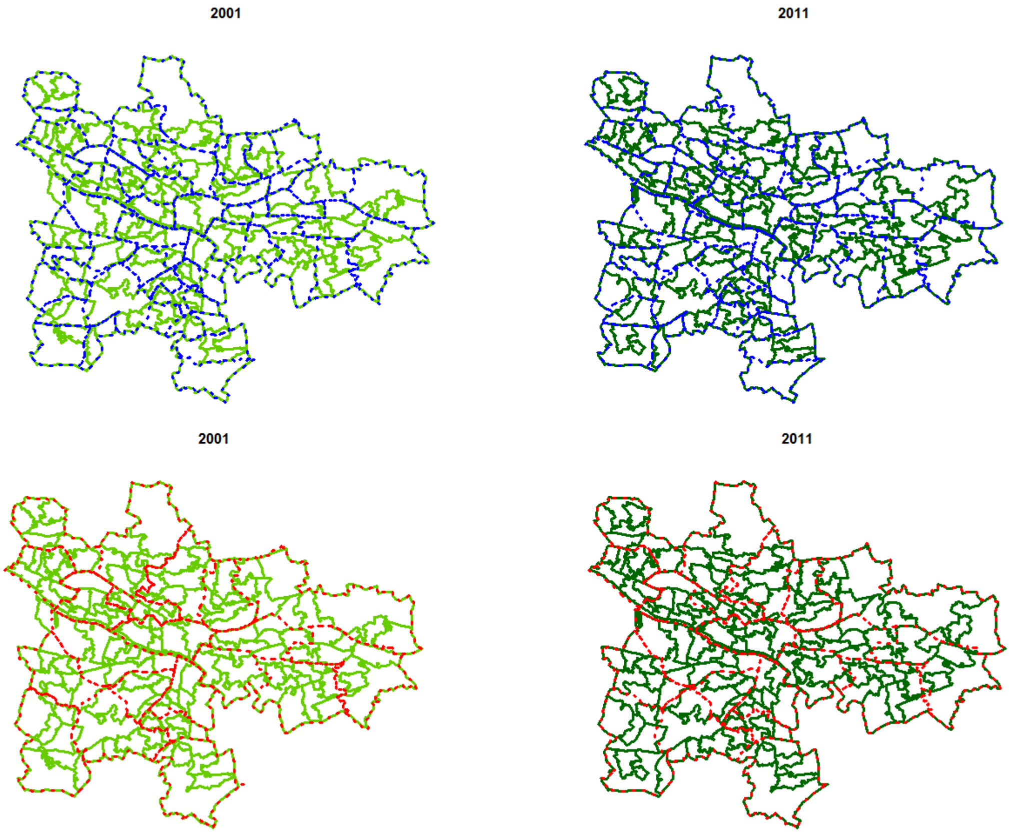

Figure 6.7: Intermediate Zones (green), localities (blue) and electoral wards (red)

There were on average 106 children in the 2001 IZ boundary, ranging from 31 to 265. The number of children in each 2011 IZ ranged from 31 to 319 with 154 on average.

Median scores ranged from 1-9 in the 2001 subset and from 1.5 to 8 in the 2011 subset (Figure 6.8). The plot shows that most areas have similar median scores and different areas are associated with higher median scores between the two subsets.

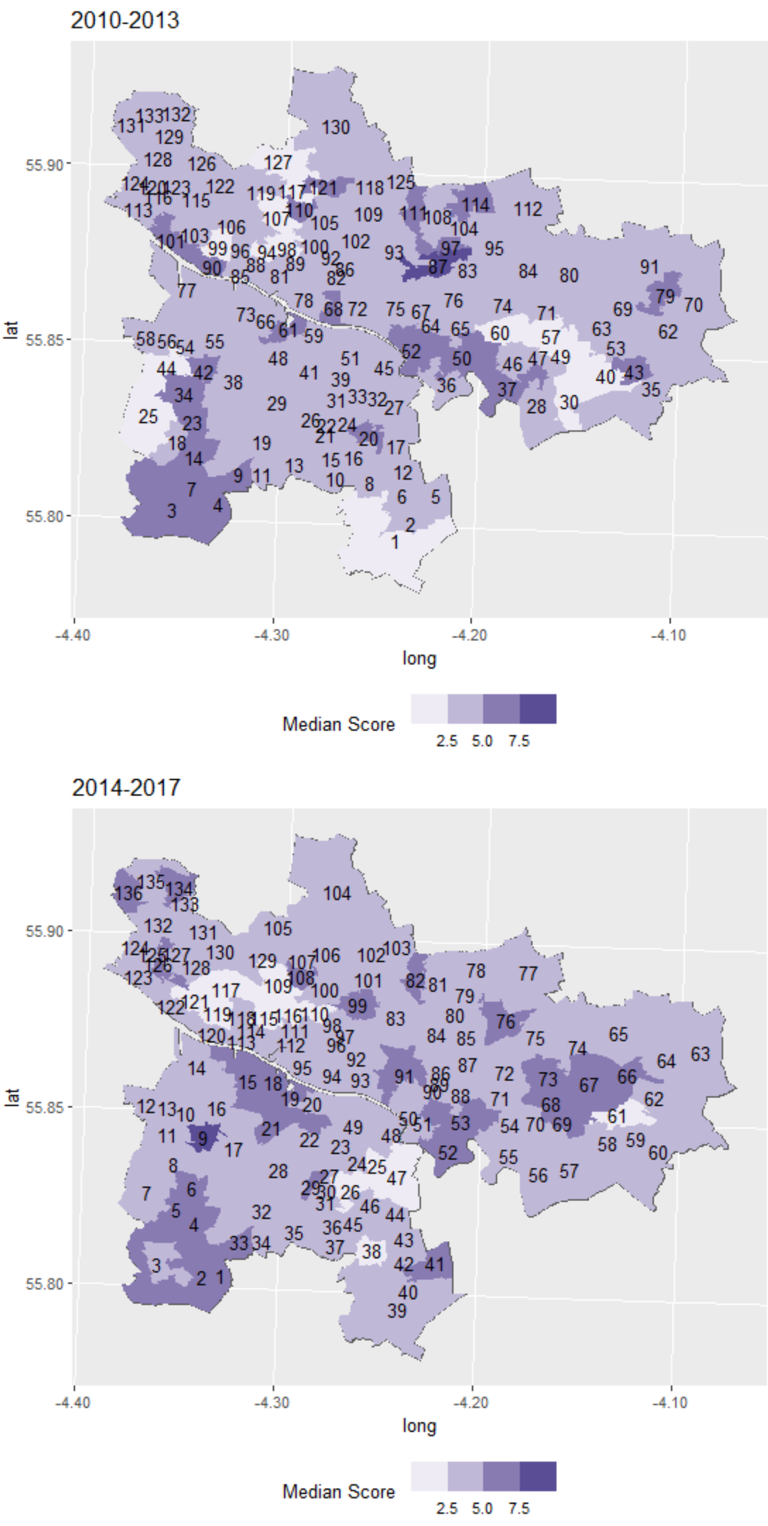

Figure 6.8: Median difficulties score by Intermediate Zone (IZ)

2010-2013

To model the scores by IZ, the adjusted spatio-temporal model equation 5.10 was applied. Now the random effect u_j allows 133 intercepts for each 2001 IZ and ϕ allows 532 intercepts for each 2001 IZ and cohort (2010-2013) interaction. The residuals of the model (DIC= 78769) were assessed for spatial correlation, this time at the level of 2001 IZ. Moran's I = 0.28 ($p<0.001$) indicates there is dependence between the neighbouring 2001 IZs. There was no evidence of spatio-temporal (Moran's I=0.02, p=0.14) or temporal (DW=1.26, p=0.19) dependence in the residuals. The model was adjusted for spatial dependence and independent spatio-temporal effects.

Following the localities spatio-temporal model, the spatial correlation was modelled using a Leroux CAR, where the dependence was ρ =0.94(0.60-1.00). There was no longer an increasing linear time trend, all other covariate effects were similar (Table 6.3).

Table 6.3: Model estimates for Equation 5.10 at 2001 IZ level

Parameter	Relative Rate	Credible Intervals
Intercept	4.373	4.012-4.510
Cohort	1.011	0.995-1.027
Sex (Male)	1.344	1.305-1.384
Deprivation (4th vs 5th)	1.123	1.056-1.194
Deprivation (3rd vs 5th)	1.152	1.082-1.226
Deprivation (2nd vs 5th)	1.208	1.135-1.286
Deprivation (1st vs 5th)	1.203	1.130-1.282
Age	1.003	1.003-1.004
	Variance	95 % Credible Intervals
2001 IZ	0.003	0.001-0.011
Preschool	0.047	0.032-0.066
Spatio-temporal	0.007	0.004-0.014
DIC	78761	

IZ Intermediate Zone DIC Deviance Information Criterion;

Spatial variance was small. Figure 6.9 shows the global spatial pattern where there are higher scores in the north-east of the city and lower scores in the south, however, the relative rate at 2001 IZ level ranged from 0.98-1.02 and according to the exceedance probability there were no areas with high certainty of increased spatial RR. As none of the estimates have reached the threshold for the exceedance probbaility (> 0.8), the spatial pattern shown in the figure may be due to chance.

There was a high certainty that the spatio-temporal effects were higher than average for 30 IZs (Figure 6.10). This was most common in 2013 (13 IZs) and least common in 2010 (4 IZs). There were no IZs that were frequently associated with higher RR across the years.

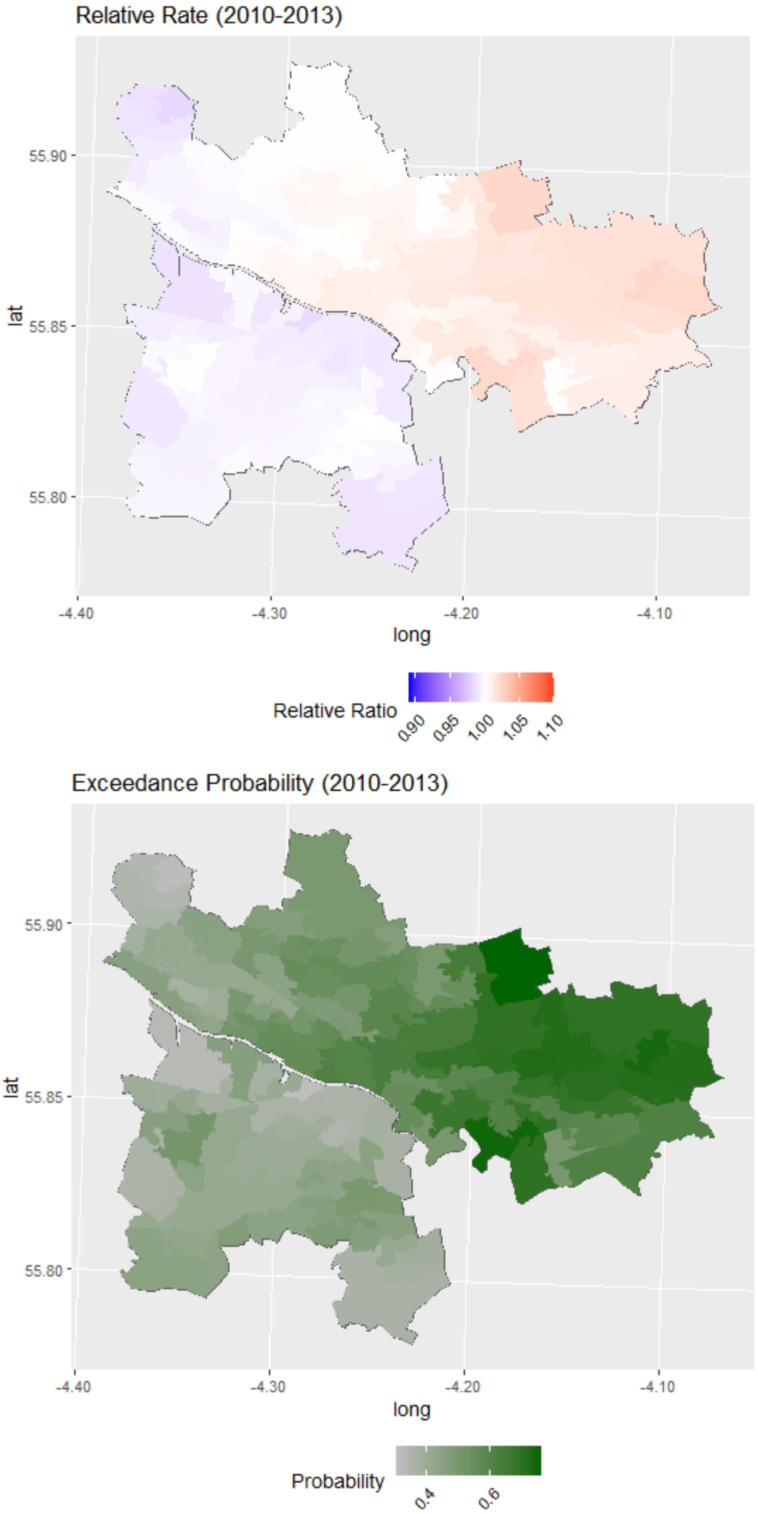

Figure 6.9: Spatial Relative Rate (RR) and Exceedance Probability (EP) at 2001 IZ Level

IZ Intermediate Zone. For Key, see Table D.1

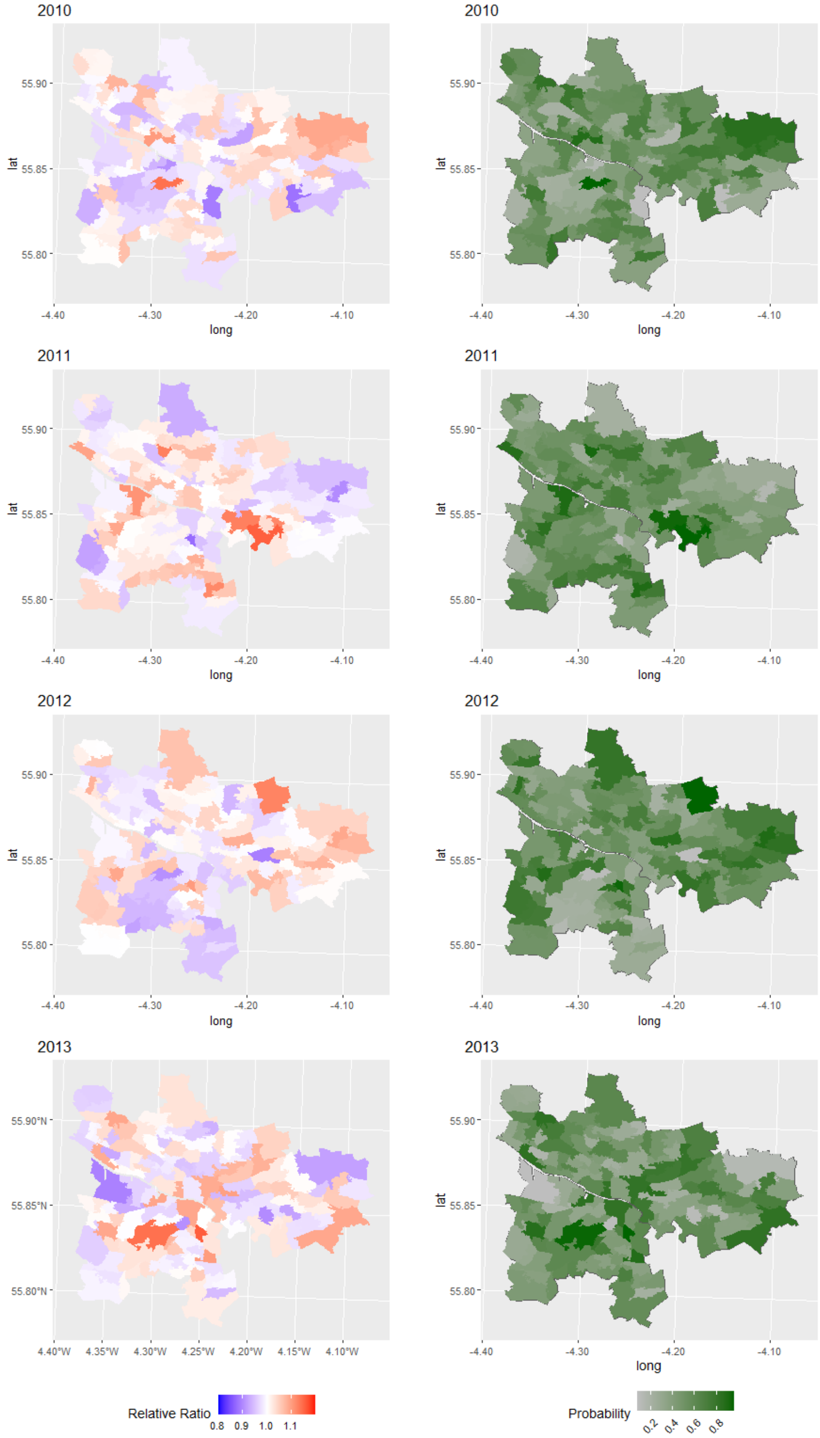

Figure 6.10: Spatio-temporal Relative Rate (RR) and Exceedance Probability (EP) at 2001 IZ Level

IZ Intermediate Zone. For Key, see Table D.1

2014-2017

The adjusted spatio-temporal model (Equation 5.10) was replicated at 2011 IZ level. However, the spatial and spatio-temporal parameters were estimated at 0 (Table 6.4).

There are a few possible explanations for the zero variance. Firstly, it could be that both random effects are attempting to capture the same variation and so are competing, resulting in reduced variance estimates [216]. Alternatively, the variance may be zero. This does not mean that there is no difference in difficulties spatially or spatio-temporally, but that the variation is no more than would be expected by chance [285]. Attempting alternative model structures helps to distinguish between the two explanations.

There was spatial dependence Moran's I = 0.25 ($p<0.001$) and very small spatio-temporal dependence in the residuals (Moran's I=0.10, p=<0.001) and no temporal dependence (DW =2.65, p=0.79). Of the spatio-temporal multilevel models in the literature, few discuss spatio-temporal dependence (as opposed to modelling spatial and temporal structures separately) and how to account for this in the model. Existing approaches do not deal with the scenario when dependence is small (e.g. [236]).

To account for the dependence in the model, and as spatio-temporal correlation was small, the MLM tCARs [230] described earlier in Chapter 3 were considered the most appropriate candidate. This would help to avoid over parameterising the model to estimate the spatio-temporal variance. These were compared with the spatio-temporal model and the spatial (& preschool) model (Equation 5.6) which was adapted to account for the spatial correlation (ρ= 0.76(0.31-0.96)).

The variance estimates, DICs, and residual spatio-temporal correlation were compared and shown in Table 6.4. In terms of goodness-of-fit (DIC), there was not a considerable difference between the models. In terms of spatio-temporal smoothing (Moran's I_{ST} is used as an indication), the best models were the adapted spatial (Equation 5.6) and the MLM CONVO. Notably, none of the models were able to completely remove the dependence in the model. This may bias the results.

Table 6.4: Spatio-temporal dependence at 2011 IZ level

		Spatio-temporal	Spatial	MLM ANOVA	MLM CONV
Variance	Structure				
Spatial	iid	0.000 (0.000-0.000)			
	Leroux		0.010 (0.004-0.022) ρ= 0.76 (0.31-0.96)	0.014 (0.009-0.025) ρ= 0.86 (0.64-0.97)	
Temporal	Leroux			0.015 (0.007-0.034) ρ=0.88 (0.71-0.97)	
Spatio-temporal	Type 1	0.000 (0.000-0.000)			0.000 (0.000-0.0002)
	Type 2				
	Type 3				0.003 (0.001-0.012)
	Type 4				
MoransI_{ST}		I=0.08, p<0.001	I=0.05, p=0.005	I=0.08, p<0.001	I=0.06, p=0.002
DIC		117126	117125	117128	117123

IZ Intermediate Zone; DIC Deviance Information Criterion. Brackets show 95% Credible Intervals. ρ is the spatial dependence parameter.

The model for 2011 IZ was chosen as Equation 5.6 as a balance of goodness-of-fit and goodness-of-smoothing.

Table 6.5: Model Estimates for Equation 5.6 at 2011 IZ level

Parameter	Relative Rate	95% Credible Intervals
Intercept	4.171	3.873-4.490
Cohort	1.006	0.994-1.017
Sex (Male)	1.389	1.355-1.425
Deprivation (4th vs 5th)	1.107	1.052-1.164
Deprivation (3rd vs 5th)	1.172	1.113-1.235
Deprivation (2nd vs 5th)	1.222	1.161-1.287
Deprivation (1st vs 5th)	1.253	1.188-1.322
Age	1.003	1.003-1.004
Parameter	**Variance**	**95% Credible Intervals**
2011 IZ	0.010	0.012-0.022
Preschool	0.082	0.083-0.112
DIC	117125	

IZ Intermediate Zone. DIC Deviance Information Criterion

The Relative Rate (RR) for the spatial effect, after adjusting for the covariates

(Table 6.5) ranged from 0.93-1.08. The spatial pattern is different from the 2001 IZs showing higher RR in the south and lower RR in the north-west and a cluster of high RR in the North East (Figure 6.11). There were 8 2011 IZs where there was 80% probability the RR was higher than expected. Five of the IZ were within the previously identified high RR wards: Cardonald South and East (Craigton), Cardonald North (Craigton), Pollokshields East (Pollokshields), Central Easterhouse (North East), North Barlanark and Easterhouse South (North East). The remaining IZs were in areas that were not previously considered high RR: Darnley East, Carnwadric West, Kingspark South. These areas differed from those previously identified in descriptive mapping for the 27-30 month review (Drumpchapel North, Petershill, Nitshill and Crookston South) (See Figure 1.2). This may be due to the fact the health review data is related to a different age group, or that the analysis does not include adjustment for demographics.

Together, these results suggest there was more variation at IZ level in 2014-2017 than in the earlier subset of the data.

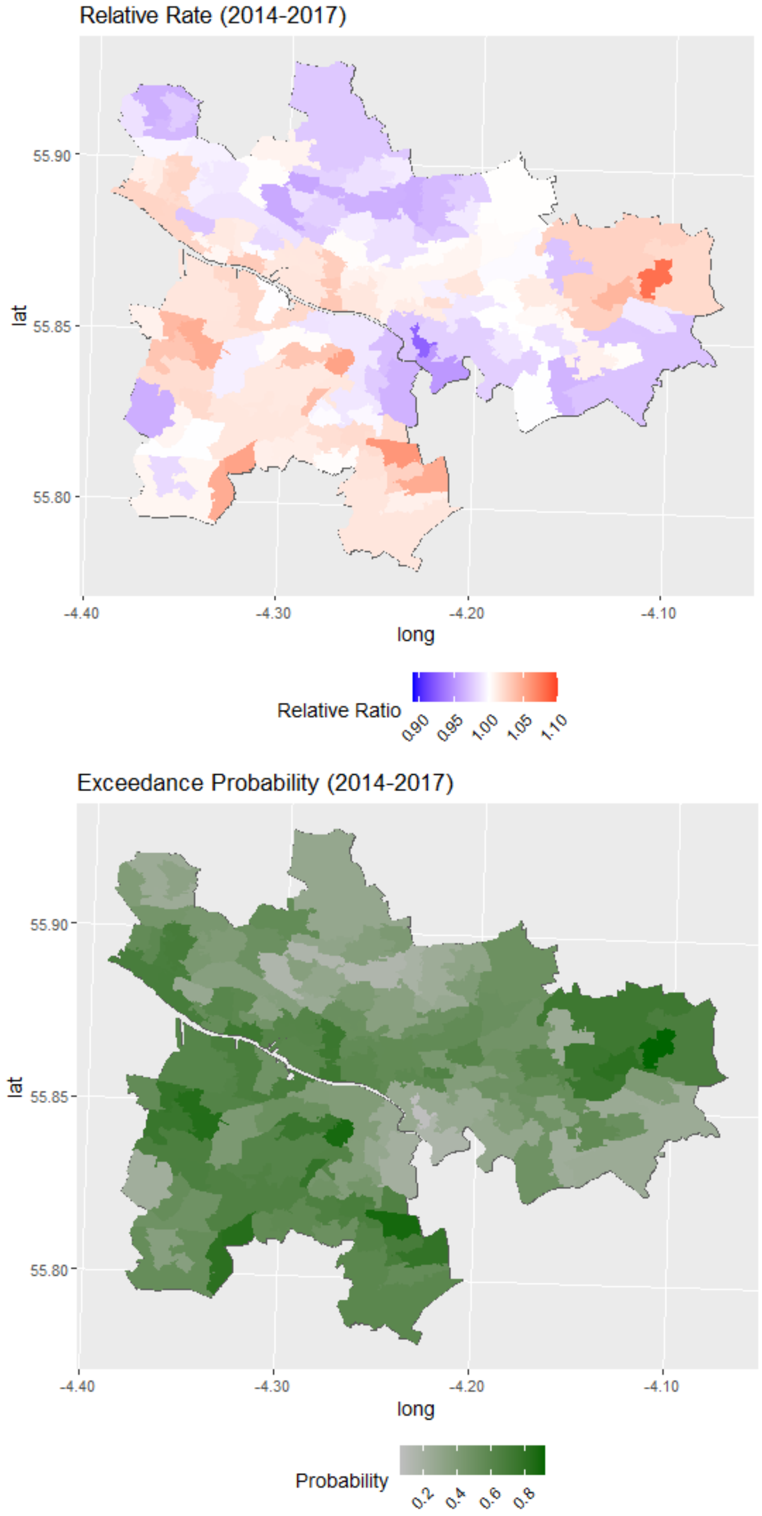

Figure 6.11: Spatial Relative Rate (RR) and Exceedance Probability (EP) at 2011 IZ Level

IZ Intermediate Zone. For Key, see Table D.2

6.1.3 Consistent Areas Through Time (CATTs)

There are various techniques used in geography to harmonise data across time and space. This includes multiple imputation approaches to create a grid, areal interpolation to redistribute the data to a new geography using area weights or creating smaller geographies [286–289]. CATTs (Consistent Areas Through Time), are Scottish statistical boundaries. CATTs are created from postcodes aggregated to census output areas which are then aggregated to areas that are consistent over time [289]. CATT boundaries have recently been updated to be consistent from across the 2001 and 2011 censuses [290].

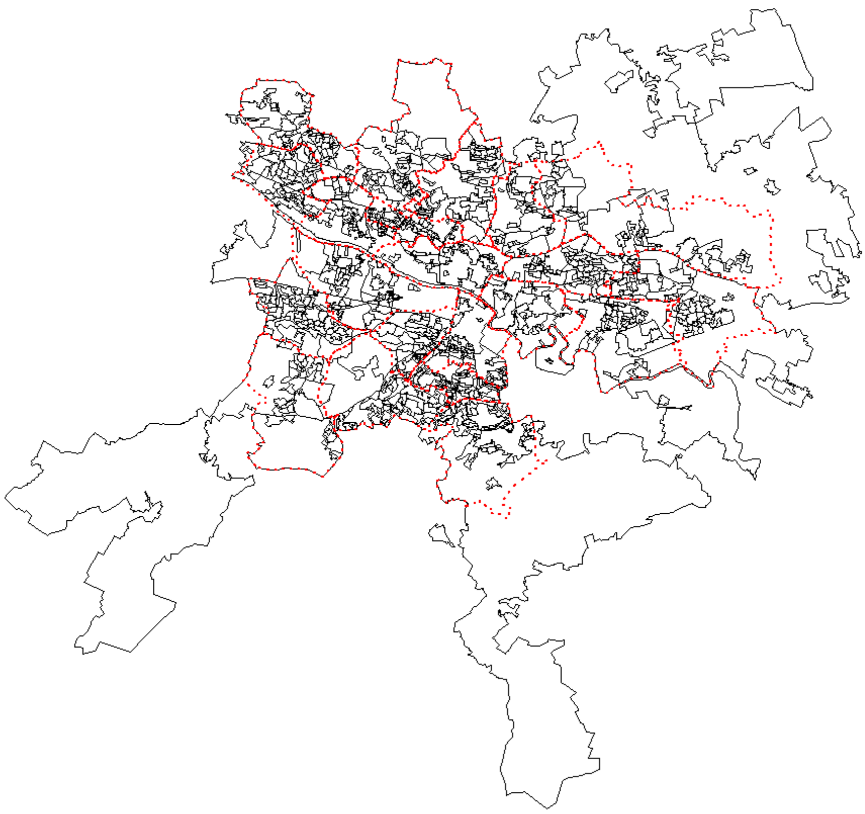

Figure 6.12: CATT boundaries (black) and electoral ward boundaries (red)
CATT Consistent Area Through Time

In the sample, 181 children did not have a CATT identified from their postcode, excluding these children created a sample of 34 990. Figure 6.12 shows the 1,118 CATTs boundaries linked to the sample.

The average number of children in each CATT was 33.4 and the median was 18. There were 14 areas with only one child, while the most populated CATT had 702 children.

There were three initial issues with using the CATT data for this sample: sample size, identification, and visibility. This is demonstrated by plotting the size of the CATTs against the sample (Figure 6.13).

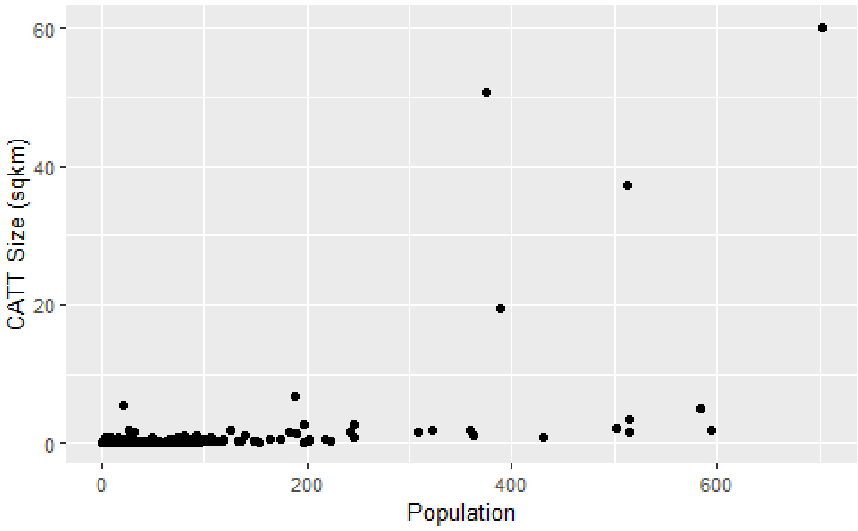

Figure 6.13: Population of children in each CATT by CATT size
CATT Consistent Area Through Time

In a multilevel data structure, the concept of sample size can become more complicated. There needs to be additional consideration of the number of spatio-temporal units and the number of individuals nested within those units. It is the latter which becomes an issue with analysing data at CATT level. A limitation of spatio-temporal analysis at CATT level is, as previously mentioned, that there are some CATTs with only 1 child for the duration of the study. There is not an observation in every CATT for every year. There were 718 CATTs out of the total 1118 that did not have an observation for each year. This leads to an issue of sample size. If there are insufficient spatio-temporal data then the model estimates may be inaccurate.

There are cases in which we can expect few individuals within a higher level unit, for example children within households. Typical advice in this case is that having fewer individuals per higher level limits the ability to make reliable estimates about variance within a single unit (e.g. children living in a particular CATT) but that comparison between CATTs would still be feasible as long as there are many CATTs and most CATTs had a sufficient sample [285].

The small sample sizes rule out some spatio-temporal models, for example the model with a separate spatially correlated structure for every year (See Model A in Chapter 3) requires observations for every CATT and year [235], therefore the authors used a complete case subset. To exclude the children who don't live in a CATT that is present every year would reduce the sample size further to 24 669.

An advantage of Bayesian spatio-temporal smoothing is that there is the opportunity to borrow strength from neighbouring areas and time periods with adequate sample size. For example, in the model developed by Neelon et al., [236] (described in Chapter 3) on average there were 84 individuals in a census block. There were four cases of zero observations for a census block in a particular year. Using a structured spatio-temporal prior meant that estimation was still possible by borrowing information over space and time. However, this would require evidence of spatio-temporal dependence in the data (this is discussed further later in this chapter).

From a decision-making perspective, singling out a CATT as being worse than the city average is not appropriate if a single child lives there. The small sample size increases the risk of that child being identifiable from the sample based on the CATT.

Secondly, due to the method used to create the CATTs, the areas are irregular in size. The largest CATTs dominate while other areas are more difficult to see (Figure 6.12). This may lead to misrepresentation. This is demonstrated by assigning random values to each CATT and visualising using alternative mapping techniques (Figure 6.14).

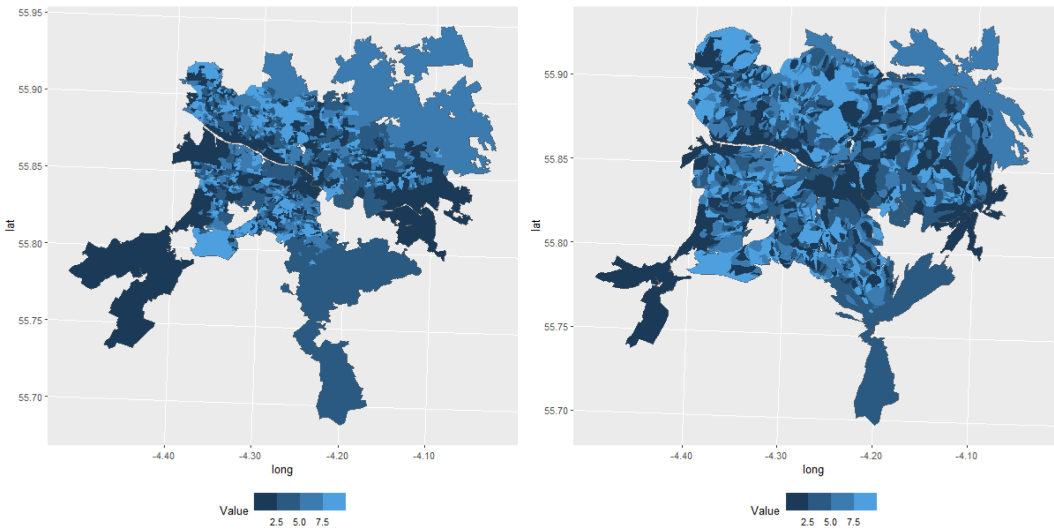

Figure 6.14: CATT values for standard choropleth (left) and cartogram (right) maps
CATT Consistent Area Through Time

Cartograms scale the map based on a measure such as population size, meaning smaller, more densely populated areas are larger on the map (Figure 6.14, right). This still does not help to maintain data privacy for areas where there is a single child [291]. One approach to overcoming both issues while still retaining the advantage of consistent small area data is the use of hexagonal binning. With hexagonal binning, nearby CATTs are binned together, the values of nearby CATTs are replaced with a summary statistic for the binned region. A hexagon is placed at the centroid of the binned area to represent the density of the summary statistic [291]. This is known as a hexogram. The number of bins (i.e. the number of CATTs that are represented by a single hexogram) can be adjusted. With an accurate degree of binning, this enables the balance of loss of information and maintaining a map that is easier to interpret.

For example, with the same random values assigned earlier (in Figure 6.14), the level of binning affects the spatial pattern in the map (in Figure 6.15). Based on these maps a bin of 30 provides the best level of aggregation for CATTs. While the decision is qualitative, the map with 30 bins ensures a finer spatial resolution than the other previous maps (localities and IZs) while allowing enough aggregation for spatial patterns to be visible. This will be used for all subsequent plots.

Figure 6.15: Binning values for CATT hexograms
CATT Consistent Area Through Time

The median total difficulties score per CATT was 4, with a minimum of 0 and maximum of 18. Figure 6.16 shows their distribution across the hexagrams.

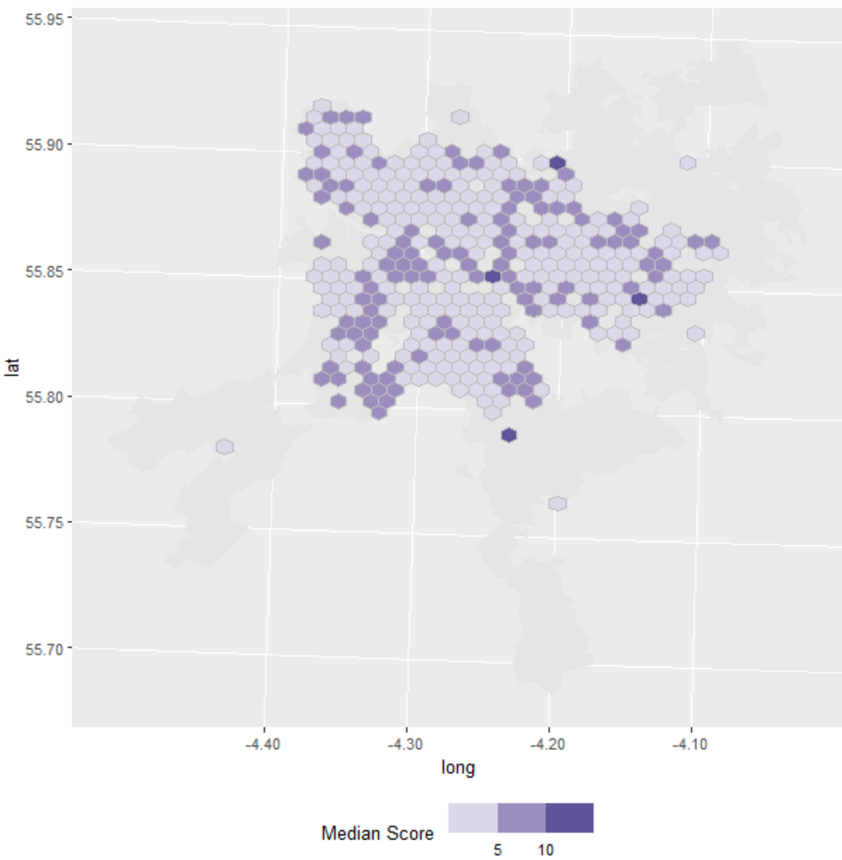

Figure 6.16: Median difficulties per CATT (hexagonal binning)
CATT Consistent Area Through Time

Table 6.6 shows the model estimates when adjusting spatio-temporal equation (Equation 5.10), to account for CATT level effects. There was residual spatial dependence (I=0.11, $p<0.001$). Spatio-temporal dependence was measured using complete data i.e. only measuring dependence in the 400 CATTs where there is an entry for each year. This was calculated by sub-setting the original spatial weights list and creating a new spatio-temporal weight. In this case, there was no evidence of spatio-temporal dependence (I=0.05, p=0.10) or temporal dependence (DW=1.76, p=0.36). Therefore, the spatial effect was given a Leroux CAR prior where dependence parameter ρ=0.87 (0.81-0.93). The high value of ρ supports the need for a structure that accounts for dependence.

Table 6.6: Model estimates for Equation 5.10 at CATT level

Parameter	Relative Rate	Credible Intervals
Intercept	4.15	3.914-4.391
Cohort	1.008	1.003-1.013
Sex (Male)	1.370	1.344-1.397
Deprivation (4th vs 5th)	1.104	1.061-1.149
Deprivation (3rd vs 5th)	1.152	1.106-1.200
Deprivation (2nd vs 5th)	1.207	1.158-1.257
Deprivation (1st vs 5th)	1.217	1.167-1.269
Age	1.003	1.003-1.004
Parameter	Variance	95% Credible Intervals
CATT	0.004	0.003-0.006
Preschool Variance	0.071	0.052-0.095
Spatio-temporal Variance	0.007	0.004-0.013
DIC	195148	

CATT = Consistent Area Through Time. DIC Deviance Information Criterion.

A limitation of the binning approach here is that though spatial dependence (ρ) is high, there is still a small amount of heterogeneity, meaning there are neighbouring areas of differing results which when binned may dilute their effects. At CATT level, the RR ranges from 0.93 to 1.07. There is high certainty of increased RR in 14 areas. The interpretation of this map differs from the others, as the bins show the extent to which neighbouring CATTs have similar scores.

Spatio-temporal effects are not shown in maps as there will be areas with no data which will impact the interpretation of the hexagonal binning. There were 24 deviations from the overall spatial effects with high certainty. This was mainly a single CATT deviating in a single year, however there were 4 CATTs that deviated over more than one year. The number of spatio-temporal deviations peaked in 2014 with 7 CATTS.

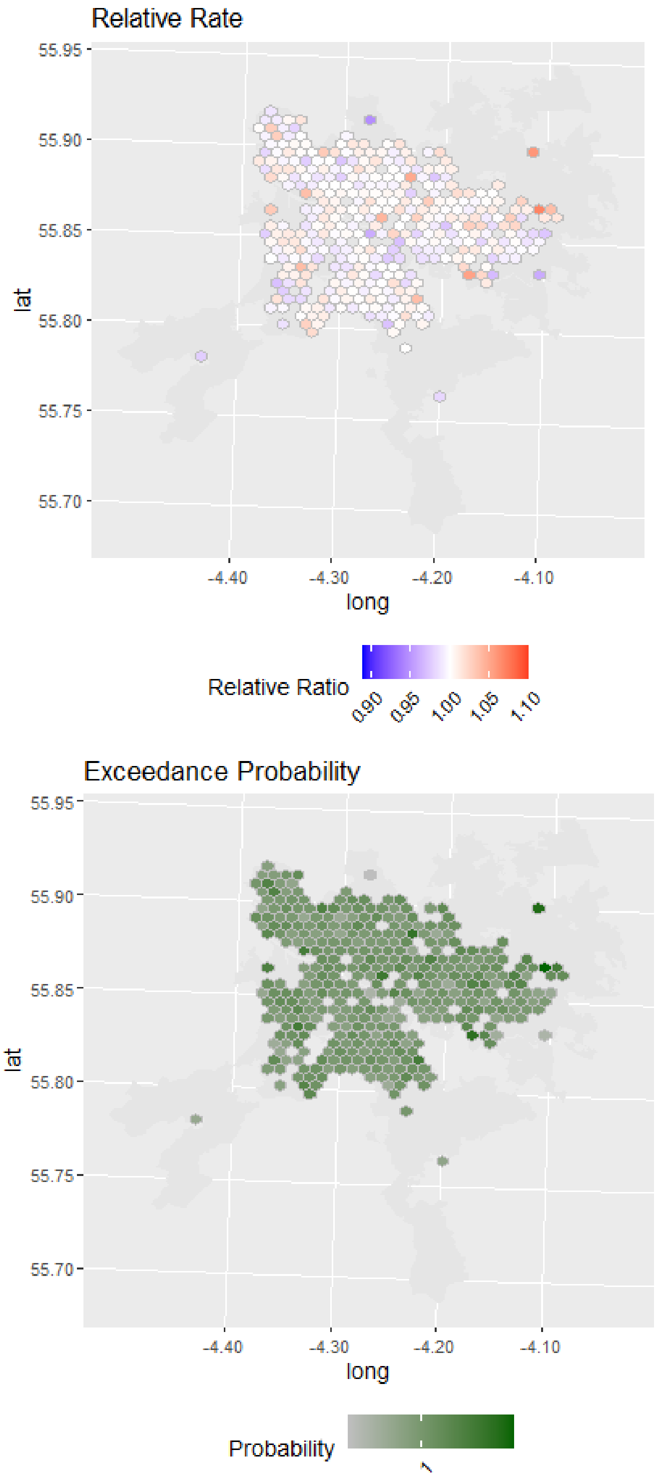

Figure 6.17: Spatio-temporal Relative Rate (RR) and Exceedance Probability at CATT level

CATT Consistent Area Through Time

Spatial Confounding

Since spatially structured random effects are included in the model, a further consideration is the presence of spatial confounding (described in Chapter 3). In particular, the focus of investigation is the SIMD score. SIMD scores are derived from data zones and have been attributed to children at an individual level as a proxy for socioeconomic status.

SIMD scores are calculated at a higher spatial unit to some of the smallest CATT areas, resulting in the same score being assigned to neighbouring CATTs. Therefore, there is a risk of spatial correlation. While techniques have been developed to adjust for spatial confounding in multilevel models [230], these are considered beyond the scope of the present study as these have not yet been developed for use with R-INLA. Instead, the degree of spatial confounding will be assessed by comparing the SIMD estimates in the model with and without the spatial term. This allows the possibility of an expansion of the model to adjust for spatial confounding in future research.

Table 6.7: Investigating spatial confounding at CATT Level

	Without Spatial Effect	With Spatial Effect
	Relative Rate (95% CrI)	Relative Rate (95% CrI)
Deprivation (4th vs 5th)	1.106 (1.063-1.151)	1.104 (1.061-1.149)
Deprivation (3rd vs 5th)	1.154 (1.108-1.202)	1.152 (1.106-1.200)
Deprivation (2nd vs 5th)	1.208 (1.160-1.258)	1.207 (1.158-1.257)
Deprivation (1st vs 5th)	1.219 (1.170-1.270)	1.217 (1.167-1.269)

CATT Consistent Area Through Time. CrI Credible Interval.

The results show that there was no clear difference in the SIMD estimates when the spatial effect was added to the model, therefore there is little evidence of spatial confounding.

6.2 Partitioning Variance

General Contextual Effects (GCE) describe the influence of a context on the outcome and can be measured by the level of cluster variation. For example, in the proposed pathways in Figure 2.1, it is unclear which of the contexts are most important to development. Using GCEs, contexts that play a larger role in the total variation present a level of intervention that would have greater impact than contexts that minimally affect variation. The proportion of total variation that is due to cluster-level differences is called the variance partition coefficient (VPC). For example, in a random intercepts model, the variation attributed to the cluster effect u_j would be calculated as:

$$VPC = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_\epsilon^2} \tag{6.1}$$

The VPC value lies between zero and one. It indicates the proportion of the variation that is between clusters. The Intraclass Correlation Coefficient (ICC) measures the amount of homogeneity within levels through the correlation between outcome values from two different individuals in the same cluster. In simple models (e.g. those without random coefficients), this equates to the VPC. The larger the VPC, the more similar individuals are within their cluster, and the more important the context is in understanding individual heterogeneity of the outcome [80]. It was previously estimated in a review of studies from 1990-2003 by Sellstrom et al. [25], that between 1% and 10% of variation in child and adolescent health and well-being outcomes can be explained by neighbourhood. The individual and family were the most important contexts. The importance of the neighbourhood context varied depending on the rater (neighbourhood was less important when behavioural problems were rated by the teacher rather than a parent) and the neighbourhood definition (smaller areas were more important). The VPC was overall consistent across different types of behavioural problems (e.g. hyperactivity and conduct problems) [25].

Of the studies reviewed by Sellstrom et al. [25], few studies focused on younger children. Only 2 out of 5 studies on behavioural problems in the review included children under 10 [25] and only 1 of those studies reported the VPC. Examples of studies that focus specifically on social, emotional and behavioural outcomes in early childhood conducted since that review are shown in Table 6.8. These studies vary in their age groups, regions, adjustments, and multilevel structures but were consistent in showing that individual differences are the largest contributor to variation in social, emotional and behavioural problems. But the role of the neighbourhood differed across studies.

Table 6.8: Variance partition coefficients (VPC) in child social, emotional and behavioural problems

Author	Age	Outcome	Individual	Family	School	Neighbourhood
Romano [292]	2-11	AGG*	66.4	29.9		3.7
Romano [292]	2-11	PRO*	65.2	25.8		9.0
Heilmann [198]	7	TOT	87		10.4	2.6
Flouri [293]	3	TOT*	96.7			3.3
Farmer [294]	3	GEN*	98.5			1.5
Ma [295]	3	INT*	100			0
Ma [295]	3	EXT*	98.7			1.3
Raos [273]	5	AGG	95			5
Raos [273]	5	HYP	96.5			3.5
Raos [273]	5	ANX	94.3			5.7

*= Caregiver Rated. AGG= physical aggression, PRO = prosocial behaviour, TOT = Total Difficulties, GEN = General Psychopathology, INT = Internalising behaviours, EXT = Externalising behaviours, HYP= Hyperactivity, ANX= Anxiety. Adjustment: age and sex [273, 292], disadvantage and country [293], income inequality [294], neighbourhood collective efficacy and behavioural problems at age 3 [295]. Countries: United Kingdom [198, 293], Canada [273, 292, 294], United States [295]

While these studies give us some indication of the importance of the neighbourhood context relative to other contexts, the partitioned variance are not regularly reported. The VPC/ICC are considered a part of quality reporting for statistical inference in multilevel models [244]. Despite the potential value of this measure in providing an indication of how meaningful a statistically significant cluster can be for policymaking, only 18 out of 118 studies identified in a systematic review of GLMMs in psychology reported their ICC [244].

A contributing factor in under-reporting is that measurement of GCEs requires the group and individual level variance estimates (σ_u^2 and σ_ϵ^2 in Equation 6.1) that are provided in a linear multilevel model equation. As noted in Chapter 4, there is no individual variance estimate in a discrete model. It is similarly difficult to calculate the GCEs for categorical outcomes [296]. Therefore, GCEs are often omitted from GLMMs. In the review of reporting quality by Bono et al., [244] most studies (where a distribution was reported) used a non-normal distribution.

6.3 Partitioning Variance Approximations

Recently, GCE calculations have been developed for Poisson and Negative Binomial distributed outcomes using the packages glmmTMB and glmmADMB in R [296, 297]. Both glmmTMB and glmmADMB are R packages used to build GLMMs. For both packages, the random effects are estimated using Laplace approximations but each package varies in its parameter flexibility (e.g. random effect structures), computational speed (glmmTMB is faster) and estimations (e.g. glmmmADMB uses numerical adjustments to ensure model convergence) [298]. The approximation for the level 1 variance (σ_ϵ^2*) and level 2 variance (σ_u^2*) in a two level negative binomial multilevel model $Y_{ij} \sim NB(\mu_{ij}, \theta)$ is shown in the Leckie [296] method for glmmTMB as:

$$\begin{aligned}\sigma_\epsilon^2* &= \lambda + \lambda^2 exp(\sigma_u^2)\frac{1}{\theta} \\ \sigma_u^2* &= \lambda^2 exp(\sigma_u^2) - 1\end{aligned} \tag{6.2}$$

The Nakagawa [297] approximation for glmmADMB recommends using a tri-gamma function for log-link models:

$$\begin{aligned}\sigma_\epsilon^2* &= \Psi_1([\frac{1}{\lambda} + \frac{1}{\theta}]^{-1}) \\ \sigma_u^2* &= \sigma_u^2\end{aligned} \tag{6.3}$$

Leckie [296] approach uses an exact algebraic expression to get the marginal variance (i.e. variance of the population average). This is used to calculate the correlation between two units in the same cluster. Nakagawa [297] approach is an approximation, based on the individual level variance being equivalent to the variance of the distribution variance and overdispersion term.

To date, these approaches have not been compared or applied to alternative modelling packages, which have different estimation methods. This is necessary as glmmADMB and glmmTMB use different convergence methods that can lead to slightly different estimates [298]. Here, the equations are compared and applied to the modelling of a discrete outcome using different model estimating procedures.

Firstly, the equations were directly compared using example values. Take the student absenteeism dataset that was used by Leckie et al., ([296]) where 66,955 children were nested in 434 schools. In a two-level model, assuming a negative binomial distribution, the marginal expectation $\lambda = 8.45$, school level variance $\sigma^2_{\mathrm{u}} = 0.093$ and the overdispersion parameter was $\theta = 0.877$. According to the Leckie method, the level 1 VPC is $77.15/(77.15 + 6.95) = 0.92$ while in the Nakagawa method, the level 1 VPC is $2.32/(2.32 + 0.093) = 0.96$. Both approaches give level 1 VPCs that are close in estimate though not identical, with the Leckie approach giving a level 1 VPC that is more conservative.

The equations can be compared in practice with the different modelling estimations through the recommended packages. To compare both approximations, the code provided by each paper was applied to toy data known to follow a negative binomial distribution: the extended Seizure Counts for Epileptics data frame [276].

The model followed a two level structure where seizure counts $i = 1, \ldots, n$ were nested in subjects $j = 1, \ldots, J$:

$$\begin{aligned} Y_{ij} &\sim NB(\beta_0 + u_j, \theta) \\ u_j &\sim N(0, \sigma^2_u) \\ \text{where } \lambda &= exp(\beta_0 + \sigma^2_u/2) \end{aligned} \tag{6.4}$$

Table 6.9 shows the differences in parameter estimation in the two approaches using their original package and with R-INLA (which can be computationally faster than glmmTMB while producing similar parameter estimates).

All models produced similar estimates for the regression parameters. Again, the

Table 6.9: Comparison of approximation methods for Negative Binomial outcomes

Method	Programme	β_0	σ_u^2	λ	$1/\theta$	Level 1 VPC
Leckie	glmmTMB	1.63	0.86	7.89	0.14	25.10
Leckie	INLA	1.64	0.83	7.80	0.13	24.56
Nakagawa	glmmAMDR	1.63	0.85	7.89	0.14	26.21
Nakagawa	INLA	1.64	0.83	7.80	0.13	26.01

level 1 VPC using the Leckie method was more conservative. The R-INLA approximations were similar in both approaches, with the VPC at level 1 mostly closely matching the Nakagawa approximation. Based on the similarities between the approximations, Nakagawa approximation was applied as its computation is easier to implement in R-INLA.

6.4 Application on ChiME Data

For application to the ChiME data, the approximations would now include up to 4 variance terms (individual, preschool, spatial and spatio-temporal) and the individual level covariates. For this project, the Nakagawa equation was extended to allow for zero inflation, which was not provided in the original approximations. In this case, the equation includes the zero inflation parameter that indicates the probability of the outcome being equal to zero. Instead of marginal expectation = λ as in Equation 6.2 and 6.3, the zero inflation parameter p alters the marginal expectation of the model so that λ is weighted by the expected proportion of zeros in the data, and includes any fixed effects.

$$\sigma_\epsilon^2 = \Psi_1([\frac{1}{(1-p)\lambda} + \frac{1}{\theta}]^{-1}) \tag{6.5}$$

This approximation was applied to four of the models developed in Chapter 5. Firstly, the spatial model, where children were nested in wards (Equation 5.1), the spatial preschool model where were children cross-classified into wards and preschools (Equation 5.3), the spatial preschool model adjusted for covariates (age, sex, deprivation, and cohort) (Equation 5.6) and the adjusted spatio-temporal model where children were also nested in ward-years (Equation 5.10).

In the adjusted spatio-temporal model in Chapter 5, 5.66% of the variation in total difficulties scores could be attributed to the preschool a child attended, while 1.10% can be attributed to the ward and 0.57% the interaction between cohort and ward. The remaining 92.65% was due to individual variability (Table 6.10).

There are few key observations from this analysis. Firstly, if preschool variation was omitted, there is a risk of underestimating the role of ward as the preschool effect increased the ward VPC from 0.26 to 0.82. Secondly, the influence of ward and preschool are not noticeably impacted by covariates i.e. their demographic. Finally, the spatio-temporal VPC increased the spatial VPC and reduced the preschool VPC.

Table 6.10: VPC for ChiME data

Model	Equation	Ward	Preschool	Ward:Cohort	Individual
Spatial	5.1	0.26	-	-	99.74
Spatial & Preschool	5.3	0.82	6.19	-	93.39
Spatial & Preschool (adjusted)	5.6	0.88	6.14	-	92.98
Spatial, Preschool & Spatio-temporal (adjusted)	5.10	1.10	5.66	0.57	92.65

VPC Variance Partition Coefficient

The VPC was estimated at each geographic boundary as shown in Table 6.11. There were consistencies across the geographies in terms of partitioned variance: over 90% is attributed to the individual, followed by the preschool, neighbourhood and finally the spatio-temporal interaction.

Table 6.11: Partitioned variance at alternative boundaries

Geography	Neighbourhood	Preschool	Neighbourhood:Cohort	Individual
Ward	1.10	5.66	0.57	92.65
Locality	0.91	6.19	0.66	91.76
2001 IZ	0.36	5.10	0.74	93.8
2011 IZ	0.93	7.63	-	91.44
CATT	0.39	6.98	0.72	91.9

CATT Consistent Area Through Time, IZ Intermediate Zone.

Compared to the other studies described in Table 6.8, the proportion of the variance attributed to neighbourhood is small. The low (less than 10%) of neighbourhood variance means it is unlikely this context plays a major role in the variation of total difficulties. There are several possible reasons for this observation. The fact that this analysis was not able to include the family/household context may be inflating the VPC at an individual level. When the family was included in Table 6.8, the individual VPC was 65-66%. Differing results may be due to the age group. It is likely that the age of a child will impact their interactions with the residential environment. The younger the child, the more relative importance their household will likely have over the neighbourhood. The largest neighbourhood VPC in Table 6.8 was for children aged 2-11 years. Alternatively, it may be due to differences in the outcomes. In the same studies (Table 6.8), there were large differences in VPC depending on the domain of development. For example, Romano et al., [292] found different influence of the neighbourhood with the same sample when the outcome was physical aggression compared to prosocial behaviour.

6.5 Discussion

This chapter examined different ways of aggregating postcode data to define the neighbourhood. Boundaries were considered based on their relevance to policy and their consistency over the study period. In addition to the Electoral Ward used in the previous chapter, there were three boundaries considered. These differed in their scale and in their construction: the Community Planning Partnership (CPP) localities developed by the Glasgow City Council (n=56), the Intermediate Zone developed by the Scottish Government (n =133 for IZ 2001, and n=136 for IZ 2011) and the Consistent Areas Through Time (CATTs) developed by statisticians (n=1118) [289]. For each boundary, the spatio-temporal model defined in Chapter 5 was adapted. There were differences in the models between neighbourhood definitions in spatio-temporal modelling performance. The chapter focused on differences in spatial patterns, variance estimates and proportional variance.

At a finer spatial resolution than ward, there was spatial correlation. Different methods for modelling spatial correlation were compared, following the suggestions by Djeudeu et al. [230] for the spatio-temporal multilevel models known as MLMtCARs. Three spatial structures (introduced in Chapter 3) were considered: a spatial convolution, a Leroux CAR and an ICAR. To avoid solely relying on goodness of fit, model comparison considered the degree of smoothing [283]. The spatial convolution was over parameterised and unable to estimate the variance. The ICAR did not account for spatial heterogeneity, therefore the Leroux CAR was considered the most appropriate. The Leroux CAR structure was used on all subsequent models where spatial correlation was observed.

Spatial correlation shows there were greater similarities between neighbouring areas when those areas were defined as localities, Intermediate Zones or CATTs. While at the ward level, neighbouring areas were heterogeneous. This supports the notion that the ward represents distinct communities. Therefore, the neighbouring areas had greater influence at a smaller spatial scale. There may be geographic peer network effects [47] for total difficulties so that interventions applied at a smaller scale influence geographic peers.

There was some agreement in the spatial distribution of the relative rate at ward, locality, and IZ 2014-2017 level. These three geographic scales showed higher RRs in the North East, Centre, and South of the city. However, for the Localities, there is only certainty with 2 areas in the North East. Other areas were high but did not meet the cut-off for certainty. Looking at these plots together, they show there are some clusters of higher RRs within the previously identified wards.

Analysis at IZ is limited by the boundary changes, necessitating a subset analysis. This affected the estimation of temporal trends and likely impacted the ability to detect spatio-temporal effects. The difference between the subsets might be because the 2001 census data that informed the 2001 IZ is less timely for the 2010-2013 sample. The 2011 census data used for the 2011 IZ is likely to more closely approximate the community boundaries for the 2014-2017 sample.

Spatio-temporal dependence was found for 2011 IZ, but the model specifications attempted were too complex to estimate the small amount of residual dependence resulting in more biased models. There was limited guidance found in the literature on modelling small, inseparable dependence as in this case.

CATTs are considered advantageous because they represent consistent communities for long term inference. But, providing information at CATT level can risk the anonymity of the sample and may lead to misrepresentation. At a spatio-temporal level, it was more challenging to examine effects due to limited sample size. The ability to visualise the small differences between CATTs is greatly reduced by the hexagonal binning and is therefore less effective than the administrative boundaries.

The final section of this chapter compared the relative importance of the neighbourhood according to the multilevel data structure and neighbourhood boundary. Based on the current literature, values ranged from 0-9% (Table 6.8). This is typically estimated by apportioning the variance to get the VPC (Variance Partition Coefficient) or ICC (Intraclass Correlation Coefficient). However, for discrete data, individual level variance must be calculated using an approximation. Two different recent approximation methods (Leckie et al., [296] and Nakagawa et al., [297]) for Negative Binomial distributions were compared for the first time. Both methods produced similar partitioned variance estimates. The Nakagawa method was expanded for Zero-Inflated Negative Binomial data and applied to models of the ward level data developed in Chapter 5. Reviewing different models shows the impact of the data structure and adjustment for covariates on the VPC. Approximations show that, proportionally, a single higher level context does not make a considerable contribution to variation. The ward VPC ranged from 0.26 to 1.10 across the models (Table 6.10). Compared to other studies, neighbourhood VPC was at the lower end of the range of values. It was proposed that this may be due to differences in the outcome or age groups.

VPC was calculated for each of the alternative boundaries to investigate whether the neighbourhood context was more or less meaningful according to its definition. Ward level analysis had the highest neighbourhood VPC, followed by 2011 IZ and Locality. Across these three boundaries, there were differences in how the other contexts were partitioned. The ward boundary model had a smaller spatio-temporal context. This is advantageous as it means wards are more consistent and, from a decision-making perspective, there is less variation in estimates according to the year. For 2011 IZ and locality, there is more clustering at the preschool level compared to the ward model VPC. Only one of the studies in Table 6.8 looked at the learning environment, however this context was a school for older children. Still, there were similar findings that the learning environment is approximately five times more important than the neighbourhood.

For decision makers, the partitioned variance suggests that considering multiple higher level contexts together [28] would have greater relevance and could help account for roughly 7% of the total variation.

Chapter 7

Investigating the Contextual Characteristics Associated with Social, Emotional and Behavioural Development in Glasgow

So far, this project has focused on the General Contextual Effects (GCEs) of higher level contexts. This chapter looks at the Specific Contextual Effects (SCEs) [80]. SCEs are the fixed effects that describe the association of the higher level characteristics on the individual level outcome. SCEs explain why there is variation between higher level contexts, after accounting for their composition (individual characteristics).

SCEs and GCEs are related. It is expected that if there is an association between an SCE and the outcome, then this would partially explain the variation at the higher level, and therefore the GCEs are smaller. Further, despite the variance at the preschool and neighbourhood level in this analysis being relatively small, this does not rule out the possibility of SCEs and in some cases may result in larger SCE estimates [80].

SCEs are thought to provide a more feasible target for intervention compared to individual level characteristics [299] as they are more amenable to change. This chapter discusses the SCEs for each higher level in the model: preschool, neighbourhood/spatial and spatio-temporal.

The adjusted spatio-temporal model in Equation 5.10 can be extended to include higher level covariates at the preschool level Q_k and/or ward level Z_j as shown in Equation 7.1.

$$\begin{aligned}
\eta_{ijk} = \exp(\beta_0 + \beta_1 \mathrm{t} + \beta_2 \mathrm{age} + \beta_3 \mathrm{sex} + \beta_4 \mathrm{deprivation} + v_{0j} + \alpha_k + \phi + \beta_5 Q_k + \beta_6 Z_j) \\
v_{0j} \sim N(0, \sigma^2_{v0}), \frac{1}{\sigma^2_{v0}} \sim \Gamma^{-1}(1, 0.0005) \\
\alpha_k \sim N(0, \sigma^2_{\alpha}), \frac{1}{\sigma^2_{\alpha}} \sim \Gamma^{-1}(1, 0.0005) \\
\phi \sim N(0, \sigma^2_{\phi}), \frac{1}{\sigma^2_{\phi}} \sim \Gamma^{-1}(1, 0.0005)
\end{aligned} \tag{7.1}$$

The random effects (α_k and v_{0j}) describe the cluster effects after accounting for the individual and higher level covariates.

Though covariates at the spatio-temporal level could be included, for reasons discussed further in the chapter, this was not possible for this work so has been omitted from the model.

7.1 Preschool Characteristics

Preschools can be provided by the local authority, private businesses or voluntary organisations. The majority of preschools in Scotland are provided by the local authority. Voluntary and private nurseries are thought to offer more flexibility in their service hours (e.g. all-year round) [84]. The 2018 Scottish Household survey showed that the type of childcare used varied in urban households compared to rural households and by area level deprivation [160].

According to Scottish regulatory reports, preschool quality can vary by provider type. Local authority preschools are the highest rated, followed by voluntary and private business preschools, though the differences are small [84]. This supports evidence synthesised from North America, Europe, and Australia that public preschools are of marginally better quality [300]. This may be due to structural differences in preschool ownership [300].

Small and colleagues, [301, 302] suggest preschool ownership can result in differences in organisational ties such as access to information, social networks, services, and resources that would benefit child development. They proposed that government funded preschools (in the United States) would have the most organisational ties compared to non-profit and for-profit preschools.

Research into the effects of school size on social, emotional and behavioural difficulties has largely focused on primary and secondary school aged children [116]. Smaller private primary schools in the US (less than 250 children) had fewer problem behaviours such as bullying and vandalism [303] though these schools are typically larger than UK schools. The average size of preschools (maximum registered capacity) in Scotland has continued to increase over the years, from 40.1 in 2011 to 44.2 places in 2016 [304]. Services tend to be even larger in urban areas, with 52 children on average [84]. There is no evidence of a clear relationship between the size of the nursery and the quality of the service according to Scottish regulatory reports [304].

The 2013 Childcare Information Services in Glasgow database (accessed through the Urban Big Data Centre [95]), provided information on provider type for all preschools in Glasgow and preschool size was provided for local authority preschools. For consistency across preschools, size is defined by the number of registered places for children aged 2 to 5. Here, the average size was 60. There were no alternative public records of private and voluntary preschool sizes during the study period. Exploratory work investigated measuring the capacity of voluntary and private business preschools by using the number of children in the sample attending the preschool each year as a proxy. With this method, the average private business had 16 children and the average voluntary preschool had 18 children and would therefore be considered small. However, preschool sizes are generally larger in private and voluntary services compared to local authority providers [84]. Therefore, proxy sizes underestimated the true capacity. This is likely due to the restricted age group of the sample (those expected to start school the following term).

There were five preschool classifications created based on the distribution of the sizes in the sample and the average preschool sizes for Scotland (Table 7.1). Most of the sample were in a medium or large local authority preschool. Though there were a similar number of private business and local authority preschools, the private business population was much smaller. This may be the result of a selection bias regarding the parents who opted out of the study or provider level differences in participation in the ChiME study. There was a higher percentage of children in the most deprived quintile in medium and large local authority preschools. Private and voluntary preschools had marginally fewer boys and fewer children outside the expected age range. Private preschools had less variation in their total difficulties and slightly lower median scores.

Table 7.1: Preschool characteristics

Name	Capacity	Number of children	Number of preschools	Median Difficulties	% Most deprived	% Boys	% Outside Expected Age
Small LA	< 42	6512	28	4 (1-9)	18.40	50.60	7.66
Medium LA	$42 - 70$	10300	39	5 (2-9)	30.43	50.84	7.55
Large LA	> 70	13541	39	4 (1-9)	33.37	51.50	7.44
Private		1931	39	2 (0-6)	10.36	49.35	6.62
Voluntary		878	16	4 (1-7)	11.50	48.63	6.37
NA		2009	19	6 (2-10)	21.06	53.56	7.12

The proportion of children attending each type of preschool varied by the ward they lived in. While the majority of children, as expected, attended a local authority preschool, there was a higher proportion of children in private preschools in Baillieston and Partick West. There were more children in voluntary preschools in Linn and Greater Pollock compared to the other wards (Figure 7.1).

There were 2009 children from 19 preschools that were not assigned to a preschool classification due to missing data. These children had a median difficulties score of 6 and IQR = 2-10. Children who lived in Shettleston, Hillhead and Baillieston were the least likely to have a provider type for their preschool (shown in grey). There may be similarities in the wards that are less likely to have information on preschool type in the Childcare Information Services database e.g. differences in the number of newer preschools opening, preschools closing down or preschools changing location, name or ownership.

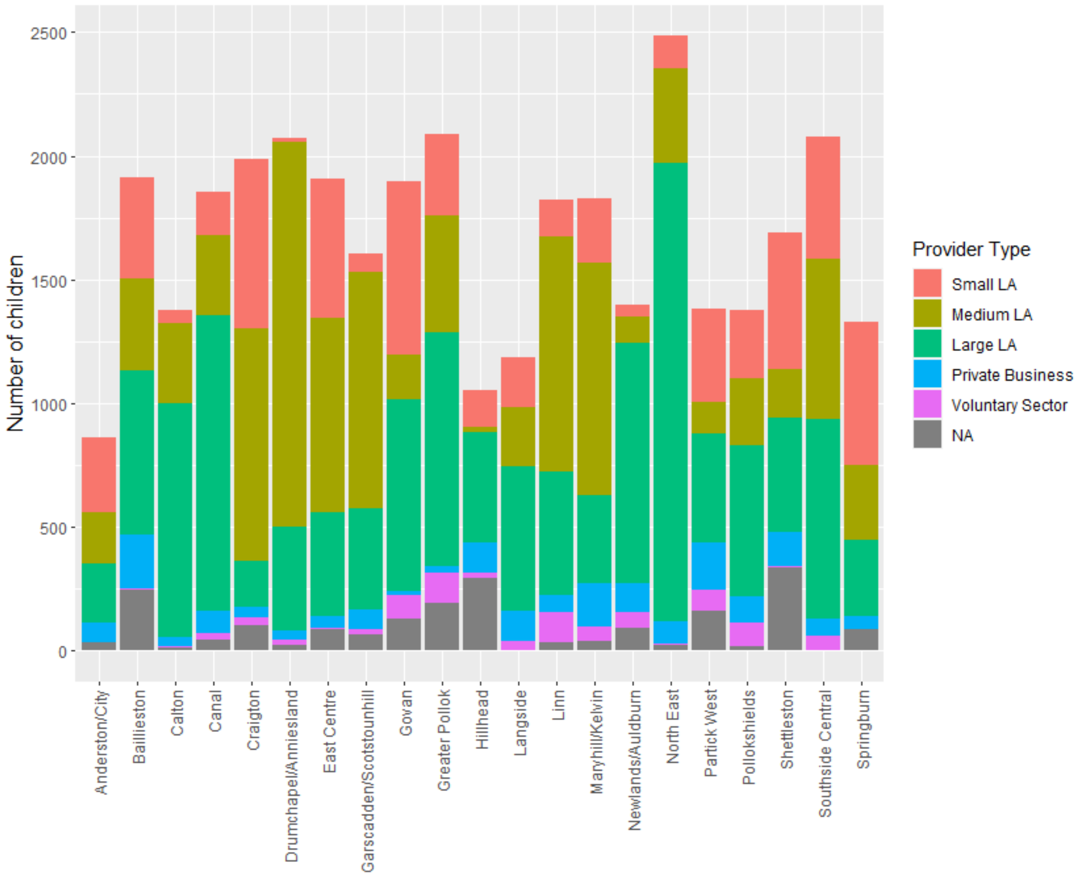

Figure 7.1: Preschool provider by residential ward

When included in the model as a dummy variable with each category compared to a small local authority school, there was a significant difference for private businesses. Private businesses had lower difficulties scores by 26.5% on average (Table 7.2).

Including the preschool provider type had a small impact on the residual preschool variance, reducing from 0.059 (0.046-0.084) to 0.051 (0.039-0.70) suggesting this does partially account for the differences in scores between the preschools. There was no notable difference in the spatial or spatio-temporal variance terms. The DIC reduced from 196173 to 196161.

Table 7.2: Preschool level effects

Parameter	Relative Rate	95% Credible Intervals
Medium LA vs Small LA	1.017	0.915-1.131
Large LA vs Small LA	0.979	0.881-1.089
Private vs Small LA	0.735	0.654-0.826
Voluntary vs Small LA	0.903	0.773-1.055

7.2 Neighbourhood Characteristics

7.2.1 Indicators

The literature review (in Chapter 2) discussed the constructs at the neighbourhood level that may impact mental health through social-interactive, physical and structural mechanisms (Figure 2.1). It is important to define how these constructs will be measured using indicators. The ability to gather this data for research purposes is affected by several challenges, and was identified as the largest practical barrier to the analysis of neighbourhood constructs [104]. There is limited availability of appropriate indicators that apply to young children living in Scotland compared to adolescents. When the NHS Child and Young People Mental Health and Well-being indicators were established, there was no suitable data for social networks, trust, safety, neighbourhood satisfaction, free time places or greenspace [109]. The Child and Young People Mental Health and Well-being report includes guidance on what information should be collected at a small area level to build a profile of local child mental health, but many are only available at a national level (Table 7.3). This is consistent with an earlier report which found that there is limited research on well-being indicators in children internationally [3].

Table 7.3: Data completeness of NHS Scotland Child and Young People Mental Health and Well-being Indicators for preschool aged children

Construct	Indicator	Source	Age	Geographic
Participation	Sense of agency	-	-	-
	Respect of children's rights	-	-	-
	Influencing local decisions	SHS	8-17	Nat
	Participation in clubs, groups etc	SHS	8-17	Nat
Social networks	Contact with peers	-	-	-
Social Support	Social Support	HBSC	11, 13, 15	Nat/LA
Trust	Neighbourhood trust	HBSC	11, 13, 15	Nat/LA
	Community Cohesion	HBSC	11, 13, 15	Nat/LA
	Informal social control	-	-	-
Safety	Neighbourhood safety	HBSC	11, 13, 15	Nat/LA
		SHS	16-17	Nat
Equality	Absolute poverty	SG	<15	Nat
	Income inequality	DWP	<17	Nat
	Relative poverty	SG	<15	Nat
	Persistent poverty	SG	<15	Nat
	Multiple Deprivation	SIMD	0-24	DZ
Discrimination	Discrimination & harassment	-	-	-
	Attitude towards children & young people	-	-	-
	Stigma towards children & young people	-	-	-
Physical Environment	Neighbourhood satisfaction	HBSC	11, 13, 15	Nat/LA
		SHS	16-17	Nat
	Free time places	HBSC	11, 13, 15	Nat/LA
	Greenspace	-	-	-
	House condition	SHCS	<17	LA
	Over crowding	SHCS	<17	LA
Violence	Domestic abuse	-	-	-
	Child protection	SCRA	0-15	LA
		SG	0-15	LA
	Neighbourhood violence	-	-	-

SHS= Scottish Household Survey, HBSC Health Behaviour in School-aged Children, SHCS = Scottish House Condition Survey, SCRA = Scottish Children's Reporter Administration, SIMD= Scottish Index of Multiple Deprivation, DWP= Department for Work and Pensions, SG= Scottish Government, LA= Local Authority, Nat= National, DZ= Datazone, *= though an indicator was identified this does not include preschool aged children

7.2.2 Data Availability Review

Alternative operationalisation (definition and measurement) of constructs can increase the potential for additional data sources. Rajartnam et al., [104] and Minh et al., [26] provide detailed examples of indicators across constructs that are used in the wider literature. There were limited indicators defined for children related to social interactions. Alternative operationalisation for social support, trust and social networks were measures of social disorder or disorganisation related to neglected buildings, cleanliness, and deviant behaviour. For discrimination and violence, there was no suitable data available at the time of the NHS indicators, alternatives from the literature include ethnic composition, child friendliness (households with young children), vandalism/property damage, public orders, drug use, and theft [26, 104].

The availability of the previous (defined by NHS) and alternative (in the wider literature) indicators at the ward or locality level in Glasgow from 2010-2017 was reviewed. Data sources were identified through the reference list of the literature review and from the following data repositories and data services:

- UK Data Service
- Urban Big Data Centre
- EU Open Data Portal
- Spatial Hub
- SpatialData.gov.scot
- Office of National Statistics (ONS)
- Cohort and Longitudinal Studies Enhancement Resources (CLOSER)
- Centre for Research on Environment Society and Health (CRESH)
- Scottish Government Statistics

To be eligible, the data source had to include a ward, locality, or postcode identifier to link to the ChiME database. There are several challenges and sources of error associated higher level effects [105, 305–307]. Key issues include information and selection bias, model specification and mediation.

Across the constructs, the level of geography available differed. In constructs related to social-interactive mechanisms, there were no identified published articles that compared the preschool indicators at a sub-national level in Scotland, instead, findings were primarily drawn using individual level data. Further research is needed to identify the effects of these constructs at a neighbourhood level in Scotland. Using general population indicators where child or parental/caregiver indicators are unavailable can provide some indication of the social-interactive mechanisms, but are limited in their validity.

For structural mechanisms, sub-national data was more easily accessible. The availability of evidence in support of structural constructs may reflect the continuing difficulties in collecting subjective data on children's social environment and advances in objective measures of the physical environment. Despite this, there remain challenges in objective measurement. For example, residents may not necessarily view nearby amenities and structures to be well-placed [308].

Ward Characteristics

Data from the Community Safety Index (CSI) was collected in 2010 and accessed through The Glasgow Indicators Project at Understanding Glasgow [309]. The CSI was collected as part of an annual assessment by Glasgow's Community Safety Partnership which includes members from the council, police, Greater Glasgow and Clyde NHS and Glasgow Life (a cultural charity which acts on behalf of the council). CSI includes data about the ward and the general population of the ward, rather than preschool populations. The CSI used reports from Police Scotland for the number of domestic abuse incidents, the number of reported incidence of antisocial behaviour, the number of persons reported for drinking in public, road traffic incidents, racist and homophobic incidents and recorded crimes of vandalism, malicious and mischief. Additional years of data collection were not available when requested through a Freedom of Information (FOI) request.

For subjective CSI data, questions were taken from Strathclyde Police's Public Consultation Survey: the percentage of people in the ward who responded 'poor' or 'very poor' to "thinking about the neighbourhood you live in, how would you rate it as a place to live?", the percentage of those who answered 'yes' to "In the past 12 months, have you been affected by antisocial behaviour?" and the percentage of people who answered 'yes' to 'Do you have a fear of crime?'. For these constructs that were measured through the aggregation of individual characteristics, this is highly influenced by the method of selection for individuals. There is an assumption that these measures reflect a group consensus or shared perception about their neighbourhood environment, but this assumption may not be accurate. The CSI uses Strathclyde Police's Public Consultation survey results. The size and representativeness of the sample for each ward were not provided. In the absence of the original individual level data, it is difficult to discern whether this sample reflects the consensus or if individuals have been misclassified. A comparison between the reported incidents and the perception of the incidents may point to some group agreement. For example, the correlation of reported antisocial behaviour and those who said they were affected in the last month was $r = 0.24$. This discrepancy may be genuine, as perceptions are not always correlated to objective measures or may point to a lack of group consensus. For example, a recent study found that mothers' perception of disadvantage differed from objective measures over time [310]. The data provided in the CSI was scaled so that the Glasgow average was 100.

Openly available urban-related data was accessed from the national data service, the Urban Big Data Centre (UBDC) [311]. In the absence of data related to preschool children's participation in decision-making and clubs, participation was measured through the number of community led inclusive projects [312] according to Glasgow City Council in 2015 using the primary address of the project and excluding any projects with a city-wide Strategic Planning Area. For free time places (i.e. neighbourhood amenities and facilities), the location and attendance of Glasgow Life facilities (libraries, museums, sports centres, music venues and community centres) was recorded between September 2013 and June 2014. This differed from the NHS Scotland Child and Young People Mental Health and Well-being Indicators definitions on the perception and satisfaction of free-time places by child residents. Other studies examine the housing composition of the neighbourhood [26], in this case residential density [313], measured as the number of residential dwellings per hectare (0.01 km sq) in 2012, was used.

As part of previous preliminary research conducted by the ChiME research group, the distance from postcodes to greenspace was calculated for the 2010-2012 subset of the data. As this is only derived from the earlier cohorts, the representativeness and geographic reach are limited. The distance was calculated creating 400 m and 800 m radii around the postcode unit following road and path networks. Any greenspace (public parks and gardens and play spaces) that partially fell within the radius was counted. For this analysis, neighbourhood greenspace was defined as the proportion of children that were 400 m or 800 m from greenspace.

Data from the 2011 Census included the percentage of households in each ward with over 1.5 persons per room to represent overcrowding, the percentage of occupied households with no central heating and the percentage of people that did not belong to a White ethnic group [314].

Proximity to derelict land used data recorded as part of the Scottish Vacant and Derelict Land Survey [152], which is collected annually. Completion of the survey is voluntary, so where Local Authorities have not provided the data on the extent of derelict land, the previous year's estimate is carried over. The distance was calculated between all properties within the ward assumed to be residential and the site of derelict land or building. The indicator is defined as the percentage of assumed residential properties within 500 m of the site of derelict land.

Child Poverty indicator was accessed from the Child Poverty Action Group [315]. It is defined as the percentage of children in each ward on low incomes using tax credit data for mid-2012. A child was considered to be in poverty if their family income is less than 60% of the median income. This aligns with the approach for neighbourhood deprivation in Canada where measures were more relevant to children and families [35].

The full list of indicators is summarised in Table 7.4 while Table 7.5 shows the ward level values (including the census population estimates for 2011). For histograms of the indicators, please see the Appendix (Figure E.1). There were some outliers in the indicators. For example, 35% of the population in Pollokshields is in a non-white ethnic group, and the Glasgow average is 10%. While in Anderston/City, the number of reports of racist and homophobic incidents was much higher than in the rest of the city. Without the ability to verify their outcomes, outliers were retained for descriptive analysis but removed from modelling.

Table 7.4: Data sources for ward indicators

Construct	Indicator	Measure	Year	Source
Violence	Domestic abuse incidents	Total	2010	CSI
Safety	Fear of crime	Percentage	2010	CSI
Social Disorder	Reported antisocial behaviour	Total	2010	CSI
Social Disorder	Affected by antisocial behaviour	Percentage	2010	CSI
Social Disorder	Reported Public Drinking	Total	2010	CSI
Social Disorder	Reported Vandalism	Total	2010	CSI
Participation	Community-led projects	Total	2015	UBDC
Physical Environment	Neighbourhood Dissatisfaction	Percentage	2010	CSI
Physical Environment	Proximity to Greenspace	Proportion	2010-2012	ChiME
Physical Environment	Free time places	Total	2013-2014	UBDC
Physical Environment	Attendance figures for free time places	Average	2013-2014	UBDC
Physical Environment	Residential Density	Rate	2012	UBDC
Physical Environment	Overcrowding	Proportion	2011	Census
Physical Environment	No Central Heating	Proportion	2011	Census
Physical Environment	Proximity to derelict sites	Average	2013-2016	SG
Physical Environment	Serious road traffic incidents	Total	2010	CSI
Equality	Child poverty rate	Percentage	2012	CPAG
Discrimination	Racist incidents	Total	2010	CSI
Discrimination	Ethnic Diveristy	Percentage	2011	Census
Discrimination	Homophobic incidents	Total	2010	CSI
Discrimination	Child-friendliness	Percentage	2011	Census

CSI= Community Safety Index, UBDC= Urban Big Data Centre, SG= Scottish Government, CPAG= Child Poverty Action Group, ChiME= Child Mental Health in Education.

Table 7.5: Ward indicator values

	And	Bai	Cal	Can	Cra	Dru	Eas	Gar	Gov	Gre	Hil
Domestic abuse incidents (N)	174	134	244	178	124	199	160	181	175	135	96
Fear of crime (%)	100	97	96	122	94	88	87	111	114	119	91
Reported antisocial behaviour (N)	286	84	156	106	94	108	97	99	146	85	143
Affected by antisocial behaviour (%)	116	79	80	99	106	101	80	121	85	105	99
Reported Public Drinking (N)	561	74	454	220	77	112	76	70	293	85	53
Reported Vandalism (N)	195	118	157	131	106	121	106	95	155	107	124
Community-led projects (N)	9	4	14	3	4	10	5	4	8	0	3
Neighbourhood Dissatisfaction (%)	87	20	137	168	17	99	110	101	104	64	134
Proximity to Greenspace (400m) (%)	42	52	62	50	22	31	55	43	45	40	75
Proximity to Greenspace (800m) (%)	79	85	81	84	54	66	91	84	85	80	95
Number of free time places (N)	11	3	6	5	4	6	6	5	7	4	4
Attendance figures for free time places (N)	29456	5126	15012	3580	9940	6728	4305	21157	15220	5373	12190
Residential Density (%)	6.47	12.51	6.39	8.32	7.29	7.32	6.22	5.87	10.26	12.36	2.93
Overcrowding (P)	0.84	0.56	0.89	0.51	0.49	0.52	0.55	0.70	0.80	0.64	0.80
No Central Heating (P)	6.66	2.16	4.93	2.99	2.34	3.08	4.36	2.26	4.63	2.19	5.80
Proximity to derelict sites (%)	56	57	99	90	24	52	67	32	72	63	39
Serious road traffic incidents (N)	384	87	115	88	79	80	84	57	140	70	136
Child poverty rate (%)	35	28	49	42	30	40	42	34	35	29	26
Racist incidents (N)	457	45	238	110	64	74	88	95	176	66	141
Ethnic Diveristy (%)	23	3	10	8	6	6	7	10	15	11	18
Homophobic incidents (N)	1085	109	282	256	62	217	57	89	135	63	83
Child-friendliness (%)	2.97	6.47	5.68	6.18	7.36	8.08	5.56	7.64	6.09	8.05	4.16
Median population (N)	29794	32087	23151	30979	30570	28959	29872	29357	29512	32573	26702

	Lan	Lin	Mar	New	Nor	Par	Pol	She	Sou	Spr	Glasgow (IQR)
Domestic abuse incidents (N)	69	108	122	60	204	117	38	107	82	150	134 (107-175)
Fear of crime (%)	69	109	125	102	113	58	64	112	139	109	102 (91-113)
Reported antisocial behaviour (N)	79	96	130	79	117	98	84	65	145	92	98 (85-130)
Affected by antisocial behaviour (%)	88	113	101	114	89	86	67	94	110	103	99 (86-106)
Reported Public Drinking (N)	137	112	179	60	244	112	32	46	189	96	112 (74-189)
Reported Vandalism (N)	64	121	128	65	160	74	98	80	125	92	118 (95-128)
Community-led projects	0	0	3	1	6	3	2	4	2	11	4 (2-6)
Neighbourhood Dissatisfaction (%)	15	55	55	102	141	76	72	122	101	188	101 (64-122)
Proximity to Greenspace (400m) (%)	56	53	44	63	49	62	63	58	73	71	52.59(43.72-62.26)
Proximity to Greenspace (800m) (%)	93	71	87	84	85	90	88	89	90	88	84.63 (81.09-89.47)
Number of free time places (N)	1	7	5	2	7	3	3	4	9	6	5 (4-6)
Attendance figures for free time places (N)	11355	6748	6792	12026	10751	7314	7527	15024	15960	6316	9940 (6727-15012)
Residential Density (%)	2.87	11.14	13.25	9.78	21.04	5.76	4.32	10.46	5.66	6.24	7.29 (5.87-10.46)
Overcrowding (P)	0.37	0.57	0.47	0.48	0.68	0.34	1.32	0.53	1.17	1.35	0.57 (0.51-0.80)
No Central Heating (P)	5.30	1.60	5.45	3.81	3.23	5.07	4.09	3.18	6.19	3.73	3.81 (2.99-5.07)
Proximity to derelict sites (%)	18	35	78	56	68	62	38	83	75	87	61.83 (39.28-74.68)
Serious Traffic Incidents (N)	112	84	139	77	85	80	101	94	102	109	88 (80-112)
Child Poverty Rate (%)	21	32	30	27	37	18	25	31	38	51	32.2 (28.2-38.1)
Racist Incidents (N)	150	62	86	119	116	52	141	41	98	184	98 (66-141)
Ethnic Diversity (%)	9	5	10	14	6	9	35	3	23	22	10.01(6.21-14.69)
Homophobic Incidents	124	67	312	55	76	110	140	50	128	68	109 (67-140)
Child-friendliness (%)	5.75	7.06	6.24	6.96	8.17	5.02	7.60	6.19	7.10	8.61	6.47 (5.75-7.60)
Median population (N)	22922	29404	28739	22557	33192	32188	22497	26984	29209	21997	29357 (26702-30570)

N Total, P Proportion. Note for Community Safety Index outcomes, the data was provided scaled so that the Glasgow average was 100.

Figure 7.2 shows how indicators vary across the four wards identified has having a higher RR of difficulties than expected based on their demographics (Pollokshields was identified in the spatial model but not the spatio-temporal model). This shows how the profiles of the wards vary across the indicators.

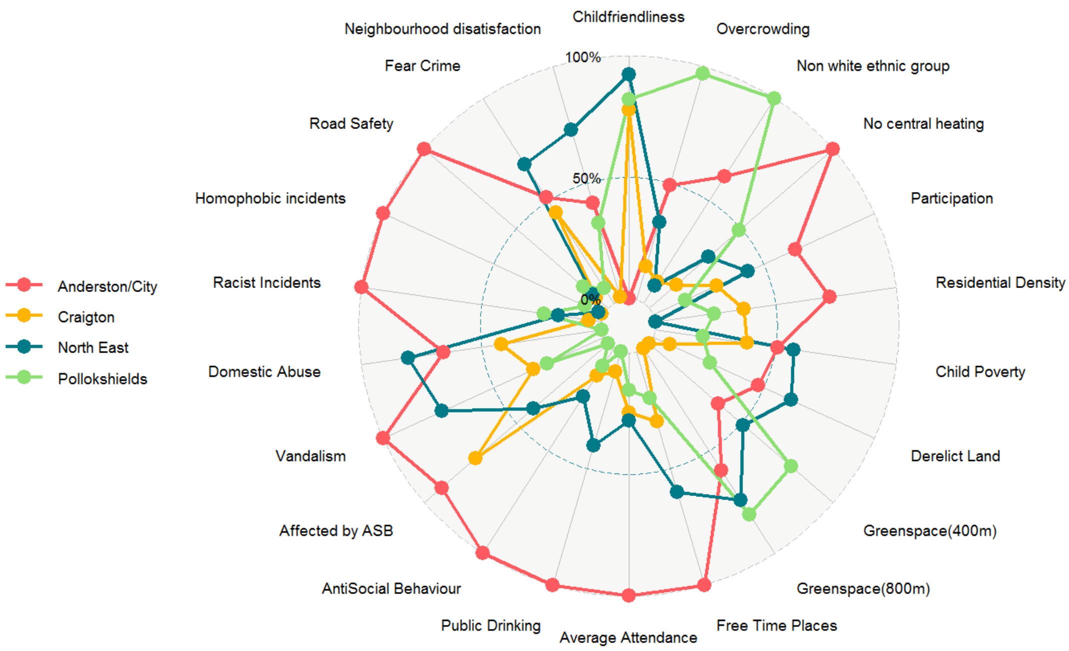

Figure 7.2: Radar plot of the ward indicators (scaled) across the wards with high relative rate (RR)

Indicators related to social disorder and discrimination were higher in Anderston/City compared to the other wards, while the other wards had a higher population of children (child-friendliness). All wards bar Craigton had high proximity to greenspace.

Locality Characteristics

As discussed earlier (Chapter 6), the spatial scale or unit can influence whether an effect is detected. Analysis has focused on ward level factors, as ward level showed the most spatial variation. This suggests this is the level at which we are most likely to see variation in the neighbourhood context.

Examining neighbourhood characteristics at a lower level helps to understand the within ward variation. The choice of scale influences the associations seen between a neighbourhood construct and outcomes. This has been shown to affect inferences made for social cohesion [316] and the built environment [47, 317].

Locality characteristics were taken from the Glasgow Children and Young People's Profiles (GCYPP) accessed through The Glasgow Indicators Project at Understanding Glasgow [318] (Table 7.6).

Table 7.6: Locality variables and their relationship to total difficulties scores

Indicator	Year	Source
Under 25yrs from a minority ethnic group	2011	GCYPP
Overcrowded households with children	2011	GCYPP
Under 16yrs within 400m of greenspace	2014	GCYPP
Referrals to SCRA	2015-2016	GCYPP
Under 16yrs within 500m of vacant or derelict land	2014	GCYPP
Off-licensed premises (per 1,000 $<$ 18yrs)	2016	GCYPP
Children in Poverty	2013	GCYPP
Child-friendliness (%Population aged 0-4 yrs)	2014	GCYPP

GCYPP = Glasgow Children and Young People's Profiles

At locality level, there were two localities within the North East ward that had a higher relative rate. Locality characteristics were examined using a similar approach by Goldfeld et al., [319] for off-diagonal effects by examining whether locality characteristics can distinguish between areas that perform worse than expected. There is no consistent pattern between the localities in the North East that were off-diagonal (Easterhouse and Robroyston & Millerston) and those that performed as expected based on their demographics (Figure 7.3).

7.2.3 Model Building for SCEs

When a higher level effect is associated with an individual level outcome, this is referred to as a cross level effect. Blakely and Woodward [305] describe three main types of cross level effects:

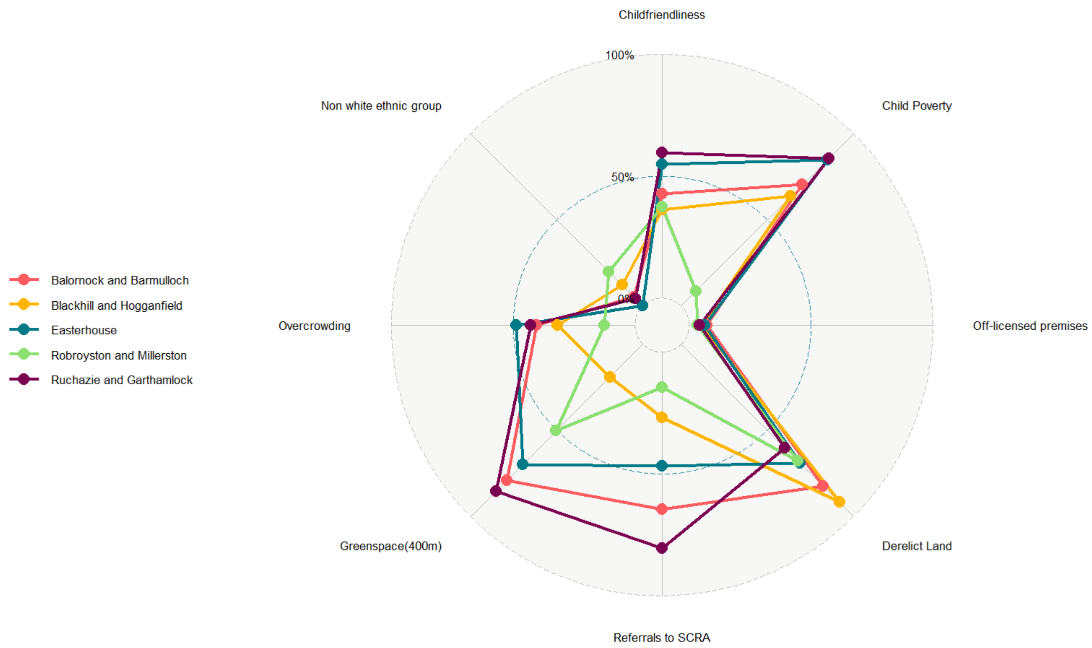

Figure 7.3: Radar plot of the locality indicators (scaled) across the North East ward

1. Direct effect on the outcome.

2. Indirect effect e.g. neighbourhood characteristic is associated with individual level risk or protective factors associated with the outcome.

3. Cross level modification of an individual effect on the outcome. The effect of a neighbourhood may depend on another explanatory variable. When this occurs between explanatory variables at two different levels of the model, it is known as cross-level modification or interaction.

Often discussions of cross level interactions assume a two level multilevel structure [320], however in our case there may be additional intermediate processes, confounding or interaction at the level of preschool too. I have expanded theoretical cross-level effects to include the potential of two higher-level contexts effects. These are represented in Figure 7.4 where letters Q and Z, represent preschool and neighbourhood effects, respectively.

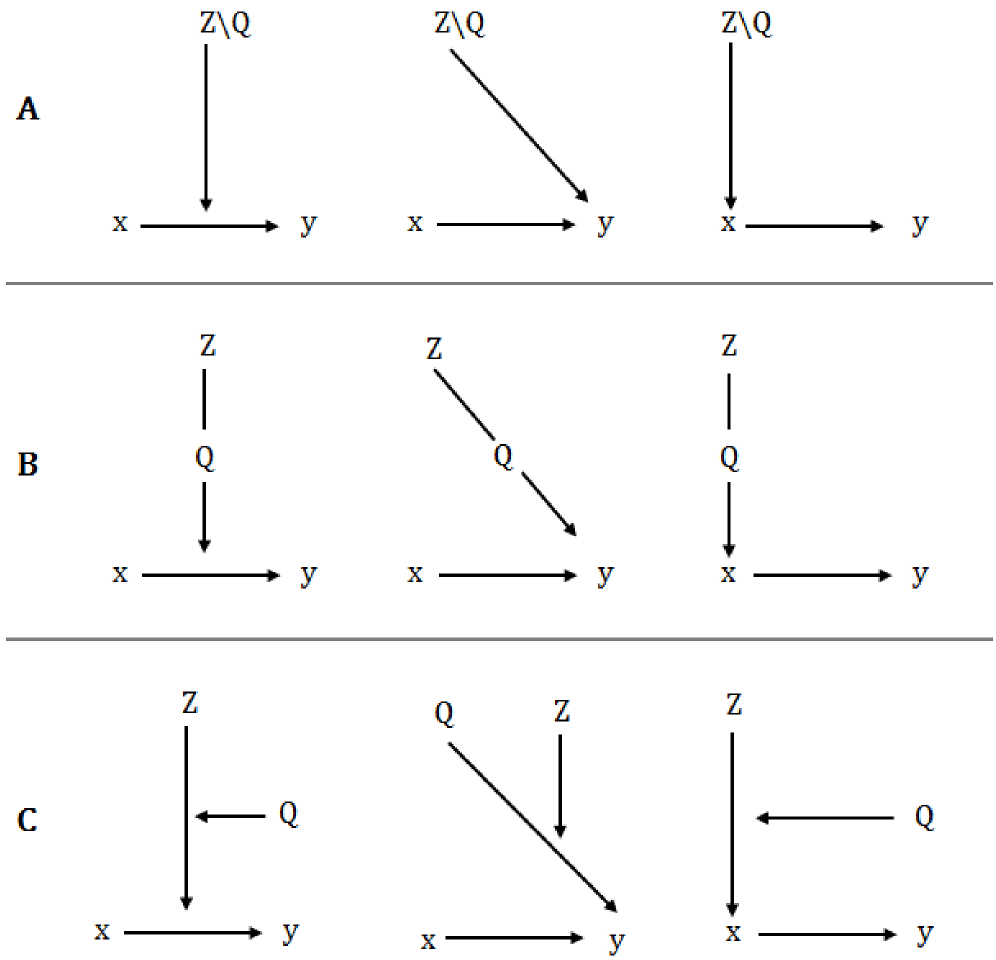

Figure 7.4: Multiple higher level contextual effects
Letters Q and Z, represent preschool and neighbourhood effects, respectively. x is the individual covariate and y is the outcome.

Row A represents separate preschool or neighbourhood associations with the outcome. This can be through cross level modification on an individual covariate x (left column), directly (centre) or indirectly via x (right). For example, Kuyvenhoven [321] et al., found there were separate direct effects at the preschool and neighbourhood level with educational inequalities.

Alternatively, the preschool may act as a mediator through which neighbourhood effects occur, this is shown in row B. For example, if the preschool is considered an institution within the neighbourhood, then neighbourhood structural mechanisms may impact the availability or quality of the preschool. Sykes and Musterd [322] found evidence of school mediating the relationship between neighbourhood and educational achievement. Other studies have examined the relationship between neighbourhood disadvantage and preschool quality [323, 324]. Alternatively, the neighbourhood may influence the characteristics of the children who attend the preschool.

Finally, there may be an interaction between the preschool and the neighbourhood (where either the preschool or the neighbourhood is the moderator) as shown in row C. This is most likely to occur through moderation of a direct or indirect effect. Using the classification by Gaias et al [325] for adolescent development, there are 4 ways the preschool and neighbourhood environment can moderate each other's contextual effects.

1. Amplified Advantages- the benefit of one positive contextual effect amplifies the positive effect of another contextual effect.
2. Compensatory Effect - the benefit of one positive contextual effect is stronger for those who also have a negative contextual effect.
3. Amplified Disadvantages - the disadvantage of one negative contextual effect amplifies the negative effect of another.
4. Contextual Adaptation - the disadvantage of one negative contextual effect is stronger for those who also have a positive contextual effect.

The presence of cross level modification or indirect effects can be investigated by including the following model variants. While causation or direction of effect cannot be determined, the models aimed to find associations between higher level effects and the outcome. Based on associations found in the literature, discussed above, [321–325] and for ease of interpretation, 5 out of the 9 contextual effects presented in Figure 7.4 were investigated (Table 7.7).

Table 7.7: Modelling neighbourhood indicators

Individual	Preschool	Ward	Interaction	Interpretation
+	+	+	-	Direct (AC)
-	+	+	-	Individual Intermediate (AR)
+	+	+	Individual* Ward	Cross-Level (AL)
+	-	+	-	Preschool Intermediate (BC)
+	+	+	Preschool* Ward	Cross-Level (CC)

The first letters (A, B and C) refer to the row in Figure 7.4. The second letters (L, C, R) refer to the left, centre and right columns of Figure 7.4.

$$\begin{aligned}\text{Model AC } &= \exp(\beta_0 + \beta_1 t + \beta_I x_{I_{ij}} + \beta_5 Q_k + \beta_6 Z_j + v_{0j} + \alpha_k + \phi) \\ v_{0j} \sim N(0, \sigma^2_{v0}), \frac{1}{\sigma^2_{v0}} &\sim \Gamma^{-1}(1, 0.0005) \\ \alpha_k \sim N(0, \sigma^2_{\alpha}), \frac{1}{\sigma^2_{\alpha}} &\sim \Gamma^{-1}(1, 0.0005) \\ \phi \sim N(0, \sigma^2_{\phi}), \frac{1}{\sigma^2_{\phi}} &\sim \Gamma^{-1}(1, 0.0005)\end{aligned} \tag{7.1 revisited}$$

In Model AC (introduced at the beginning of the chapter), preschool α_k and ward v_{0j} are cross-classified and wards are nested in ward-years ϕ. β_0 is the intercept, $\beta_1 t$ the coefficient for the overall time trend and $\beta_I x_{I_{ij}}$ are the individual level covariates (sex, age and deprivation). The model includes higher level covariates at the preschool level $\beta_5 Q_k$ and the ward level $\beta_6 Z_j$.

$$
\begin{aligned}
\text{Model AR} &= \exp(\beta_0 + \beta_5 Q_k + \beta_6 Z_j + v_{0j} + \alpha_k + \phi) \\
v_{0j} &\sim N(0, \sigma^2_{v0}), \frac{1}{\sigma^2_{v0}} \sim \Gamma^{-1}(1, 0.0005) \\
\alpha_k &\sim N(0, \sigma^2_{\alpha}), \frac{1}{\sigma^2_{\alpha}} \sim \Gamma^{-1}(1, 0.0005) \\
\phi &\sim N(0, \sigma^2_{\phi}), \frac{1}{\sigma^2_{\phi}} \sim \Gamma^{-1}(1, 0.0005)
\end{aligned} \tag{7.2}
$$

Model AR is the same as Model AC, however, the lower level covariates have been removed.

$$
\begin{aligned}
\text{Model AL} = \exp(\beta_0 + \beta_1 t + \beta_I x_{Iij} + \beta_5 Q_k + \beta_6 Z_j + v_{0j} + \alpha_k + \phi + \beta_7 x_{Iij} * Z_j + v_{1j} x_{Iij}) \\
v_{0j} \sim N(0, \sigma^2_{v0}), \frac{1}{\sigma^2_{v0}} \sim \Gamma^{-1}(1, 0.0005) \\
\alpha_k \sim N(0, \sigma^2_{\alpha}), \frac{1}{\sigma^2_{\alpha}} \sim \Gamma^{-1}(1, 0.0005) \\
\phi \sim N(0, \sigma^2_{\phi}), \frac{1}{\sigma^2_{\phi}} \sim \Gamma^{-1}(1, 0.0005) \\
v_{1j} \sim N(0, \sigma^2_{v1}), \frac{1}{\sigma^2_{v1}} \sim \Gamma^{-1}(1, 0.0005)
\end{aligned} \tag{7.3}
$$

For the cross-level interactions in Model AL, random slopes were included for the lower level covariate to ensure the estimates were conservative [326]. For individual level variable $\beta_I x_{Iij}$ (its coefficient describes the effect in an average neighbourhood and average preschool), the interaction between the individual level and neighbourhood variable $\beta_6 Z_j$ is represented by $\beta_7 x_{Iij} * Z_j$ and a random slope for the individual variable $v_{1j} x_{Iij}$. The effect of $x_{I_{ij}}$ changes with every unit increase in Z_j and the size of this increase is β_7. Therefore, the effect of x_{Iij} on Z_j is $\beta_I + \beta_7$.

$$
\begin{aligned}
\text{Model BC} &= \exp(\beta_0 + \beta_1 t + \beta_I x_{Iij} + \beta_6 Z_j + v_{0j} + \alpha_k + \phi) \\
v_{0j} &\sim N(0, \sigma^2_{v0}), \frac{1}{\sigma^2_{v0}} \sim \Gamma^{-1}(1, 0.0005) \\
\alpha_k &\sim N(0, \sigma^2_{\alpha}), \frac{1}{\sigma^2_{\alpha}} \sim \Gamma^{-1}(1, 0.0005) \\
\phi &\sim N(0, \sigma^2_{\phi}), \frac{1}{\sigma^2_{\phi}} \sim \Gamma^{-1}(1, 0.0005)
\end{aligned} \tag{7.4}
$$

Model BC has individual and preschool covariates, but no ward covariates.

$$
\begin{aligned}
\text{Model CC} = \exp(\beta_0 + \beta_1 t + \beta_I x_{Iij} + \beta_5 Q_k + \beta_6 Z_j + v_{0j} + \alpha_k + \phi + \beta_7 Q_k * Z_j + v_{kj} x Q_k) \\
v_{0j} \sim N(0, \sigma^2_{v0}), \frac{1}{\sigma^2_{v0}} \sim \Gamma^{-1}(1, 0.0005) \\
\alpha_k \sim N(0, \sigma^2_{\alpha}), \frac{1}{\sigma^2_{\alpha}} \sim \Gamma^{-1}(1, 0.0005) \\
\phi \sim N(0, \sigma^2_{\phi}), \frac{1}{\sigma^2_{\phi}} \sim \Gamma^{-1}(1, 0.0005) \\
v_{1j} \sim N(0, \sigma^2_{v1}), \frac{1}{\sigma^2_{v1}} \sim \Gamma^{-1}(1, 0.0005)
\end{aligned}
\tag{7.5}
$$

As in Model AL, Model CC has a cross-level interaction, this time between preschool and ward covariates. The interaction between the preschool covariate $\beta_5 Q_k$ and neighbourhood covariate $\beta_6 Z_j$ is represented by $\beta_7 Q_k * Z_j$ and a random slope for the individual variable $v_{kj} x Q_k$.

Direct Effects

For further information on the mechanisms of the constructs, the relationship between early development and neighbourhood characteristics across the domains of the SDQ was examined using the correlation. Previous research has found that neighbourhood effects can vary by SDQ domain [327]. For most indicators, there was a stronger relationship with internalising scores (peer relationship problems and emotional symptoms) than externalising scores (conduct problems, and hyperactivity/inattention) (Figure 7.5).

Some indicators had unexpected results. As shown in Figure 7.5 free-time places and participation were both moderately positively correlated with difficulties. The proportion of children aged under 5 was intended to reflect the neighbourhood perceptions of childfriendliness, however this had a weak positive association with difficulties. And finally, the proportion of households with no central heating had a weakly negative association with difficulties. Galster [105] discusses how neighbourhood contextual characteristics can give an unexpected result if they co-occur with factors that counteract their effects, these are known as antidotes.

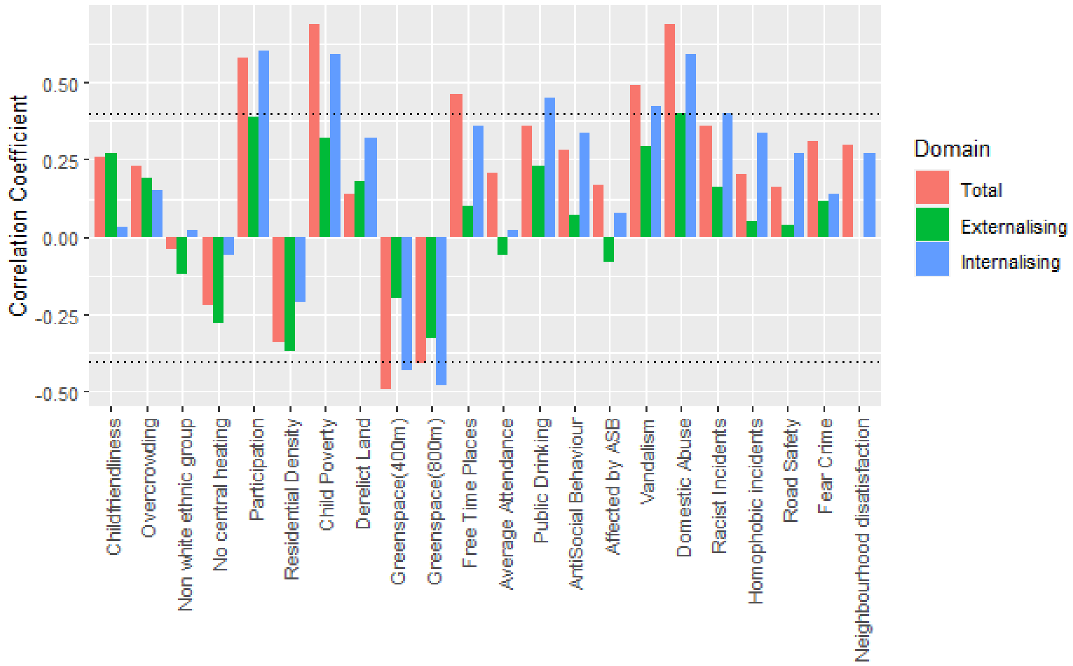

Figure 7.5: Relationship between neighbourhood characteristics and SDQ domains
SDQ Strengths and Difficulties Questionnaire

The relationship between these indicators and the other indicators in the study is shown in Figure 7.6. It has been previously shown that the distribution of resources in Glasgow does not always disadvantage more deprived communities [328] meaning that there may be more free time places in disadvantaged communities. The relationship between fear of crime and the number of free time places in the sample may be related to the link between free time places and vandalism, antisocial behaviour and more incidents of discrimination. Zuberi and Teixeria [329] found that neighbourhood disorder had an unexpected relationship with child health and hypothesised that parents of children with poor health may choose safer and less disordered neighbourhoods, causing a spurious association between better health and neighbourhood disorder. Moreover, as mentioned in the literature review (Chapter 2), objective measures do not take into account residents' satisfaction with the quality of the neighbourhood characteristic [308, 330].

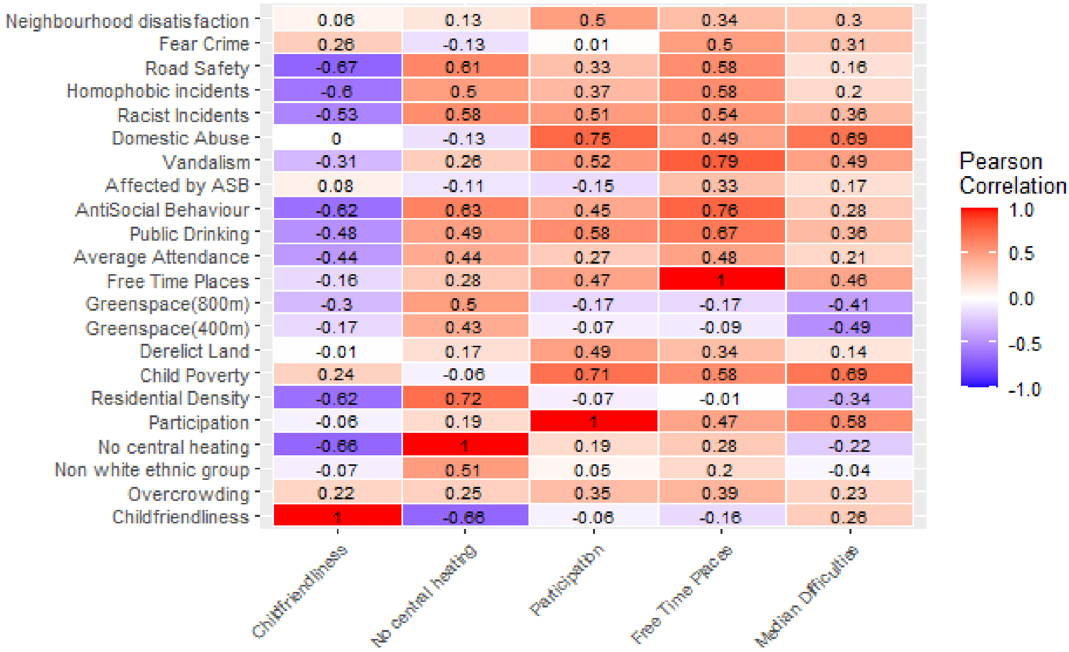

Figure 7.6: Exploring antidote effects in contextual characteristics

To reduce the variable list, a correlation coefficient greater than +/- 0.4 was considered a moderate correlation. This created a shortlist of indicators to include in the model as higher level covariates: participation, child poverty, domestic abuse, free-time places and vandalism were all positively correlated with median total difficulties scores while proximity to greenspace (at 400 m and 800 m) was negatively correlated (see Figure 7.5).

So far, a linear relationship is assumed. It is worth noting that there may be non-linear relationships between the other indicators and domain scores which need to be modelled as a categorical variable or with a non-linear function e.g. a polynomial. This was explored by plotting the covariates against individual scores and adding a generalized additive model smoothing line to estimate the relationship. Focusing on the indicators that did not have a linear correlation with the outcome, there did not appear to be a non-linear association either (Figure 7.7).

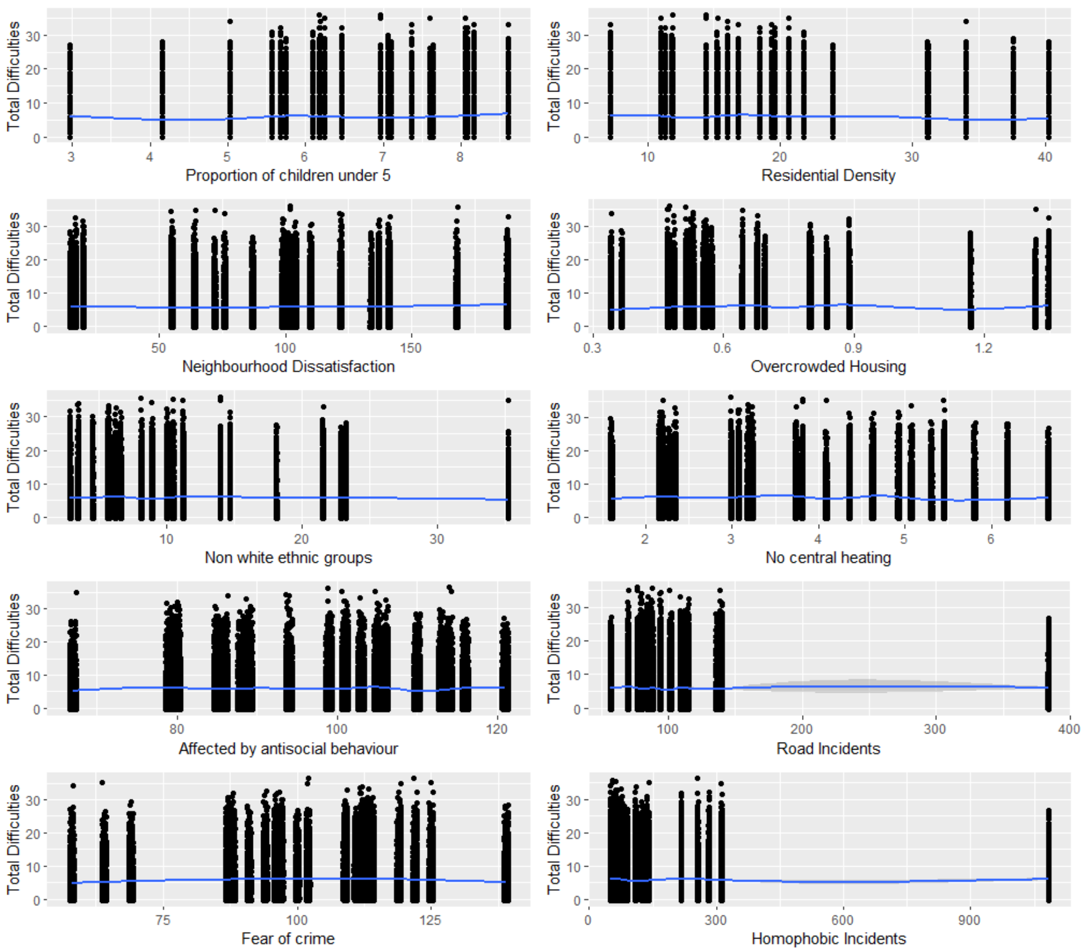

Figure 7.7: Non-linear relationship between neighbourhood characteristics and total difficulties scores

SDQ Strengths and Difficulties Questionnaire

Including the neighbourhood covariate Z_j to the existing model spatio-temporal with the preschool covariate Q_k (Equation 7.1) allows the model to examine whether there is a direct neighbourhood effect. The beta coefficient β_6 describes whether there is an association between the neighbourhood covariate and total difficulties score outside the association between individual covariates x_i , preschool provider type, and total difficulties scores.

It is recommended for SCEs that there are 10 units per higher level covariate [285]. Therefore, with 21 electoral wards, modelling ward effects is limited to two ward-level covariates. To account for this limitation, all ward SCEs were investigated using a stepwise variable selection approach. The estimates for β_6 are shown in Table 7.8 which were added to the model one at a time. Merlo et al., [331] discuss the value of including measures of variance along with measures of association (i.e. the beta coefficient). The change in the neighbourhood level variance (σ^2_{v0}) after adjustment indicates how much of the neighbourhood variance can be attributed to that higher-level covariate.

All estimates of β_6 included the null value of 1, suggesting there is no relationship between these higher level covariates and total difficulties scores. Without adjustment for higher-level covariates, the neighbourhood variance was 0.011 (0.007-0.018) which accounted for 1.1% of the total variance. There was no considerable change to the variance estimates (Table 7.8).

Table 7.8: Modelling neighbourhood indicators

Indicator	Association	Variation
	Relative Rate (95% CrI)	Ward Variance (95% CrI)
Child Poverty Rate	0.997(0.992- 1.002)	0.009 (0.007-0.012)
Participation	0.995 (0.982-1.006)	0.012 (0.007-0.018)
Domestic Abuse	0.997 (0.999-1.005)	0.012 (0.007-0.018)
Free-time places	0.994 (0.977-1.011)	0.009 (0.005-0.009)
Vandalism	1.000 (0.999-1.001)	0.009 (0.005-0.014)
Greenspace (400m)	1.000 (0.996-1.003)	0.009 (0.007-0.009)
Greenspace (800m)	1.000 (0.995-1.004)	0.010 (0.007-0.013)

The removal of individual or preschool covariates through Models AR and BC did not notably change the estimates of association as shown in Figure 7.8 therefore the variance terms are not reported. Note the values in the figure assume all other covariates are fixed (i.e. where the covariates are included, this represents estimates for a girl of average age, in the least deprived quintile, at a small local authority preschool in 2010).

There was no evidence to support area level deprivation being associated with total difficulties scores after considering our individual level deprivation proxy measure (alongside the other demographics). The ward level child poverty measure had a strong, positive correlation with the proportion of children in the most and second most deprived quintile for each ward, $r = 0.80$ supporting the validity of the measure. This may result in limited further information being added by the area level indicator. This supports findings in a recent review, that individual level measures of disadvantage are more strongly associated with child outcomes than area level measures [36]. From a policy perspective, the discrepancy between area and individual deprivation is important, as any spatial targeting based on area level deprivation will not capture everyone affected by the relationship between deprivation and development.

Some results differ from studies in other contexts. For example, other multilevel studies have found that residential density, greenspace [43, 332] and the availability of libraries [333] are all associated with socio-emotional outcomes for populations in Australia and Mexico. This may reflect a difference in the relative importance of each characteristic depending on the setting [104].

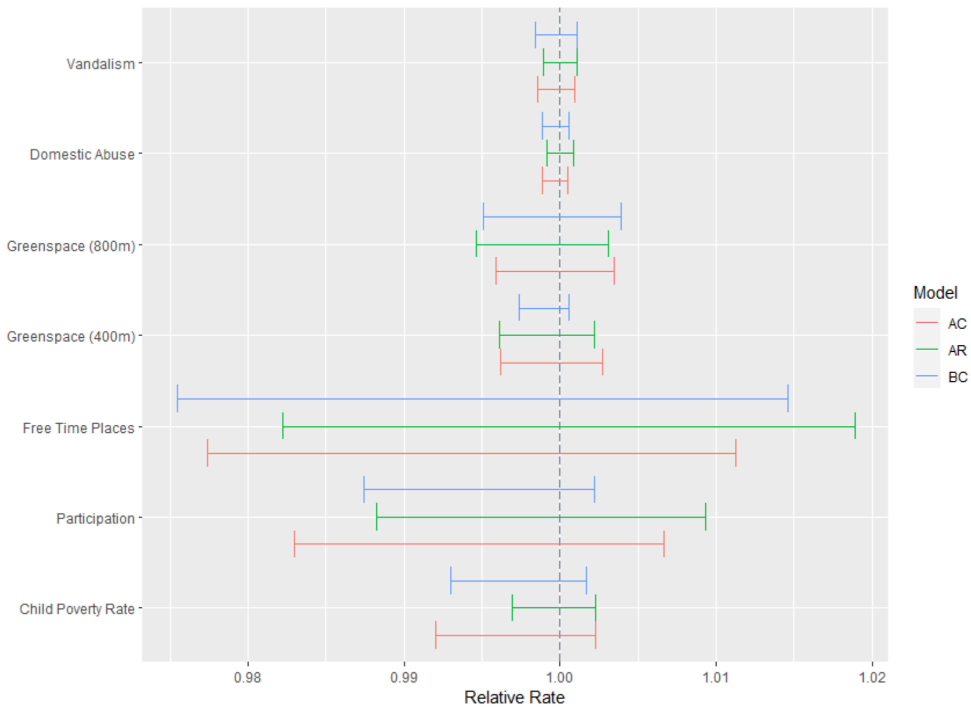

Figure 7.8: Neighbourhood level effects
Direct (AC), without individual covariates (AR) and, without preschool covariates (BC)

Sensitivity Analysis

A previous study found that the method of measurement for greenspace can impact whether an association is observed for child mental health in Scotland [127]. Following this, public parks and gardens and play spaces can be distinguished from overall greenspace and libraries from free-time places to understand the impact of measurement. Separating these categories does have an impact on the wards identified as having the highest proximity to greenspace. If including all, the highest percentage of children within 400 m of greenspace was 70% of children in Hillhead, if only looking at play space this becomes Calton with 49% and for public parks, this is Southside Central with 67%. There was a negative correlation between proximity to public parks and neighbourhood difficulties ($r = -0.67$) and no correlation for play space ($r = 0.16$). Neither public park (RR=1.000 (0.998-1.003)) nor play space (RR=0.998 (0.995-1.001)) was associated with total difficulties scores.

In Mexico, libraries were the only institution measured that were associated with socio-emotional development in 3 to 5-year-olds [333]. For libraries, there was limited variation between the wards to warrant adding to the model. Baillieston, Garscadden/Scotstounhill, Langside, Maryhill/Kelvin, Newlands/Auldburn, Pollokshields and Shettleston all have 1 library, while the remaining wards have 2 with the exception of Greater Pollok which had no libraries. There was however greater variation in the average attendance of the libraries which ranged from 1844 in Canal to 14377 in Anderston/City (where there is the largest library in Glasgow). Moreover, wards with only 1 library were still among the most visited (e.g. Langside, Newlands/Auldburn, Pollokshields and Shettleston). There was no correlation between neighbourhood difficulties and the number of libraries ($r = 0.27$) or the attendance of libraries ($r = -0.02$), therefore this indicator was not taken forward for modelling.

Indirect Effects

A lack of association in the direct neighbourhood effects does not mean there are no SCEs, but rather there is no evidence to support a direct effect. There may be indirect or cross-level effects that have yet to be modelled.

Individual level data in the ChiME dataset was limited to the variables previously discussed. Other variables such as looked-after status and ethnicity had a high degree of missing values, so could not be included. Instead, additional data from the SDQ can be used. Prosocial behaviour is a domain of the SDQ, but not represented in the total difficulties scores. It is considered a measure of child mental well-being according to the Scottish NHS Indicators [109] and is included as part of mental health competence in the EDI [334]. Various studies report an association between higher levels of prosocial behaviour and lower externalising behaviours [335]. In the Millenium Cohort Study (MCS), prosocial behaviour was negatively associated with total difficulties scores trajectories [336].

There is limited research on the role of positive health outcomes compared to measures of poor mental health when considering the role of the neighbourhood [38]. Figure 7.9 shows the distribution of prosocial scores across the wards. In our sample, prosocial behaviour is negatively correlated with total difficulties at the neighbourhood level $r = -0.60$.

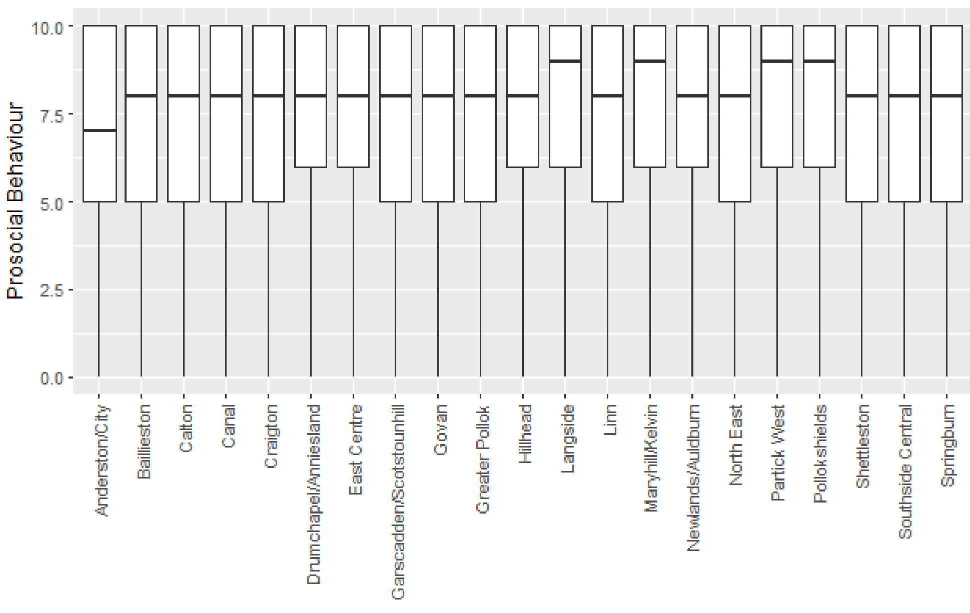

Figure 7.9: Prosocial behaviour by ward

Adding prosocial behaviour to the model (centred to maintain interpretation of the intercept), reduced the DIC from 196161 to 183479, and on average, a unit increase in prosocial scores was associated with a 17% reduction in total difficulties (RR=0.834 (0.832-0.837)). According to the model (shown in Table 7.9), differences by sex were partly due to sex differences in prosocial behaviour (girls had average scores of 9 while boys had average scores of 7). There are no longer significant changes to average difficulties over time.

Table 7.9: Impact of prosocial behaviour on model parameters

Parameter	Without Prosocial behaviour RR (95% CrI)	With Prosocial behaviour RR (95% CrI)
Intercept	4.344 (3.957-4.769)	4.741 (4.420-5.084)
Cohort	1.009 (1.002 -1.016)	1.003 (0.997-1.008)
Sex (Male vs Female)	1.370 (1.344 -1.397)	1.064 (1.048-1.080)
Deprivation (4th vs 5th)	1.110 (1.068 -1.154)	1.067 (1.037-1.099)
Deprivation (3rd vs 5th)	1.168 (1.123-1.216)	1.086 (1.053-1.119)
Deprivation (2nd vs 5th)	1.226 (1.178- 1.275)	1.117(1.084-1.151)
Deprivation (1st vs 5th)	1.235 (1.186- 1.286)	1.143 (1.108- 1.178)
Age	1.003 (1.003-1.004)	1.001 (1.001- 1.002)
Medium LA vs Small LA	1.017 (0.915-1.131)	1.063 (0.982-1.150)
Large LA vs Small LA	0.979 (0.881-1.089)	0.999 (0.924-1.081)
Private vs Small LA	0.735 (0.654-0.826)	0.920 (0.843 -1.005)
Voluntary vs Small LA	0.903 (0.773-1.055)	0.934(0.831- 1.049)
Prosocial	-	0.834 (0.832-0.837)
	Variance (95% CrI)	Variance (95% CrI)
Ward	0.011 (0.007-0.018)	0.005 (0.002-0.007)
Preschool	0.051 (0.039-0.071)	0.031 (0.024-0.041)
Spatio-temporal	0.005 (0.003-0.007)	0.003 (0.002-0.005)
DIC	196161	183481

CrI Credible Interval; DIC Deviance Information Criterion

Accounting for individual differences in prosocial behaviour, there are no longer differences in provider type over and above this. It may be that prosocial behaviour is an intermediate process through which private preschools have lower total difficulties scores. The distribution of prosocial behaviours is much less varied for private businesses, which also have higher median scores (Figure 7.10).

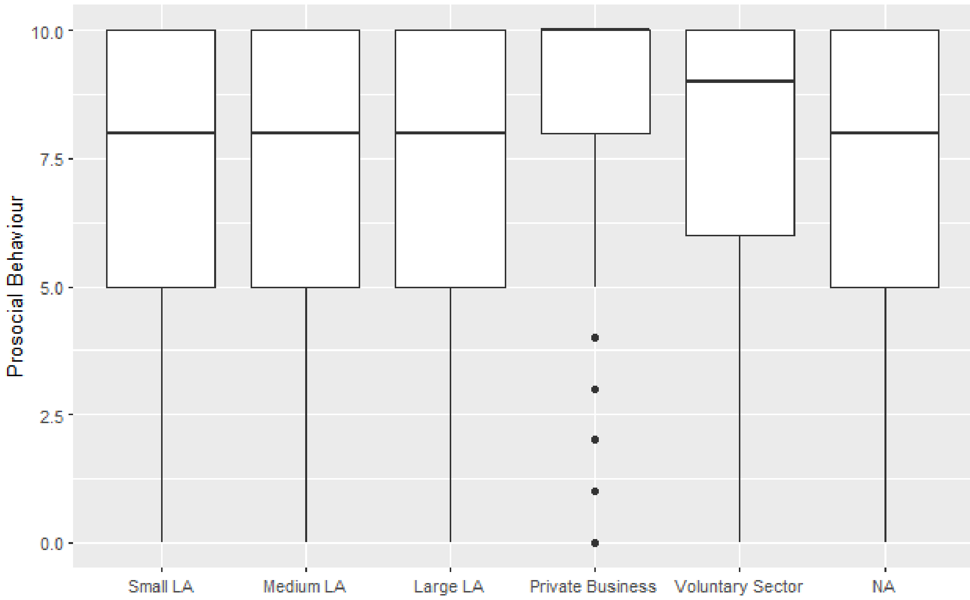

Figure 7.10: Prosocial behaviour by preschool

Preschool variance has reduced, and the ward variance has greatly reduced, showing that higher level contextual variation can partly be attributed to prosocial behaviour.

At the neighbourhood level, there were several variables that were not moderately correlated with neighbourhood difficulties but were correlated with neighbourhood prosocial behaviour (Table 7.10): fear of crime, road safety, homophobic incidents, affected by antisocial behaviour, reports of antisocial behaviour, attendance for free-time places. Conversely, proximity to greenspace (both at 400 m and 800 m) was correlated to neighbourhood difficulties but not prosocial behaviour. This supports the notion that prosocial behavioural may operate through an additional mechanism. While there is limited evidence to support prosocial mediation for the variables that were correlated to total difficulties score, there may be an association for variables that are uniquely correlated to prosocial behaviour.

Table 7.10: Correlation between ward indicators and average SDQ domain scores

Indicator	Total Difficulties	Prosocial Behaviour
	Correlation Coefficient	Correlation Coefficient
Childfriendliness	0.26	0.16
Overcrowding	0.23	-0.15
Non-white ethnic group	-0.04	0.06
No central heating	-0.22	0.10
Participation	**0.58**	**-0.40**
Residential Density	-0.34	0.17
Child Poverty	**0.69**	**-0.50**
Derelict Land	0.14	-0.18
Greenspace (400m)	**-0.49**	0.19
Greenspace (800m)	**-0.41**	0.31
Free Time Places	**0.46**	**-0.65**
Average Attendance	0.21	**-0.48**
Public Drinking	0.36	**-0.44**
AntiSocial Behaviour (ASB)	0.28	**-0.53**
Affected by ASB	0.17	**-0.47**
Vandalism	**0.49**	**-0.56**
Domestic Abuse	**0.69**	**-0.47**
Racist Incidents	0.36	**-0.46**
Homophobic incidents	0.20	**-0.42**
Road Safety	0.16	**-0.44**
Fear of Crime	0.31	**-0.45**
Neighbourhood disatisfaction	0.30	-0.34

SDQ Strengths and Difficulties Questionnaire

Of those uniquely correlated, the strongest relationship was with antisocial behaviour. There was a high correlation (>0.8) between antisocial behaviour and many other variables (public drinking, vandalism, racist incidents, homophobic incidents and road safety) that would suggest that they are interrelated [270]. There was no evidence of an association between difficulties scores and reports of antisocial behaviour with (RR=1.000(0.999-1.000)) or without (RR=1.000(0.999-1.001)) the inclusion of prosocial behaviour.

The correlation between characteristics and SDQ domain scores was examined at locality level (Table F.1). None of the indicators at locality level were moderately correlated with average prosocial scores or total difficulties scores.

Cross Level Interactions

Minh et al., [26] carried out a review of neighbourhood effects related to child development that included several cross-level interactions. There were inconsistent results, leaving the authors to conclude that the interaction between child and neighbourhood characteristics is likely to depend on the developmental domain and the specific characteristics. Relevant cross-level interactions mentioned in the review that could be considered for this study are:

- the interaction between sex and type of greenspace on individual internalising and externalising scores in Scottish 4-6-year-old children [127]
- the interaction between neighbourhood socioeconomic status and sex on social competence and emotional maturity for 3-7-year-olds in Canada [337]
- the interaction between neighbourhood disadvantage and prosocial behaviour on internalising and externalising scores in 3-7-year-olds in the UK [336]

In addition, based on the relationships found in the data so far:

- an interaction between prosocial skills and provider type

For cross-level interactions, there is a main covariate effect, that depends on the value of the interaction term. The RR of the interaction term is the change in the main effect for every unit increase of the interaction term. Therefore, the full effect of an interaction is the main RR plus the interaction RR (Please refer to Equations 7.5 and 7.3 for further information). Table 7.11 shows the main effect and the interaction effect for each of the covariates. From these investigations, it appears that attending a private preschool moderates the relationship between prosocial behaviour and total difficulties (Table 7.11). A visualisation of the predicted relationship between prosocial behaviour (centred) and total difficulties and how this is moderated by provider type is shown in Figure 7.11. The negative slope between prosocial and total difficulties scores is steeper for private preschools (blue).

Table 7.11: Modelling cross level lnteractions

Main Effect	Main RR (95% CrI)	Interaction	Interaction RR (95% CrI)
Playspace*	0.999 (0.997-1.002)	Playspace x Sex (boys)	0.999 (0.996-1.002)
Public Park*	1.000 (0.999-1.001)	Public Park x Sex (boys)	1.000 (0.999-1.001)
Child Poverty*	0.997 (0.992-1.002)	Child Poverty x Sex (boys)	1.001 (0.997-1.004)
Child Poverty	0.995 (0.991-1.000)	Child Poverty x Prosocial	1.001 (0.999-1.002)
Medium LA **	1.059 (0.976-1.150)	Medium LA x Prosocial	0.999 (0.992-1.007)
Large LA **	0.993 (0.915-1.078)	Large LA x Prosocial	0.994 (0.987-1.002)
Private **	0.914 (0.835-1.001)	Private x Prosocial	0.971 (0.956-0.987)
Voluntary **	0.923 (0.818-1.042)	Voluntary x Prosocial	0.990 (0.968-1.011)

*Note that separate models were also run without prosocial skills included to rule out confounding. ** compared to a small local authority preschool. LA Local Authority preschool.CrI Credible Interval. RR Relative Rate.

The interaction between provider type and prosocial skills further reduced the DIC from 183481 to 183465. The ward level variance term was reduced to 0.000 (0.000 - 0.000). With the inclusion of this interaction effect, there were no longer any wards with an increased relative rate according to the exceedance probability (i.e. > 0.8). There was still unexplained variation at the preschool (0.031 (0.023-0.047)) and spatio-temporal (0.004(0.003-0.005)) levels that warranted further investigation. For residual preschool variation, assuming the role of organisational ties [301, 302], it is hypothesised that the relationship between provider type and total difficulties scores may depend on the availability of relevant organisations in the area. The number of free-time places was used to explore this further. There was evidence of cross-level modification across the characteristics and a change to the direct preschool effects. Table 7.12 shows the

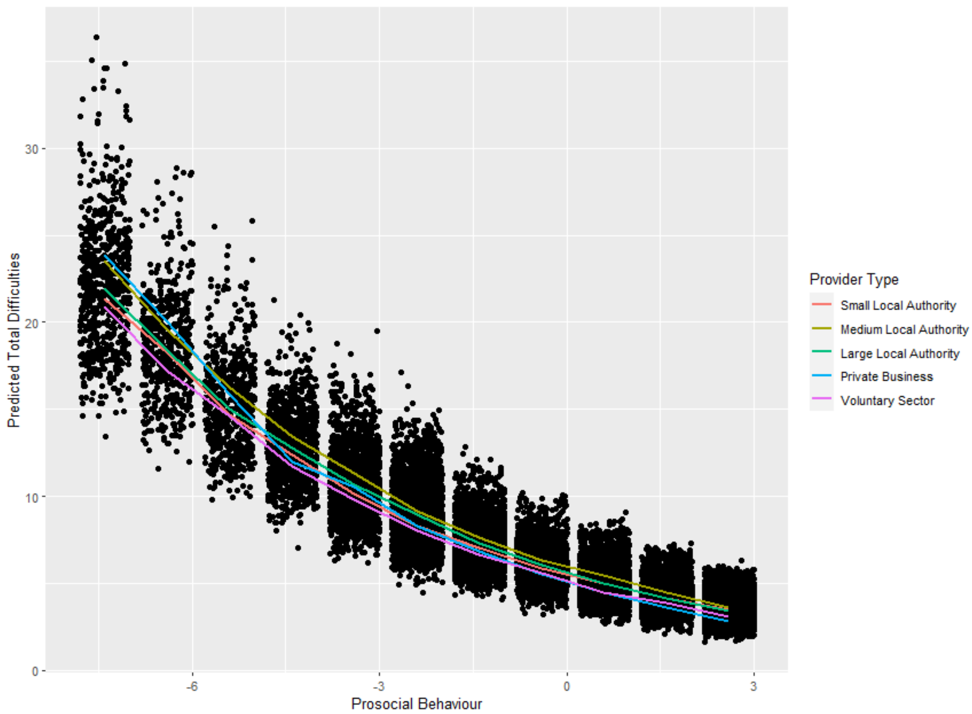

Figure 7.11: Interaction between prosocial behaviour and provider type on predicted difficulties scores

main effect of each provider type, and the RR of its interaction with the number of free time places.

Table 7.12: Impact of free time places on model parameters

Parameter	Main RR (95% CrI)	Free time Places Interaction RR (95% CrI)
Medium LA*	1.166 (1.034 -1.314)	0.983 (0.967 - 0.998)
Large LA*	1.037 (0.932-1.154)	0.991(0.978 - 1.005)
Private*	0.827(0.716- 0.956)	1.022 (0.999- 1.046)
Voluntary*	0.843 (0.686 -1.035)	1.018 (0.984-1.052)
Parameter	Variance (95% CrI)	
Ward	0.000 (0.001- 0.000)	
Preschool	0.032 (0.040 - 0.027)	
Spatio-temporal	0.003 (0.008-0.002)	
DIC	183456	

* Compared to a small local authority preschool. CrI Credible Interval. RR Relative Rate

Figure 7.12 shows private preschools as previously discussed have lower predicted difficulties scores than small local authority preschools. Scores are higher for children who attend medium-sized local authority preschools and live in wards with more free time places. After adjustment there is a marginal improvement to the DIC, however there is no major change in preschool variance and 57 preschools still have an increased relative rate. This is weak evidence in support of the higher cross-level interaction.

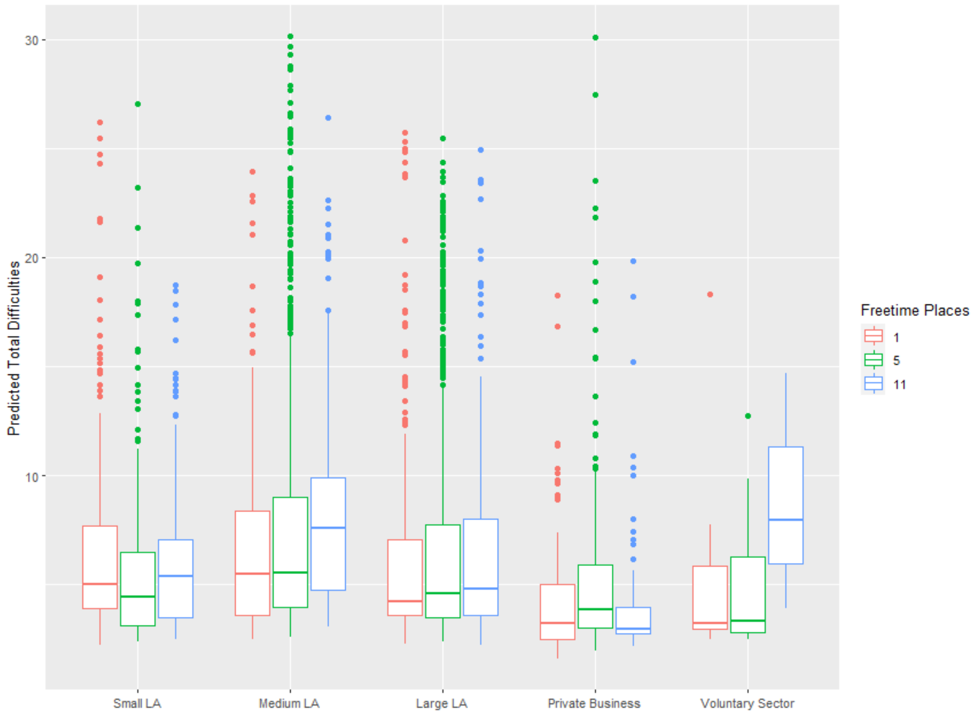

Figure 7.12: Interaction between free time places and provider type on predicted difficulties scores

Values were chosen to show the effect differences by provider type for the minimum (1), median (5) and maximum (11) number of free time places by ward (See Figure E.1)

7.3 Spatio-temporal Characteristics

Effective measurement of the construct requires consideration of its administration. Questions include how often is a child exposed to this construct and for how long, at what intensity, and if this is consistent over time or space. [105, 307].

While there are wards identified to be worse than expected consistently over time, spatio-temporal effects point to the existence of deviations from this trend. Therefore, one of the wards identified as being worse than expected overall, may not be worse than expected in a particular year.

The profile of the ward can vary by year. Figure 5.20 in Chapter 5 showed the overall spatial effect (uj) and the spatio-temporal deviation (vj) combined for the wards identified as having an increased RR overall. The year 2014 appears to be the only one where each ward is considerably worse than expected. However, this is not the year provided in the majority of the indicators (Table 7.4). Finally, there may be a time lag between exposure and a change in outcome.

In the absence of complete yearly data, the assumption is made that a single year indicator is reflective of the entire time period. A variable taken from a single year is unlikely to capture the true variation in effects. Most indicators were only available for a single year (e.g. those taken from the CSI).

Figure 7.13 shows the temporal trends for indicators that were available for multiple years. The majority of wards have a similar proximity to derelict sites over the years, there are six wards that appear to change over time, though this may be due to imputation discussed earlier. There is less year on year change in the proportion of households with low income families with children 0-4, with only Southside Central showing a clear change over time. While for the proportion of children in the sample, an indication of the “child-friendliness” of the ward, there was an increase over time seen in Southside Central and Calton while the other highlighted areas show a decrease over time.

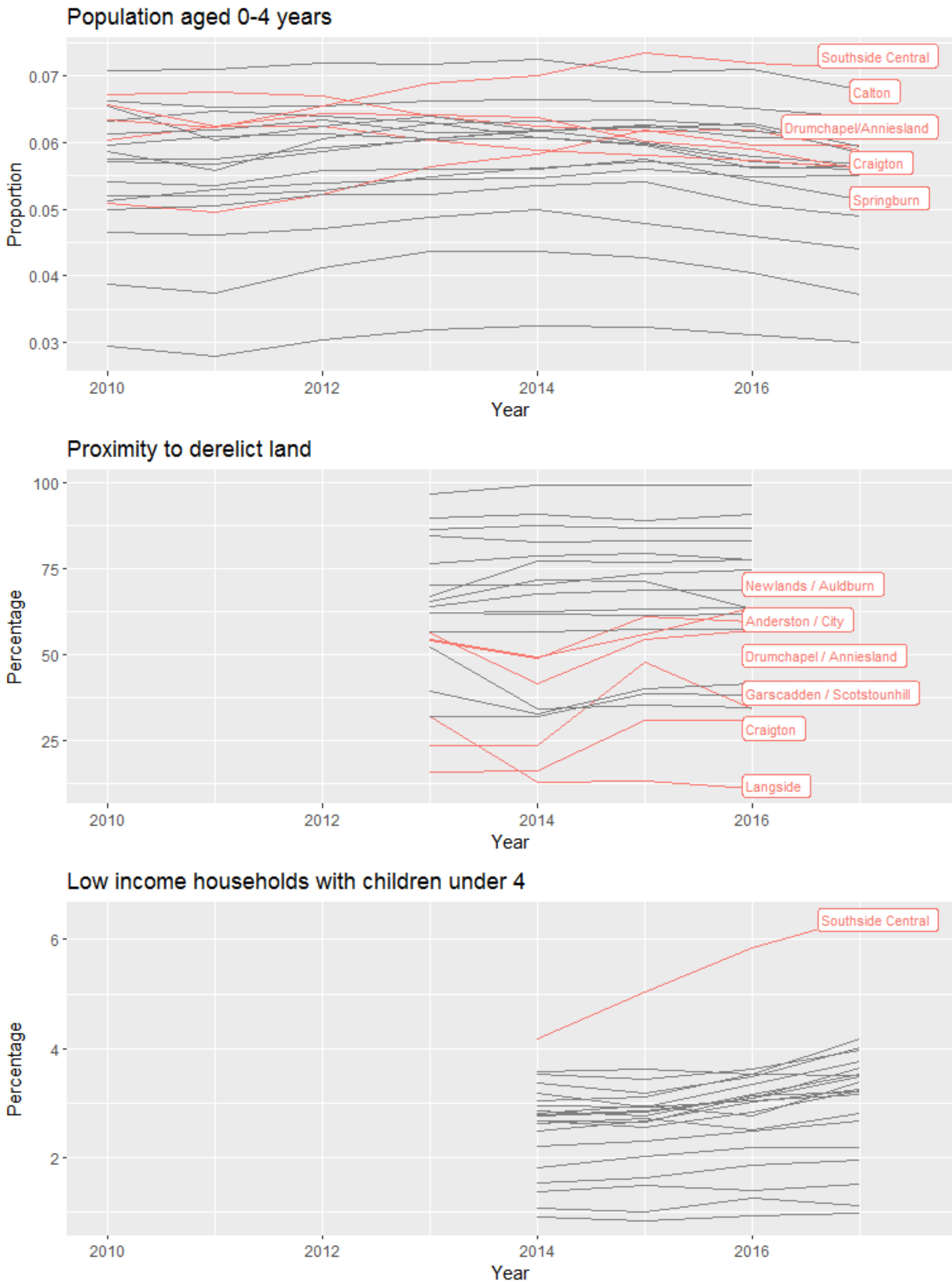

Figure 7.13: Yearly ward variables

Not all variables are expected to change yearly. The spatio-temporal variation in this sample could be due to the changing characteristics of the neighbourhood or changing characteristics of the neighbourhood population. What Works Centre for Wellbeing [338] describe how aspects of the neighbourhood can vary based on their ability to change or be modified. For example, the perceptions of residents are considered more fluid than location or rurality which is more fixed. Since the spatio-temporal variation observed in this study occurs within a year, it is more likely due to the changing characteristics of the population (or the representativeness of the ChiME sample) in the neighbourhood each year, excluding the demographics already included in the model.

The data collected yearly were not always available for the full-time period of the study or at the same level of geography due to boundary changes. As discussed previously in Chapter 6 with the subset data at the IZ level, conducting analysis on only a few years reduces the ability to detect spatio-temporal contextual effects. Correlations between individual level prosocial scores or total difficulties for the spatio-temporal level indicators were weaker or not present, therefore there was no further modelling (Table 7.13).

Table 7.13: Yearly ward variables and their correlation to total difficulties scores

Indicator	Source	Years	Total Difficulties	Prosocial
Proximity to Derelict Land	SG	2013-2016	0.15	-0.03
Low income households (0-4 years)	DWP	2014-2017	0.20	0.04
Population aged 0-4 years	DWP	2010-2017	0.19	-0.07

SG= Scottish Government, DWP = Department for Work and Pensions

7.4 Discussion

This chapter aimed to understand the Specific Contextual Effects (SCEs) that are associated with total difficulties scores. To identify the SCEs, the spatio-temporal model from Chapter 5 was expanded to include higher level covariates at the preschool or ward level.

First, this chapter examined the effects of preschool on total difficulties. At the preschool level, open access data from 2013 was used to classify the preschools depending on their provider type (voluntary, local authority, private) and their size (local authority only). A limitation of the data is that there is no measure of the quality of the preschool, and provider type could not be assigned to all preschools. This missing data may impact the findings of this research.

Most children were in a large local authority preschool – this varied by ward. The range of difficulties scores was lower in private preschools, where children were less deprived. When added to the model, compared to small local authority preschools, total difficulties scores were 26.5% lower on average in private preschools. According to the literature, it was previously expected that private preschools would have larger class sizes [84] and poorer quality [300] than local authority preschool. These are characteristics that are assumed to relate to worse developmental outcomes. In this sample, lower scores in private preschools may be connected to the low percentage of most deprived children attending private school or relate to differences at the level of the preschool (or teacher) that are captured by provider type e.g teacher-child relationship [339]. It should be noted that the private preschool sample was relatively small and may have been affected by selection bias.

Further, there may be measurement bias due to differences in completing the SDQ forms for teachers in private/partnership preschools compared to local authority preschools. Preschool staff in Glasgow can use routinely collected SDQ scores to highlight developmental needs [102]. There may be differences in motivation for recording those needs and how this information is used by provider type. For example, staff mentioned being anxious about how parents would react to the results, and that this may influence how information is recorded. This anxiety could be more pronounced in private preschools, leading to outcomes being recorded more positively.

White et al., [102] found that where data was collected, the approach varied, for some preschools, the SDQ was collected as part of a collaborative exercise, and some preschools had scores verified by a head teacher. In 2010, 57% of preschool teachers in partnership schools worked across several centres, compared to 20% in partnership preschools [94]. It is unclear for the ChiME project, whether SDQ forms were recorded collaboratively, verified or collected by the same members of staff across the different preschool provider types.

The chapter went on to review the neighbourhood characteristics that are associated with total difficulties. The literature review in Chapter 2 discussed the poor availability of neighbourhood level data relevant to child development. A data availability search was conducted to find different data sources at ward and locality level using the reference list of the literature review, data repositories and data services.

Data was accessed from the Glasgow Indicators Project at Understanding Glasgow [309, 318], the 2011 Census [314], the Scottish Government and the Urban Big Data Centre (UBDC) [311]. As can be the case with routinely collected data, the quality of these indicators and their relevance to the population of interest varied. By using a range a data sources, there were differences in methodologies and in some cases limited information on their reliability and validity [185].

Indicators were ranked and visually compared across the high risk wards. The profile of the wards varied. Within the North East ward, the characteristics of the localities were similar, based on the data that was available.

Model building of cross-level associations between neighbourhood characteristics on individual difficulties was based on three main types of cross-level effects: direct, indirect and cross-level modification. These effects considered the role of the preschool as an additional level of the model, which was represented schematically.

For direct effects, a shortlist of indicators was considered based on their moderate correlation to average total difficulties scores: participation, child poverty, domestic abuse, free time places, vandalism, and proximity to greenspace (at 400 m and 800 m). Some indicators e.g. free time places had contradictory relationships with total difficulties scores. This may be related to the fact that deprived areas may have better access to facilities, as mentioned in the literature review in Chapter 2 [165, 166]. O'Neil et al., [340] suggest that regeneration and renewal projects (that improve neighbourhood services) can lead to further issues in accessibility and inclusion that may worsen mental health outcomes.

The ecological correlations between total difficulties and the neighbourhood indicators did not translate to direct cross-level effects. This highlights an area of caution for future research where, in the absence of individual level data, ecological fallacies may be made. The lack of cross-level associations may be due to confounding by unmeasured family and household factors that mitigate the effect of the neighbourhood on development [98].

While spatio-temporal data seems unattainable at present, the analysis would have benefited from indicators that describe variation that was consistent across time. Knowing that there is spatio-temporal variation means that indicators from a single year are unlikely to explain overall spatial effects.

The measurement of the neighbourhood indicators may benefit from further analysis to create a composite measure of the neighbourhood environment (e.g. the Child Opportunity Index used in cities in the US [341] or distinct neighbourhood profiles [342]).

Prosocial scores had ecological correlations with neighbourhood characteristics that were not correlated to total difficulties. This supports previous findings that neighbourhood is more meaningful to prosocial behaviour than to physical aggression [292].

Residual ward variation was explained by the interaction of individual and preschool characteristics, specifically prosocial behaviour and provider type. The relationship between neighbourhoods, preschools and developmental outcomes has been found in other settings. In a review of preschool characteristics associated with developmental outcomes, factors related to the preschool location (e.g. urban vs rural, area level deprivation) were not frequently examined but were consistently associated with early mental health [343]. In Canada, neighbourhoods that had better than expected teacher rated EDI scores based on their socioeconomic status (i.e. off-diagonal), had better quality childcare [344]. Since neighbourhood variation was explained by preschool quality, it was proposed that preschool was a mediating factor [344].

In the current study, the spatial variation in total difficulties may relate to the characteristics of the preschools within neighbourhoods or the characteristics of the children who attend that preschool. The separation between an individual characteristic (reflecting the composition of the neighbourhood) and a higher level effect (reflecting the context) is challenging, as the composition of the neighbourhood is shaped by the context and vice versa [345].

Chapter 8

Conclusion

8.1 Summary

There is growing interest in using place-based approaches to tackle inequalities. However, the current evidence to support the use of place-based interventions to improve early developmental outcomes is limited [28, 346]. Chapter 1 discusses the methodological challenges that affect the delivery and evaluation of place-based initiatives. Population data can be a valuable resource for addressing these issues. With population data, multilevel approaches can be used. Multilevel modelling allows the investigation of the different contexts that are associated with developmental outcomes. This project uses the Child Mental Health in Education (ChiME) study (preschool children in Glasgow from 2010-2017) to explore how neighbourhood variation relates to social, emotional and behavioural (total) difficulties. An overview of 13 potential neighbourhood constructs that may be associated with early development in Scotland is provided in Chapter 2. A limitation of the multilevel approach is that there is increased model complexity. The components of multilevel spatio-temporal models are reviewed in Chapter 3. Model building can be supported with Bayesian approaches introduced in Chapter 4. A Bayesian Workflow [237] supports the use of Zero Inflated Negative Binomial distribution of total difficulties scores and the use of approximation methods for estimation. Chapter 5 investigates the different contexts (individual, preschool and electoral ward) and the demographic characteristics (age, sex, deprivation) related to variation in development for the ChiME sample. The definition of the neighbourhood as an electoral ward was compared with other neighbourhood boundaries. Chapter 6 quantifies the relative importance of each context, (in addition to other neighbourhood boundary definitions) using recently developed variance partition equations. The preschool context was found to be more important than the neighbourhood in relation to variation in developmental outcomes. Chapter 7 reviews the availability of data to reflect preschool and neighbourhood characteristics for children. Preschool but not neighbourhood characteristics were associated with total difficulties. There is a need for more spatio-temporal data, that can be linked to population data, to understand how the neighbourhood is associated with development at an individual level. Similar studies have shown how this research can be used to generate administrative databases, support classroom teaching, create place-based interventions and develop policies [8, 52, 109, 347]. The final section returns to the research questions introduced in Chapter 1, to discuss how this work may be used to support policy development and future research.

8.2 Implications for policy and research

8.2.1 How Does Early Development Vary Over Space and Time?

With limited methodological guidance on how to model spatio-temporal variation in multilevel models, Chapter 3 provides a methodological review of the approaches used to date. These strategies for incorporating different structures of spatio-temporal dependence are then applied to ChiME data. This improves the relevance of this work to current practice.

Chapter 4 shows the advantages of modelling total difficulties using a Generalised Linear Mixed Model (GLMM) to deal with the skewed, over-dispersed and zero-inflated data. To address some reporting issues typically found in GLMMs for psychological outcomes [244], model building followed a Bayesian Workflow. The Bayesian approach is an emerging approach for child psychology, though not widely in use [241]. This workflow is recommended as it provides a flexible template that supports replication of this analysis in a manner that best suits the data, in the same way, that this analysis built on the initial model of the 2010-2012 subset of the ChiME data [64]. The findings from these models on average population difficulties can be used as a baseline to monitor the effectiveness of interventions.

Though the educational context in Scotland differs from the rest of the UK and further afield, these models can be used to compare spatial patterns in early development across settings. This includes other cities in Scotland, in the UK where there are similar levels of deprivation such as Manchester and Liverpool [66], or international populations [348, 349]. There was greater spatial variation in EDI outcomes, for example, in Melbourne, Australia than Montreal, Canada [349].

In Chapter 5, the models found evidence of variation between wards. This may be due to neighbourhood effects that cause clustering of outcomes, or similarities between households who choose to live in certain wards [187]. Wards with worse outcomes could be used to identify areas with greater needs. This was defined as wards that were worse than expected based on their demographics (i.e. had a relative rate greater than 1, with 80% certainty). Using these criteria, four wards were highlighted: Anderson/City, Craigton, North East and Pollokshields. These wards were distributed around the city with no spatial relationship to one another. There was not a unifying characteristic at the individual or ward level that could distinguish these wards from those that were as (or better than) expected.

There was an independent spatio-temporal interaction. Therefore, depending on the year, the spatial pattern can change. The presence of spatio-temporal variation supports the inclusion of the spatio-temporal context to proposed pathways of neighbourhood effects (for example Figure 2.1).

The spatio-temporal profile of an area can be used to provide more informative place-based interventions. The spatio-temporal variation identifies when and how neighbourhoods change. This can help to narrow down the contributing factors to why neighbourhoods differ. In this project, as yearly changes are relatively short-term, spatio-temporal variation in the ChiME profile may be related to changes to the population (or sample).

We have limited information on how long the child was exposed to their neighbourhood. Without information on residential history, we make the assumption that all children have lived in their neighbourhoods for the same amount of time. This is unrealistic. Some neighbourhoods will have greater residential mobility than others, and some households are more likely to be mobile [350]. A neighbourhood where individuals frequently leave may not have the same degree of clustering as a neighbourhood with more residential stability. As a result, spatial heterogeneity can be underestimated when residential mobility is not accounted for in multilevel modelling [351]. A further limitation of the data is the changing preschool sample every year which means that characteristics of the sample vary non-randomly each year. While some changes (such as those shown in Table A.1) can be accounted for in the modelling, there may be unmeasured characteristics that impact the sample each year.

The analysis assumes that the time spent in their neighbourhood and at their preschool is the same. This is unlikely [352] as different preschools have different service provisions and the number of funded preschool places changed over the period of study. Children could have been attending their preschool from different ages and over differing hours. This is particularly relevant for the cohorts after 2014 as the Children and Young People (Scotland) Act 2014 led to increased funded childcare for 3 and 4-year-olds and vulnerable 2-year-olds [140]. Preschool variation remained after accounting for the role of the cohort but, there may be variation in exposure to the preschool, which is likely influenced by family and preschool characteristics, that have not been recorded. The extent to which these assumptions have limited the models depends on the rate and pattern of mobility [194]. This is difficult to resolve in the absence of historical individual level information. In some neighbourhoods of Glasgow, over 40 % of the population in 2011 have changed by 2020 [353]. Residential mobility in the Growing Up Scotland sample [61] provides a further indication. Of the 3833 children who were 5 years old in 2009/2010, 2482 were still at the same address the following year (64.1 %). Going forward, any further population data collection should consider this. However, residential mobility may not account for all the spatio-temporal variation observed as Gracia et al., [354] found a spatial pattern in neighbourhoods of elevated risk for child maltreatment over 12 years. There were also spatially varying temporal trends after accounting for neighbourhood SES, education, immigration and residential stability. The spatio-temporal characteristics that account for these fluctuations should be investigated further.

This could have implications for the selection of delivery areas for place-based interventions. A worse than expected area may represent a one-off deviation. For example, once considering the spatio-temporal variation, Pollokshields no longer met the criteria of a worse than expected ward. Considering the time it takes to implement an intervention, it may be that the neighbourhood is no longer considered worse than expected or that the needs of the neighbourhood population have changed by the point of evaluation. Policymakers should consider the extent that spatio-temporal variation may account for any spatial profiles measured over the short term, especially in areas with higher residential mobility.

Another temporal assumption in the data is that the SDQ reflects a persistent mental state. The SDQ reflects the mental state of a child at a point in time. For some children, this may be persistent. The differences between the neighbourhoods with higher average scores at 27/30 months (Figure 1.2) and in this sample further supports how population high scores may no longer be present in the same population at an older age. Follow-up data could be used to distinguish between persistent and transient difficulties and the neighbourhoods associated with each.

8.2.2 How Can We Define the Neighbourhood?

Neighbourhood boundaries are a key component to spatial analysis [355]. In Glasgow, place-based interventions are delivered across many boundary definitions (Chapter 1). Ten localities were selected by Glasgow CPP to reduce inequalities as part of the 2013 Thriving Places initiative [68]. Areas selected for the GoWell programme were not aligned with administrative or statistical boundaries [67]. Children's Neighbourhoods Scotland [74] used fluid boundaries. There was limited understanding of the impact this had on the effectiveness of place-based interventions [28].

Chapter 6 examines different ways of aggregating postcode data to define the neighbourhood. In addition to the ward (n=21), there were three boundary definitions considered. These differed in their scale and in their construction: the Community Planning Partnership (CPP) localities developed by the Glasgow City Council (n=56), the Intermediate Zone developed by the Scottish Government using 2001 (n=133) and 2011 (n=136) census boundaries, and the statistical boundary Consistent Areas Through Time (CATTs) (n=1118). These boundaries were all smaller than the ward but did not nest directly into ward boundaries. The impact of the geographic boundary was compared based on spatial variation and the relative importance of the context.

This project found the definition of the neighbourhood can determine what places are considered to be worse than expected (Chapter 6). Most place-based initiatives discussed in Chapter 1 are delivered at a smaller geographic scale than the electoral ward. However, this analysis shows that at a smaller scale, there are slightly smaller neighbourhood contextual effects and weaker ecological correlations. While this does suggest that there is less justification for intervention at the smaller level, the spatial correlation at smaller scales shows there is variation within the ward. There may be spill-over effects that benefit children in neighbouring small areas [47].

The electoral ward was considered the most appropriate scale for the current analysis. The ward had the most between-cluster variance and the worse than expected areas identified by the ward overlapped with other boundaries (localities and 2011 Intermediate Zones) supporting the reliability of the ward boundary.

The most appropriate definition of the neighbourhood is highly influenced by the point in time the analysis is being conducted. The ward, locality and 2011 Intermediate Zones were all created to reflect the communities at the time the ChiME sample was born or growing up. Therefore, it is expected that these are the most relevant neighbourhood definitions for the sample. Due to boundary changes, the ward boundaries are only relevant from 2007 to 2017. Any follow-up research on this population would use different ward boundaries and not be directly comparable. While localities have not been changed in 20 years, the representativeness of these boundaries to relevant communities is likely to decrease over time.

Looking at the different spatial scales together could help support diffuse or more concentrated intervention delivery. For example, in the North East ward, there appear to be smaller areas that are worse than expected (at locality and Intermediate Zone level), while other wards did not have concentrated areas. One strategy that could be employed if resources are scarce is to monitor population outcomes at a larger spatial scale (e.g. ward). Wards of interest can then be investigated at the smaller spatial scale (e.g. locality or Intermediate Zone) to find clusters for intervention. This supports current practice that the size and selection of target areas may vary even within the same intervention [28].

Our neighbourhood definitions were based on areal units. Follow-up research could investigate distance-based measures to define a child's neighbourhood. For example, there is evidence that neighbourhood amenities are related to early behavioural development at 400-800m [47] and natural space at 500m is related to total difficulties scores [127]. This would address the issue of how relevant statistical and administrative boundaries are to the social and physical interactions of a preschool aged child [352]. Distance based neighbourhoods could avoid challenges related to boundary changes. Ultimately, there may be geographical clustering in the data that is explained better by the social environment than by any physical marker.

8.2.3 How Much Does the Neighbourhood Matter?

The proportion of total variation that is due to cluster-level differences is called the variance partition coefficient (VPC). The larger the VPC, the more similar individuals are within their cluster. Contexts that play a larger role in the total variation present a potential level for intervention that would have a greater impact than contexts that minimally affect variation. In recent literature, between 0-9% of variance in early child development was due to neighbourhood environment [198, 273, 292–295]. The VPC varied across different samples and levels of analysis but consistently showed that the individual context is more important than the neighbourhood, preschool or family.

As the analysis was conducted using GLMM (assuming a zero-inflated negative binomial distribution), the VPC was calculated using approximations [296, 297]. In agreement with the literature (which used non-discrete distributions), the individual context was found to be the most important. Intervening at the individual level can be challenging. Some individual level factors (e.g. perceptions) are more modifiable, while others (e.g. genetics) are not.

The individual context accounts for most but not all the variation of total difficulties. Having more individual level data such as the ethnicity of the child, and whether the child had been looked after would help lead to more informative models. It is also likely, based on the literature, that part of the variation attributed to the individual context is due to the inability to measure family level effects.

There is a clustering of worse scores in certain preschools and neighbourhoods. The cross-classified data structure means there is an additive effect from the preschool and ward contexts - a child in a ward and preschool that are both worse than expected is at even higher risk. Approximately 19% of children live in a worse than expected ward, and the ward a child lives in accounts for 1% of the variation in total difficulties. Therefore, targeting interventions in the neighbourhood context may miss a large proportion of children who are disadvantaged at an individual or preschool level. This was seen in Wales where the Flying Start programme, which targets children in deprived neighbourhoods, excluded on average 44% of children with household deprivation from the programme because they did not belong to a deprived neighbourhood [356].

Goldfeld et al., [40] describe how policies to reduce child inequalities can be more precise by identifying key populations, time points, durations, and combinations for policy. To tackle inequalities, the findings from this work suggest that a single higher level context alone (e.g. changing preschool or residence) is not associated with a meaningful difference in outcomes. Higher level contexts should be considered with a multi-context perspective to have the greatest impact [28]. Targeting multiple contexts could reduce the target population, but increase the potential impact on the outcome. For example, Childcare and Nurture Glasgow East [73] (CHANGE, described in Chapter 1) targets early learning environments within specific neighbourhoods. Other existing place-based initiatives are associated with positive outcomes at the family or learning environment level [28], supporting a multi-level approach. As already mentioned, it would be important to consider the spatio-temporal context (e.g. long term trends, changing neighbourhood characteristics and residential history), which is approximately half as important as the neighbourhood context.

Though the VPC of the neighbourhood is small in this study, these results do not completely rule out the use of local level action for child development. This analysis only examines total social, emotional and behavioural difficulties. Place-based initiatives may be more relevant to other developmental outcomes. Morrissey and Vinopal found that household factors were more strongly associated with behaviour, while the neighbourhood was more strongly associated with academic achievement [357]. The authors proposed that a reason for this may be that academic performance is more easily standardised. Similarly, spatial patterns in developmental outcomes were found to be stronger for verbal scores than behavioural outcomes in both the UK and the US [348].

This work has focused on spatial effects within a relatively small city. Spatial variation examined in Canada and Australia encompasses much larger metropolitan areas [46, 273]. There may be stronger spatial effects that occur on a larger scale (e.g. those related to structural determinants).

The lack of meaningful variation in total difficulties at the neighbourhood levels may present an opportunity for early intervention. For example, Humphrey and Root did not find any associations with SDQ scores at 7 years but found associations with the same sample aged 11 years old [327]. Sources of variation could be identified now, and minimised while differences are small. This could reduce the scale of intervention required. Further, it may prevent the widening of inequalities later in the life course [358].

8.2.4 What Characteristics Are Related to Variation in Child Development?

Chapter 2 gives a comprehensive review of the grey and academic literature on neighbourhood characteristics associated with early mental well-being in Scotland. This included factors such as routes, trust, greenspace and neighbourhood satisfaction. The factors were selected on the basis of the NHS Scotland Children and Young People

Mental Health constructs [109]. This informed the neighbourhood indicators that were included in the data availability search and consequently the spatio-temporal models. There will be research areas beyond these constructs that could be investigated in future.

Residual variation at preschool, neighbourhood and spatio-temporal level found in Chapter 5 point to unmeasured covariates. At the preschool level, open access data from 2013 was used to classify the preschools depending on their provider type (voluntary, local authority, private) and their size (for local authority only). Spatial variation was explained by prosocial behaviour and its interaction with preschool providers. From this analysis, it is not possible to conclude these are contributing risk factors, but it does highlight relationships that should be investigated further. This highlights a potential difference in the rating or presentation of prosocial skills by provider type. There may be a bias in reporting in private preschools. Previous qualitative research showed that preschools vary in their approach to recording SDQ scores, in some preschools it was a collaborative exercise, while in others the scores were verified by a headteacher. It is unknown if these practices differed by the provider type [102]. There may also be different interests in the SDQ outcomes by provider type. More information is needed on how scores were validated during data collection or if there were any competing interests in recording the SDQ scores.

The provision of preschools within a neighbourhood could explain neighbourhood differences. As already discussed, where a child lives can inform preschool choice. While most of the sample stayed in their neighbourhood, those that left were most likely to go to a neighbouring area.

The strength of association at the preschool and individual level supports the need for multilevel approaches to neighbourhood research. If found to be contributing factors to early development, promoting prosocial behaviours and reducing differences in service provision by provider type would be a more feasible intervention compared to changing the physical and social aspects of the neighbourhood.

Recently, in Australia, neighbourhood indicators have been identified through administrative data that will be assessed against child outcomes to create a framework

[347]. A similar approach is used here where neighbourhood level indicators have been identified and assessed in relation to SDQ scores.

At the neighbourhood level, there were ecological correlations that did not lead to cross-level associations with individual level outcomes (e.g. domestic abuse, access to greenspace, free time places, children in poverty and vandalism). This supports previous evaluations of place-based initiatives that found more evidence of an effect at a higher contextual level than at an individual level [28]. Neighbourhood level characteristics may be more strongly associated with neighbourhood level outcomes (i.e. the average difficulties in a ward) than with outcomes at an individual level. For example, ecological associations have been made between neighbourhood-level developmental outcomes and the built environment (e.g. private garden space [265] and neighbourhood socioeconomic status [35]). It is worth noting that the sample under investigation is already receiving interventions at various levels. Unique to the ChiME sample in particular is the Triple P parenting programme, a population wide intervention. Though Triple P was found to not have an effect at a population level, this may have had an effect at other contextual levels [63]. But even if the sample did not receive the Triple P intervention, Chapter 1 details some of the various place based initiatives in Glasgow as well as the national interventions that children in the ChiME sample may have received [52]. An individual child may be experiencing various levels of intervention at the point of the study, making it more difficult to pinpoint the associations that can be attributed to an individual risk factor or intervention. However, this approach more closely reflects normal practice.

Where other population studies had found cross-level effects (with greenspace e.g. [43] or libraries e.g. [333]), this may be due to genuine differences in the relevant factors for this population of interest [46]. Alternatively, there may be data quality limitations to neighbourhood constructs when accounting for long term spatial data where other studies have found cross-level effects using single year data (e.g. [333] and [43]). There are several temporal aspects to neighbourhood constructs including short term versus long term effects, the lag between exposure and outcome, the intensity, frequency, and duration of exposure [31]. However, most of the neighbourhood data available were taken from a single year. Similarly, when modelling spatio-temporal variation in child maltreatment, Gracia et al., noted a lack of available 12 year spatio-temporal data for the city of Valencia, Spain. This limited the covariates that could be included in the model [354].

Spatio-temporal data was not available through Freedom of Information (FOI) requests, there may be a need for improved retention of neighbourhood level data. Where spatio-temporal data were available for this project, it supported the case that a single measure is unlikely to be stable over the eight-year study period for all neighbourhoods. A measurement from a single time point would only be appropriate for more fixed neighbourhood characteristics that are unlikely to change considerably over the period of study. There are likely population changes over the period of study (supported by the spatio-temporal clustering) that mean that our understanding of a ward's social and physical environment in 2010 may not reflect that environment in 2017. Moreover, a child might not have been living in a neighbourhood when the data were collected, leading to exposure misclassification [359]. Considering the residential history can strengthen the association between neighbourhood characteristics and an outcome [359].

Further work should evaluate how an indicator reflects the neighbourhood context for all children across all years in the target population to get a more consistent picture of the spatial distribution. Any further spatio-temporal population research should consider how the changing sample contributes to spatio-temporal clustering. In this case, it was determined that allowing different preschools to take part each year improved the representativeness of the sample compared to those who were involved every year. There was very limited information on the data quality of the neighbour characteristics. This project relied on data that was readily available. Future evaluation of the neighbourhood characteristics is needed and should consider whether these are valid indicators. In 2023 the Scottish Government's Perinatal and Infant Mental Health Programme Board published guidance for incorporating the voice of young children. Any critical review of data sources could consider the relevance of the indicator to early development using these areas of practice [360].

An emerging policy area in Scotland is the 20-minute neighbourhood. This aims to make key neighbourhood services and facilities accessible within a 20 minute walk or 800m radius [361]. Successful implementation of the policy will mean that most neighbourhoods in Glasgow will have access to many facilities represented by the indicators investigated. In future, accessibility may not be a discerning characteristic for neighbourhood effects. This is an opportunity to collect more informative spatio-temporal indicators related to the intensity, frequency, and duration of exposure for young children.

Appendix A

Demographics by Cohort

Table A.1: Demographics by Cohort

Demographic		2010	2011	2012	2013
Age	4-4.5	276 (9.0%)	281 (8.4%)	263 (6.8%)	198 (5.1%)
	4.5-5	133 (43.3%)	1574 (47.2%)	1816 (46.8%)	1802 (46.2%)
	5-5.5	1369 (44.4%)	1381 (41.4%)	1675 (43.1%)	1745 (44.8%)
	>5.5	104 (3.4%)	100 (3.0%)	128 (3.3%)	154 (4.0%)
Sex	F	1451 (47.1%)	1628 (48.8%)	1867 (48.1%)	1922 (49.3%)
	M	1631 (52.9%)	1708 (51.2%)	2015 (51.9%)	1977 (50.7%)
SIMD Quintile	5 (least)	515 (16.7%)	327 (9.8%)	507 (13.1%)	509 (13.1%)
	4	542 (17.6%)	493 (14.8%)	645 (16.6%)	585 (15.0%)
	3	566 (18.4%)	628 (18.8%)	674 (17.4%)	698 (17.9%)
	2	644 (20.9%)	808 (24.2%)	883 (22.7%)	966 (24.8%)
	1 (most)	815 (26.4%)	1080 (32.4%)	1173 (30.2%)	1141 (29.3%)
Demographic		2014	2015	2016	2017
Age	4-4.5	287 (5.4%)	256 (4.9%)	290 (5.3%)	261 (5.3%)
	4.5-5	2527 (48.0%)	2492 (47.5%)	2572 (46.9%)	2340 (47.1%)
	5-5.5	2217 (42.0%)	2306 (44.0%)	2425 (44.3%)	2179 (44.8%)
	>5.5	244 (4.6%)	192 (3.7%)	193 (3.5%)	191 (3.8%)
Sex	F	2592 (49.1%)	2563 (48.4%)	2699 (49.3%)	2488 (50.1%)
	M	2683 (50.9%)	2683 (51.1%)	2781 (50.7%)	2483 (49.9%)
SIMD Quintile	5 (least)	891 (16.8%)	829 (15.8%)	827 (15.1%)	666 (13.4%)
	4	854 (16.2%)	852 (16.2%)	828 (15.1%)	811 (16.3%)
	3	1041 (19.7%)	1035 (19.7%)	1043 (19.0%)	1011 (20.3%)
	2	1162 (22.0%)	1200 (22.8%)	1341 (24.5%)	1175 (23.6%)
	1 (most)	1327 (25.2%)	1330 (25.4%)	1441 (25.3%)	1308 (25.3%)

Appendix B

Strengths and Difficulties Questionnaire for 2-4 year olds

Strengths and Difficulties Questionnaire

2-4

For each item, please mark the box for Not True, Somewhat True or Certainly True. It would help us if you answered all items as best you can even if you are not absolutely certain or the item seems daft! Please give your answers on the basis of the child's behaviour over the last six months or this school year.

Child's Name .... Male/Female

Date of Birth...

	Not True	Somewhat True	Certainly True
Considerate of other people's feelings	☐	☐	☐
Restless, overactive, cannot stay still for long	☐	☐	☐
Often complains of headaches, stomach-aches or sickness	☐	☐	☐
Shares readily with other children (treats, toys, pencils etc.)	☐	☐	☐
Often has temper tantrums or hot tempers	☐	☐	☐
Rather solitary, tends to play alone	☐	☐	☐
Generally obedient, usually does what adults request	☐	☐	☐
Many worries, often seems worried	☐	☐	☐
Helpful if someone is hurt, upset or feeling ill	☐	☐	☐
Constantly fidgeting or squirming	☐	☐	☐
Has at least one good friend	☐	☐	☐
Often fights with other children or bullies them	☐	☐	☐
Often unhappy, down-hearted or tearful	☐	☐	☐
Generally liked by other children	☐	☐	☐
Easily distracted, concentration wanders	☐	☐	☐
Nervous or clingy in new situations, easily loses confidence	☐	☐	☐
Kind to younger children	☐	☐	☐
Often argumentative with adults	☐	☐	☐
Picked on or bullied by other children	☐	☐	☐
Often volunteers to help others (parents, teachers, other children)	☐	☐	☐
Can stop and think things out before acting	☐	☐	☐
Can be spiteful to others	☐	☐	☐
Gets on better with adults than with other children	☐	☐	☐
Many fears, easily scared	☐	☐	☐
Sees tasks through to the end, good attention span	☐	☐	☐

Signature .... Date ....

Parent/Playgroup leader/Nursery teacher/Other (please specify:)

Thank you very much for your help

Appendix C

Sample size by contextual level

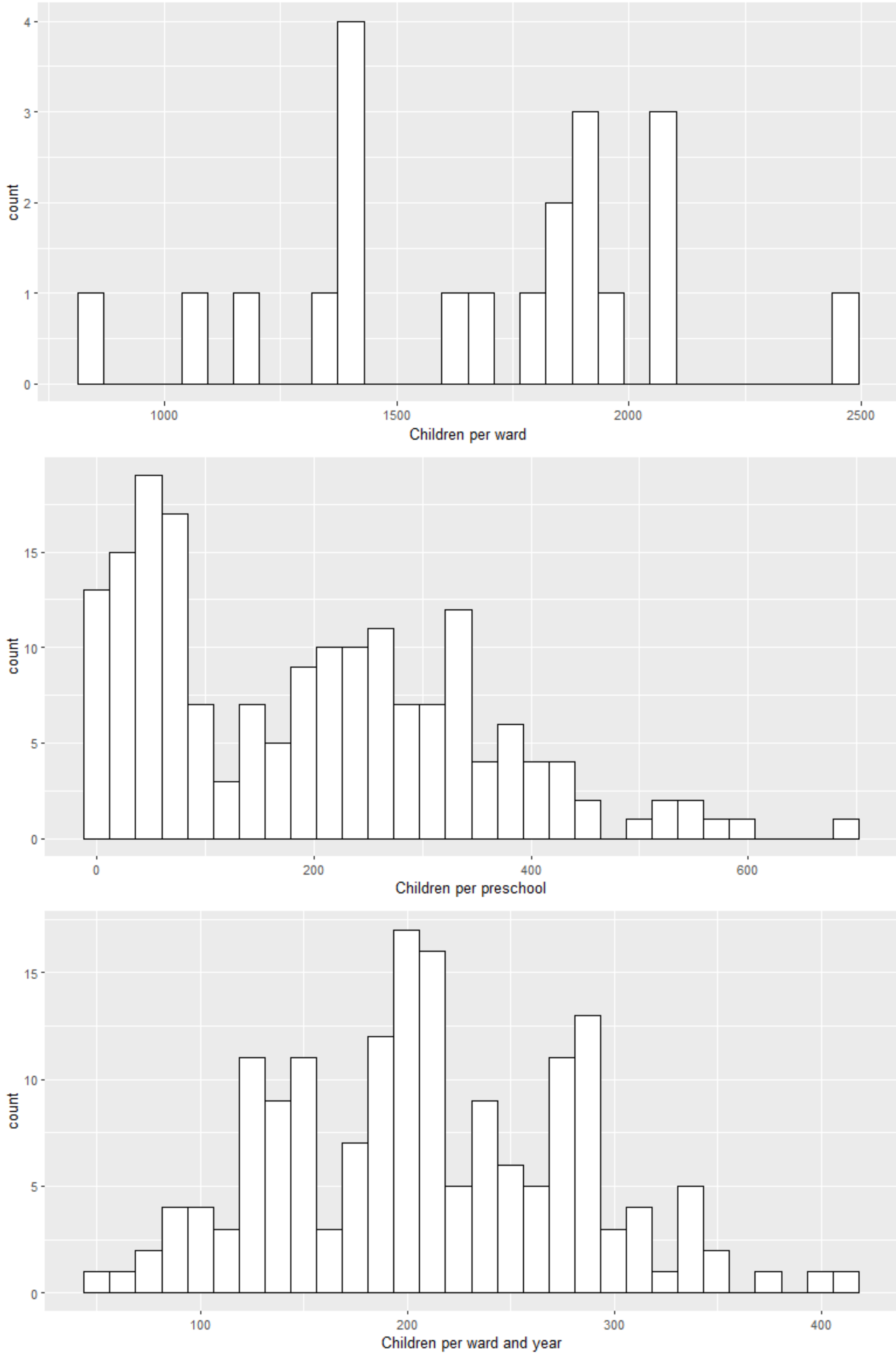

Figure C.1: Number of children per unit for each contextual level

Appendix D

Intermediate Zone Names

Table D.1: 2001 Intermediate Zone Names

Number	Name	Number	Name	Number	Name
1	Carmunnock South	46	Parkhead East and Braidfauld North	91	Garthamlock, Auchinlea and Gartloch
2	Glenwood South	47	Tollcross	92	Firhill
3	Darnley West	48	Kingston West and Dumbreck	93	Cowlairs and Port Dundas
4	Darnley East	49	Shettleston North	94	Partickhill and Hyndland
5	Glenwood North	50	Parkhead West and Barrowfield	95	Blackhill and Barmulloch East
6	Castlemilk	51	Laurieston and Tradeston	96	Broomhill
7	Darnley North	52	Calton, Gallowgate and Bridgeton	97	Petershill
8	Carmunnock North	53	Garrowhill West	98	Dowanhill
9	Carnwadric West	54	Cardonald North	99	Victoria Park
10	Muirend and Old Cathcart	55	Craigton	100	North Kelvin
11	Carnwadric East	56	Hillington	101	Scotstoun South and West
12	Kingspark South	57	Greenfield	102	Keppochhill
13	Newlands	58	Penilee	103	Scotstoun North and East
14	Nitshill	59	Kinning Park and Festival Park	104	Barmulloch
15	Merrylee and Millbrae	60	Old Shettleston and Parkhead North	105	Ruchill
16	Cathcart	61	Ibrox East and Cessnock	106	Kelvinside and Jordanhill
17	Kingspark North	62	Garrowhill East and Swinton	107	Kelvindale
18	Crookston South	63	Barlanark	108	Springburn
19	Pollokshaws	64	Gallowgate North and Bellgrove	109	Possil Park
20	Mount Florida	65	Carntyne West and Haghill	110	Wyndford
21	Langside	66	Ibrox	111	Springburn East and Cowlairs
22	Shawlands East	67	Dennistoun	112	Robroyston and Millerston
23	Crookston North	68	Anderston	113	Yoker South
24	Battlefield	69	North Barlanark and Easterhouse South	114	Balornock
25	Pollok South and West	70	Easterhouse East	115	Knightswood Park East
26	Shawlands West	71	Cranhill, Lightburn and Queenslie South	116	Knightswood East
27	Toryglen and Oatlands	72	City Centre West	117	Maryhill West
28	Shettleston South	73	Govan and Linthouse	118	Milton West
29	Maxwell Park	74	Carntyne	119	Anniesland East
30	Carmyle and Mount Vernon South	75	City Centre East	120	Knightswood West
31	Strathbungo	76	Dennistoun North and Alexandra Parade	121	Maryhill East
32	Govanhill East and Aikenhead	77	Drumoyne and Shieldhall	122	Anniesland West
33	Govanhill West	78	Finnieston and Kelvinhaugh	123	Knightswood Park West
34	Pollok North and East	79	Central Easterhouse	124	Yoker North
35	Baillieston East	80	Craigend and Ruchazie	125	Milton East
36	Dalmarnock	81	Hillhead	126	Blairdardie East
37	Braidfauld	82	Woodlands	127	Summerston North
38	Mosspark	83	Roystonhill, Blochairn, and Provanmill	128	Blairdardie West
39	Pollokshields East	84	Riddrie and Hogganfield	129	Drumchapel South
40	Mount Vernon North and Sandyhills	85	Glasgow Harbour and Partick South	130	Summerston Central and West
41	Pollokshields West	86	Woodside	131	Drumry West
42	Cardonald South and East	87	Sighthill	132	Drumchapel North
43	Baillieston West	88	Partick	133	Drumry East
44	Cardonald West and Central	89	Kelvingrove and University		
45	Gorbals and Hutchesontown	90	Whiteinch		

Table D.2: 2011 Intermediate Zone Names

Number	Name	Number	Name	Number	Name
1	Darnley East	46	Mount Florida	91	City Centre East
2	Darnley North	47	Toryglen and Oatlands	92	City Centre West
3	Darnley West	48	Gorbals and Hutchesontown	93	City Centre South
4	Nitshill	49	Laurieston and Tradeston	94	Anderston
5	Crookston South	50	Calton and Gallowgate	95	Finnieston and Kelvinhaugh
6	Crookston North	51	Bridgeton	96	Woodlands
7	Pollok South and West	52	Dalmarnock	97	Woodside
8	Pollok North and East	53	Parkhead West and Barrowfield	98	Firhill
9	Cardonald South and East	54	Parkhead East and Braidfauld North	99	Keppochhill
10	Cardonald North	55	Braidfauld	100	Ruchill
11	Cardonald West and Central	56	Shettleston South	101	Possil Park
12	Penilee	57	Carmyle and Mount Vernon South	102	Milton West
13	Hillington	58	Mount Vernon North and Sandyhills	103	Milton East
14	Drumoyne and Shieldhall	59	Baillieston West	104	Summerston Central and West
15	Govan and Linthouse	60	Baillieston East	105	Summerston North
16	Craigton	61	Garrowhill West	106	Maryhill East
17	Mosspark	62	Garrowhill East and Swinton	107	Maryhill West
18	Ibrox	63	Easterhouse East	108	Wyndford
19	Ibrox East and Cessnock	64	Central Easterhouse	109	Kelvindale
20	Kinning Park and Festival Park	65	Garthamlock, Auchinlea and Gartloch	110	North Kelvin
21	Kingston West and Dumbreck	66	North Barlanark and Easterhouse South	111	Kelvingrove and University
22	Pollokshields West	67	Barlanark	112	Hillhead
23	Pollokshields East	68	Greenfield	113	Glasgow Harbour and Partick South
24	Govanhill West	69	Shettleston North	114	Partick
25	Govanhill East and Aikenhead	70	Tollcross	115	Partickhill and Hyndland
26	Battlefield	71	Old Shettleston and Parkhead North	116	Dowanhill
27	Strathbungo	72	Carntyne	117	Kelvinside and Jordanhill
28	Maxwell Park	73	Cranhill, Lightburn and Queenslie South	118	Broomhill
29	Shawlands West	74	Craigend and Ruchazie	119	Victoria Park
30	Shawlands East	75	Riddrie and Hogganfield	120	Whiteinch
31	Langside	76	Blackhill and Barmulloch East	121	Scotstoun North and East
32	Pollokshaws	77	Robroyston and Millerston	122	Scotstoun South and West
33	Carnwadric West	78	Balornock	123	Yoker South
34	Carnwadric East	79	Barmulloch	124	Yoker North
35	Newlands	80	Petershill	125	Knightswood West
36	Merrylee and Millbrae	81	Springburn	126	Knightswood East
37	Muirend and Old Cathcart	82	Springburn East and Cowlairs	127	Knightswood Park West
38	Carmunnock North	83	Cowlairs and Port Dundas	128	Knightswood Park East
39	Carmunnock South	84	Sighthill	129	Anniesland East
40	Glenwood South	85	Roystonhill, Blochairn, and Provanmill	130	Anniesland West
41	Glenwood North	86	Dennistoun North	131	Blairdardie East
42	Castlemilk	87	Alexandra Parade	132	Blairdardie West
43	Kingspark South	88	Carntyne West and Haghill	133	Drumchapel South
44	Kingspark North	89	Dennistoun	134	Drumchapel North
45	Cathcart	90	Gallowgate North and Bellgrove	135	Drumry East
				136	Drumry West

Appendix E

Distribution of Ward Indicators

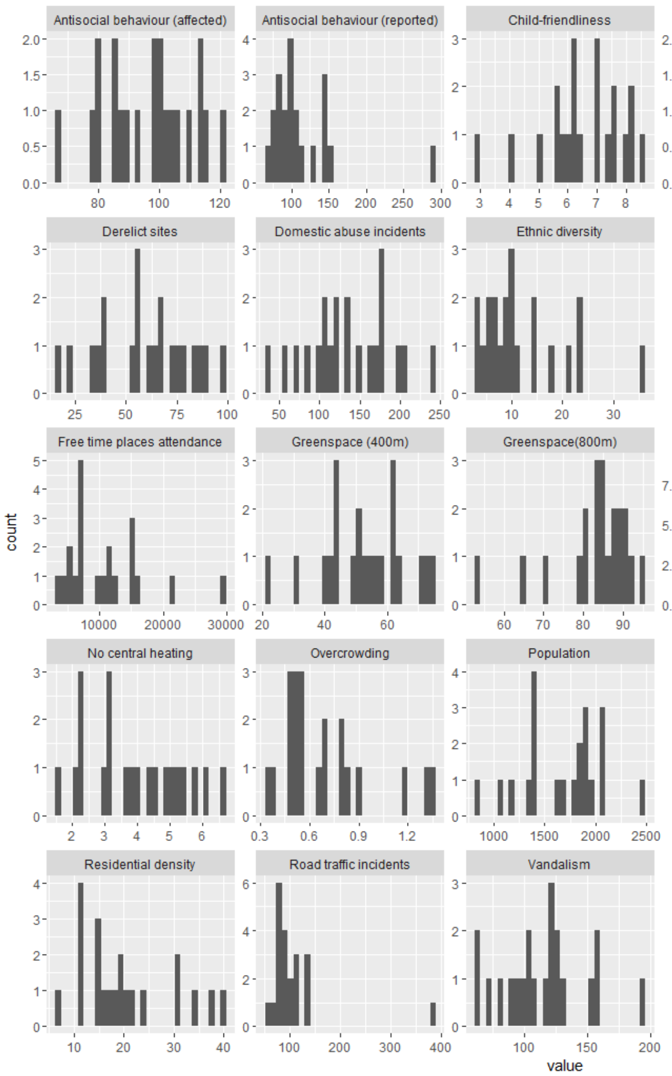

Figure E.1: Histogram of ward indicators

Appendix F

Locality Indicators and their relationship to SDQ scores

Table F.1: Locality Variables and their relationship to total difficulties scores

Indicator	Total Difficulties	Prosocial
Under 25yrs from a minority ethnic group	-0.07	0.10
Overcrowded households with children	0.11	-0.18
Under 16yrs within 400m of greenspace	0.16	-0.30
Referrals to SCRA	0.20	-0.14
Under 16yrs within 500m of vacant or derelict land	-0.01	0.02
Off-licensed premises	0.03	-0.15
Children in Poverty	0.36	-0.28
Child-friendliness	0.08	-0.01

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