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Multilevel Logistic Modelling: A Register-Based Study of Mental Disorder, Socioeconomic Status and Regional Variation among Children in Finnish Municipalities

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Tiivistelmä – Referat – Abstract

Mental disorders are common during childhood and they are associated with various negative consequences later in life, such as lower educational attainment and unemployment. In addition, the reduction of socioeconomic health disparities has attracted both political, research and media interest. While mental health inequalities have been found consistently in literature and regional disparities in health have been well documented in Finland altogether, the question of possible variation in mental disorder inequalities during childhood among Finnish regions is not fully examined. This master's thesis contributes to this gap in the research with a statistical perspective and use of a multilevel logistic model, which allows random variation between levels. Using register-based data, I ask whether the association between socioeconomic status and mental disorder in childhood varies between the child's municipality of residence, and which regional factors possibly explain the differences. The second objective of this thesis is to find out whether the use of a multilevel logistic model provides additional value to this context.

The method used in the thesis is a multilevel logistic model, which can also be called a generalized linear mixed-effects model. In multilevel models, the observations are nested within hierarchical levels, which all have corresponding variables. Both intercept and slopes of independent variables can be allowed to vary between the Level 2 units. Intraclass correlation coefficient and median odds ratio (MOR) are used to measure group level variation. In addition, centering of variables and choosing a suitable analysis strategy are central steps in model application.

High-quality Finnish register data from Statistics Finland and the Finnish Institute of Health and Welfare is utilised. The study sample consists of 815 616 individuals aged 4–17 living in Finland in the year 2018. The individuals who are used as Level 1 units are nested within 306 Level 2 units based on their municipality of residence. The dependent variable is a dichotomous variable indicating a mental disorder and it is based on visits and psychiatric diagnoses given in specialised healthcare during 2018. Independent variables in Level 1 are maternal education level and household income quintile, and models are controlled for age group, gender, family structure and parental mental disorders. In Level 2, the independent variables are urbanisation, major region, share of higher-educated population and share of at-risk-of-poverty children.

In the final model, children with the lowest maternal education level are more likely (OR=1.37, SE=0.0026) to have mental disorders than children with the highest maternal education level. Odds ratios for the household income quintile mostly decline close to one when control variables are included. Interestingly, children from the poorest quintile have slightly lower odds for mental disorder (OR=0.84, SE=0.017) compared with children from the richest quintile. Urbanisation, share of higher-educated population and share of at-risk-of-poverty children are statistically insignificant variables. Differences are found between major regions; children from Åland are more likely (OR=1.5, SE=0.209) to have a mental disorder compared with Helsinki-Uusimaa residents, whereas children from Western Finland (OR=0.71, SE 0.053) have lower odds compared to the same reference. Random slopes for maternal education are not significant, and the model fit does not improve. However, there is some variation among municipalities (MOR=1.34), and this finding defends the usefulness of the multilevel model in the context of mental disorders in childhood.

The results show that mental disorder inequalities persist in childhood, but there is complexity. Although no variation in socioeconomic inequalities among municipalities is found, there are still contextual effects between municipalities. Health policies should focus on reducing overall mental health inequalities in the young population, but it is an encouraging finding that disparities in childhood mental disorders are not shown to be stronger in some municipalities than others. Multilevel models can contribute to the methodology of future mental disorder research, if societal context is assumed to affect the outcomes of individuals.

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Chapter 1

Introduction

A significant proportion of children and young people have mental health problems and disorders. In Finland a recent approximation is that 10–15 per cent of children and 20–25 per cent of adolescents have mental health problems (Aalto-Setälä et al., 2020). In addition, the prevalence of the use of specialised psychiatric healthcare services during childhood and adolescence by the age of 21 was 14.4 per cent in a follow-up study on people born in 1987 (Paananen et al., 2013).

Mental disorders cause both economic and societal negative consequences especially during the early life course, which also raise a need for policies to prevent these illnesses and conditions (Viinikainen et al., 2018). For example, mental health disorders have an association with non-completion and choice of study track in Finnish upper secondary education (Mikkonen et al., 2021), receipt of social assistance in young adulthood (Vaalavuo and Bakkum, 2021), educational attainment (Mikkonen et al., 2020), unemployment, lower education and income (Hakulinen et al., 2019) and not being long-term in education, employment or training (NEET) (Ringbom et al., 2021).

There is clear political interest to reduce socioeconomic health differences. For instance, the government programme of Prime Minister Marin (2019) mentions goals to reduce well-being and health disparities and to prevent social exclusion. However, in order to reach these objectives, more information on the mechanisms of inequalities is needed.

Although public health policies and programmes have been performed, health inequalities in Finland are still shown to be wide among the adult population (Palosuo and Sihto, 2016). Moreover, for many diseases regional disparities persisted during the years 2017–2019 (Parikka et al., 2022). In addition, the interest to study the relation between children's mental health and socioeconomic status has been growing since the 1990s (Reiss, 2013). Nevertheless, the regional aspects and possible regional differences in children's mental disorders in Finland are still partially unknown.

This thesis approaches the theme of regional mental health inequalities from a statistical perspective. Regression models are commonly used methodological tools in research of health inequalities. A key feature of regression models is that they assume the observations to be independent of each other. However, when data is hierarchically structured, this assumption is often violated. Observations belonging to, for example, the same regions or districts are often similar and can therefore not be assumed independent. (Keskimäki et al., 2001.) To solve this problem, multilevel models have been developed. They provide a possibility to allow random variation between levels.

Another aspect, which supports the use of a multilevel model, is that mental health services are regionally organised in Finland and these services differ between regions (Viertiö et al., 2017). This leads to the assumption that the access and availability to services varies between regions and municipalities, which also impacts the service use.

Therefore, in this study I present both the statistical features and the application of the multilevel logistic model to study regional disparities in children's mental disorders in Finland. The multilevel approach provides a useful method to study health inequalities in spatial structures.

To accomplish this, I use Finnish register data provided by the Finnish Institute for Health and Welfare (THL) and Statistics Finland. The use of this high-quality register data provides this thesis good statistical power, an opportunity to study the whole population and, therefore, reduces concerns of data bias issues.

This thesis aims to find out to what extent mental disorder inequalities in childhood vary between Finnish municipalities and how a multilevel model can be applied to this research context. The research questions are: 1. Does the association between socioeconomic status and mental disorder in childhood vary between the child's municipality of residence and which regional factors possibly explain the differences? 2. Does the use of a multilevel logistic model provide additional value to this context?

In Chapter 2, I begin by presenting the statistical properties of multilevel modelling. The definition, estimation and application procedures are covered. Chapter 3 briefly examines the social theory of socioeconomic mental health inequalities from several perspectives. Although the focus of this thesis is statistical, this theory section is important in order to choose suitable variables for analysis. In Chapter 4, I present the data, study sample and variables which are used in model application and analysis. Thereafter, Chapter 5 describes the analysis procedure and results and, finally, Chapter 6 concludes this thesis with a discussion on the research process and results.

Chapter 2

Multilevel modelling

Multilevel models, which are also called mixed-effects, hierarchical and random coefficient models, are useful when cross-level interaction is in the interest. The use of multilevel models in epidemiological settings has become more popular in the last 20 years, when computing power has developed to better and faster. (Moineddin et al., 2007.)

The purpose of multilevel modelling is to, for example, attach characteristics of social groups or contexts into the individual level. Individuals are nested within groups in a hierarchical system, where there are levels and variables corresponding to each level. This approach works well in research of societal questions, where social context is thought to influence the individuals and vice versa. (Hox et al., 2010.)

Individuals can be nested within different types of clusters, depending on the research question. The possibilities are various. To name a few, classrooms, organisations and hospitals could be used as higher level units. In the context of this thesis, the nesting is geographical, and individuals are nested in municipalities of residence. One argument supporting this choice of nesting is that in Finland, municipalities have been organising the healthcare services until the end of 2022, which may have caused regional differences in terms of organisation of care for mental health disorders.

The multilevel logistic model definition, notation and features presented in this chapter are based on the book *Multilevel Analysis: Techniques and Applications* by Hox et al. (2010), if not cited otherwise.

2.1 Definition of a multilevel logistic model

Logistic models are used for dichotomous dependent variables, which usually have value one, when the studied event occurs and zero when it does not occur. In multilevel context, the response variable is usually measured at the lowest Level 1. Multilevel logistic models are generalized linear mixed-effects models (GLMM). (Hox et al., 2010.)

I start by defining a single-level logistic model, after which I move towards a two-level logistic model.

2.1.1 Logistic regression

A logistic regression model belongs to the family of generalised linear models (GLM). These models have three main components. Firstly, a random component determines the dependent variable y and its probability distribution. Observations $\mathbf{y} = (y_1, \dots, y_n)$ are assumed to be independent. The second component, linear predictor, is $\eta = \mathbf{X}\beta$. The third one is the link function $g(\cdot)$, which connects the first two components. Let $\mu_i = E(y_i)$, then link function is $\eta = g(\mu_i)$. In logistic models, the link function is logit, $\log[\mu_i/(1-\mu_i)]$, also called log odds. Logit is the canonical link function for dichotomous random components. (Agresti, 2015.)

In logistic models, the probability distribution for parameter π_i is assumed to be binomial (μ, n) with the mean μ and number of trials n. In the case of dichotomous data, the trial is always one, and the possible outcomes are zero and one. The outcomes are Bernoulli distributed $B(\mu)$. (Hox et al., 2010.)

Logistic regression has two formulations. Defined by Agresti (2015) with logit, the formula is

$$\text{logit}(\pi_i) = \log\left(\frac{\pi_i}{1-\pi_i}\right) = \sum_{j=1}^{p} \beta_j X_{ij}, \tag{2.1}$$

and with logistic function it is

$$\pi_i = \frac{\exp\left(\sum_{j=1}^{p} \beta_j X_{ij}\right)}{1 + \exp\left(\sum_{j=1}^{p} \beta_j X_{ij}\right)}, \tag{2.2}$$

where β_j is the slope for the predictor variable X_{ij}.

Odds ratio (OR) is often used to interpret the results of logistic regression instead of using coefficients. It is interpreted as odds between the compared categories of dependent variable given the control variables. Odds ratio for the slope β_j is $\exp(\beta_j)$. (Rabe-Hesketh and Skrondal, 2022.)

2.1.2 Two-level logistic model

In a two-level logistic model the probability distribution for parameter π_{ij} is assumed to be binomial as well. The link function is still the same as in a single-level logistic regression.

An empty two-level logistic model is defined as

$$\begin{aligned} \pi_{ij} &= \text{logistic}(\eta_{ij}) \\ \eta_{ij} &= \gamma_{00} + \mu_{0j}, \end{aligned} \tag{2.3}$$

which written in a compact form is

$$\pi_{ij} = \text{logistic}(\gamma_{00} + \mu_{0j}), \tag{2.4}$$

where γ_{00} is the fixed intercept of the model and random effect μ_{0j} is the Level 2 residual. Random effect μ_{0j} is assumed to have normal distribution, with the mean zero and variance $\sigma^2_{\mu_0}$. (Sommet and Morselli, 2017; Hox et al., 2010.)

When we add the Level 1 and 2 predictors, a random slope for predictor variable X_{ij} and a cross-level interaction term to the model, the equation extends to

$$\pi_{ij} = \text{logistic}(\beta_{0j} + \beta_{1j} X_{ij}), \tag{2.5}$$

where

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + \gamma_{01} Z_j + \mu_{0j} \\ \beta_{1j} &= \gamma_{10} + \gamma_{11} Z_j + \mu_{1j}. \end{aligned} \tag{2.6}$$

When equations 2.5 and 2.6 are written together in mixed-effects form and the terms are rearranged, the model is defined as

$$\pi_{ij} = \text{logistic}([\gamma_{00} + \gamma_{10} X_{ij} + \gamma_{01} Z_j + \gamma_{11} X_{ij} Z_j] + [\mu_{1j} X_{ij} + \mu_{0j}]). \tag{2.7}$$

Here, γ_{10} is the slope for the Level 1 predictor variable X_{ij} and γ_{01} is the slope for the Level 2 predictor variable Z_j. γ_{11} is the effect of Z_j on X_{ij} and μ_{1j} is the error for unit j, also known as the random slope for X_{ij}. (Luke, 2019.)

The first brackets in the equation 2.7 represent the fixed part of the model and the second brackets the random part. This form of equation illustrates why multilevel model is also sometimes called the mixed-effects model. Mixed effects include both fixed and random terms, where random terms can be thought to be additional error terms. (Luke, 2019.)

The term $\gamma_{11}X_{ij}Z_j$ is the cross-level interaction component of the model. This means that the intercept and slopes of Level 1 are modelled with the use of the Level 2 predictor variable. Both the intercept and slopes are outcomes of the model. (Luke, 2019.)

2.1.3 Intraclass correlation coefficient

The assumption of multilevel analysis is that individuals in the same group are more similar to each other than to those in different groups. In single-level regression models, the observations are assumed to be independent, which then does not fit well together with the group similarity assumption. Intraclass correlation coefficient (ICC) can be calculated to measure the group dependence. (Hox et al., 2010.)

Intraclass correlation ρ expresses the proportion of variance, that is explained by the grouping structure. It is usually derived from an empty intercept-only null model shown in equation 2.4, where all explanatory variables in each level are excluded. (Hox et al., 2010.) It is defined by

$$\rho = \frac{\sigma^2_{\mu_0}}{\sigma^2_{\mu_0} + \sigma^2_e}, \tag{2.8}$$

where in logistic context $\sigma^2_e = \frac{\pi^2}{3}$, which is the variance of a standard logistic distribution and $\sigma^2_{\mu_0}$ is the variance of the random intercept (Moineddin et al., 2007). This means that ICC is simply the proportion of group-level variance of the total variance.

2.1.4 Median odds ratio

For the purpose of measuring the variation and contextual effects of the multilevel logistic model, the median odds ratio (MOR) has been proposed. According to Merlo et al. (2005), it may offer more useful and better interpretable information than ICC in social epidemiology, since it is translated to the odds ratio scale.

The median odds ratio indicates the size of the heterogeneity between the Level 2 units. It represents the median odds ratio between the lowest and the highest risk Level 2 units. It can also be interpreted as the median odds that would increase when an individual moves from a lower risk Level 2 unit to a higher risk unit. (Merlo et al., 2016.)

The median odds ratio is calculated by

$$MOR = \exp(\sqrt{2\sigma^2_{\mu_0}}\Phi^{-1}(0.75)), \tag{2.9}$$

where $\Phi^{-1}(\cdot)$ is an inverse cumulative standard normal distribution function. MOR taking on the value one would mean that there was no variation between the Level 2 units. The greater the MOR the greater the general contextual effect. MOR can also be compared to odds ratios of individual variables. (Merlo et al., 2016.)

2.2 Estimation and goodness of fit

The estimation of parameters both in GLM and in multilevel models is usually performed with maximum likelihood methods in an iterative process. Nonetheless, the estimation of multilevel logistic model is computationally rather complex, and quasi-likelihood approach is often used. This is done by approximating a nonlinear link by an almost linear function using Taylor series expansion. (Hox et al., 2010.)

However, this thesis does not go any deeper into the questions of estimation. Instead, different values of goodness of fit and model comparisons are presented.

Deviance is a statistic, which can be used to compare nested models. Two models are nested, if one can be derived from the other by extracting parameters.

Deviance is defined as $-2\ln(Likelihood)$, where $Likelihood$ is a converged value of the likelihood function. A lower deviance means that the model fits better than the one with a higher deviance. A difference of deviance test is also called the likelihood ratio test. (Hox et al., 2010.)

2.3 Multilevel model application

Multilevel applications are often more complex than modelling in one-level situations (Hox et al., 2010). In this section I will discuss some statistical and methodological concerns, that need to be acknowledged in the modelling procedure to cope with the model complexity. However, these guidelines are not written in stone by nature, but they are merely methodological suggestions.

Firstly, as seen in equation 2.7, multilevel model has various terms and the number of parameters in the model can be large. Thus, the interpretation of the coefficients can be challenging, even when the number of independent variables is small. Therefore, the expertise of previous research of the chosen topic proves to be important, and it is rational to include only the variables that have been demonstrated to have a meaningful association with the topic. (Hox et al., 2010.)

Secondly, in multilevel modelling the sample size plays an important practical role in application. Number of clusters is often considered to be more significant than the number of observations in each cluster (Hox et al., 2010). The sufficient minimum amount of Level 2 units is often suggested to be 50; otherwise, Level 2 estimates of standard errors might be biased (Maas and Hox, 2005).

In the case of dichotomous outcome variable, even larger sample sizes are needed in multilevel models. Moineddin et al. (2007) recommend that when the prevalence of the event of interest is low, the number of groups should be at least 100 and the group size at least 50. (Moineddin et al., 2007.)

Next, I will present two central technical aspects in multilevel modelling, centering of variables and analysis strategies.

2.3.1 Centering of variables

Before the multilevel model can be applied, the variables will often need to be modified first. Centering is the most common type of data modification. This process can be thought to be a new parameterisation of the model – the same model is transformed to make a clearer interpretation (Hox et al., 2010). Sommet and Morselli (2017) call this a preliminary phase in the modelling procedure. Centering is usually recommended for continuous variables, but some authors, such as Yaremych et al. (2021), also propose that categorical variables should be centered.

In regression models, the intercept is interpreted as the value of outcome when all independent variables take on the value zero. However, if the slopes are allowed to vary between the Level 2 clusters, the model is not invariant for linear transformations and then zero might not even be a feasible value. The solution is to transform the value so that zero becomes an observable value. (Hox et al., 2010.)

There are two main ways for centering the independent variables in Level 1, grand mean centering and group mean centering. For Level 2, only grand mean centering is possible. (Sommet and Morselli, 2017.) The situation and research question impact the choice of centering method in Level 1 (Hox et al., 2010).

In the case of grand mean centering, the grand mean value of a variable based on all observations in the data is subtracted from all values of the variable (Hox et al., 2010). After the grand mean centering, the interpretation of the intercept would be that it was the expected value of the outcome variable, when all independent variables were set to their mean values. In the case of group mean centering, the subtracted mean is calculated separately for each cluster in the group level (Hox et al., 2010).

Grand mean centering is often recommended due to its simpler application. Then again, some authors warn that the use of group mean centering can be tricky and complex, and lead to bias and random-measurement errors (Kelley et al., 2017).

According to Hox et al. (2010), centering also makes the interpretation of variances in the model easier, as they can be thought to be expected variances for an average observation in the data. Moreover, the use of interaction effects, which are common in multilevel models, becomes possible, since the value zero needs to be a possible value in order to interpret the interaction terms. The computational calculation is often faster, and there are fewer convergence issues after centering.

As Hox et al. (2010, pp.63–64) illustrates, grand mean centering has an impact only on the intercept, which is often not the focus of the model interpretation anyway. Model deviance, residuals and fit stay the same, as in a model which is conducted without centering. In the case of group mean centering, the model does not stay the same.

2.3.2 Analysis strategy

Analysis strategy in the multilevel approach requires a bit more thought and decisions than what is required in a single-level analysis. This section introduces two strategies, top-down and bottom-up, out of which the bottom-up strategy will be used in this thesis and therefore is presented in detail.

Top-down strategy is an exploratory method, which starts with including all possible variables in the model. Often the first step is to include all fixed and interaction terms and the second step is to attach random terms. In between the steps, all the insignificant terms are removed. The disadvantage of this approach is that the model gets very complicated, it might be difficult to interpret and computation takes a lot of time. (Hox et al., 2010.)

Bottom-up strategy is the opposite of the top-down strategy, because it starts with the simplest possible model and moves toward complexity by including more terms step by step. Usually, the fixed part of the model is built first and random terms are added afterwards. In the approach of Hox et al. (2010) this strategy has five steps.

First step in the bottom-up strategy is to perform an intercept-only model (equation 2.4). This model is mainly used for the estimation of the intraclass correlation coefficient ρ. In addition, we get a reference point for deviance, which can be used in model comparisons.

In the second phase, all fixed Level 1 variables are included. In this step, the associations of each of these variables with the dependent variable are analysed. In addition, the significance of them is tested.

In the third step the Level 2 variables are added to the model. The purpose of this step is to evaluate whether the Level 2 variables explain the between-group variation of the dependent variable.

In steps two and three, the intercept is allowed to vary between the Level 2 groups, but the slopes are still fixed. These models are also called variance component models. The goal is to first find a fitting, fixed part of the model before the random part is added.

The model in the fourth step is called the random coefficient model. This model is used to evaluate whether independent variables have a variance component between the Level 2 units. It is recommended to do this by testing each variable separately for their random slope variation, because otherwise overparameterisation and problems with estimation are likely to occur.

Moreover, if any variables were not significant in the step two and were therefore were excluded from the model, they can be tested again for random slope variation, because their slope might still have a significant variance component. When all significant variance components of slopes are chosen, they can be added to a same model at the same time and chi-square test can be made between the step three and four models.

Finally, in the last fifth step the cross-level interaction terms can be added. These are tested between the Level 2 and Level 1 variables with significant slope variation from step four.

I have discussed the principal statistical characteristics of the multilevel logistic model from definition and estimation to application. Before moving to the actual data and analysis, I will briefly introduce a literature review on socioeconomic mental disorder inequalities. Although the focus of following chapter is not statistical, I find this step important in order to understand the background in which the phenomenon takes place and to choose the correct variables for my empirical analyses.

Chapter 3

Socioeconomic mental disorder inequalities

Socioeconomic status (SES) displays the resources and position of an individual in a societal context. Commonly used variables to measure socioeconomic status of children and adolescents are household income, social class, relative poverty, parental education, parental occupation status, receipt of welfare benefits and family affluence (Reiss, 2013).

Socioeconomic health inequalities have been studied widely with consistent results (Kröger et al., 2015). There are two main hypotheses that offer possible explanations for the social gradient of health: social causation and health selection hypotheses. Social causation theory argues that people with lower socioeconomic status have worse life circumstances, such as resources, behaviour and stress, which contribute to poorer health. Health selection theory claims that people with poorer health have worse possibilities and abilities to achieve higher socioeconomic positions and to invest in their education and career. However, these hypotheses are not mutually exclusive. (Hoffmann et al., 2018; Kröger et al., 2015; Reiss, 2013.)

Moreover, a systematic review found that both theories are quite equally supported by research (Kröger et al., 2015). However, the SES indicators which were used influenced the results and the support for the alternative theories. Another possible explanation is indirect selection, where SES and (mental) health are assumed to be caused by common background genetic factors, for example, cognitive and physical characteristics (Hoffmann et al., 2018).

Mental health problems can be measured in different ways. In research on health inequalities, mental health of children and adolescents is often measured with surveys such as the Strengths and difficulties questionnaire SDQ (e.g. Bøe et al., 2012). Surveys are either self or proxy reported, depending on the age of the person whose health is in question. They often measure psychiatric symptoms rather than clinical diagnoses. In addition, there is a growing amount of research, especially from the Nordics, which uses healthcare registers and doctor-given disorder diagnoses as mental health measures (e.g., Hakulinen et al., 2019; Mikkonen et al., 2021). Surveys and registers as data sources differ, which might cause different interpretations of results.

In addition, in survey-based research psychiatric conditions are often grouped into internalising and externalising disorders. Internalising disorders refer to emotional problems, such as anxiety or depression, whereas externalising disorders to different behavioural problems in social situations, such as ADHD or conduct problems (Mikkonen et al., 2021).

I begin this chapter by discussing literature on mental disorders in childhood, after which I move to mental disorder disparities. Thereafter, the association of parental mental disorders and regional differences in disorders are covered. Both Finnish and international literature are discussed.

3.1 Mental disorders in childhood

Typically, many mental disorders first appear in childhood and adolescence, and most mental disorders begin before the age of 24 (Kessler et al., 2005). While the age of onset is earliest in impulse-control disorders and some anxiety disorders also appear early, mood disorders and substance use disorders often first appear in teens and adolescence, but the median age of onsets have larger ranges (Kessler et al., 2007). In addition, in a Danish study, the risk of diagnosis for a mental disorder was 15 per cent before the age of 18. For girls, the most common disorder was anxiety disorder and for boys ADHD. (Dalsgaard et al., 2020.)

In Finland, the use of health services for mental disorders has increased among adolescents. The largest absolute increases were in emotional disorders (depression and anxiety) and ADHD. The pattern in disorders varied between genders. (Gyllenberg et al., 2018.) In addition, the age-specific prevalence of diagnoses for autism spectrum disorder, childhood autism, hyper kinetic disorder, obsessive compulsive disorder and Tourette syndrome has risen in the Nordics between years 1990 and 2007 (Atladottir et al., 2015).

Another important aspect of mental health during early life is that mental problems in childhood are associated with mental health issues later in life. A Swedish study found that 9- and 12-year-old children with conduct problems had an increased risk of developing both mental health and other issues, such as criminal behaviour and substance and alcohol misuse, in emerging adulthood during ages 17–22 (Lichtenstein et al., 2020).

3.2 Socioeconomic disadvantage and mental disorders

There is convincing evidence of health inequalities both in Finland and globally. Some studies even suggest that mental health inequalities have grown in recent years. For example, the prevalence of self-reported depression has increased in Finland from 2000–2001 to 2010–2011 among adolescents aged 14–16, who have unemployed and lower-educated parents. In the time period of the study, severe depression of adolescents with low socioeconomic status increased for boys from 6.5 per cent to 12.8 percent and for girls from 6.4 per cent to 11.4 per cent. (Torikka et al., 2014.)

Finnish pupils in classes eight and nine, who had low educated mothers, were doing worse than others in many aspects. The study by Kestilä et al. (2019) used questionnaire data from Finnish School Health Promotion Study. Self-reported health was worse among students with lower-educated mothers. They reported more often anxiety, bad health and lack of friends and free time activities. The disparities were bigger among boys than among girls. Similar patterns were also found among upper secondary and vocational school pupils. (Kestilä et al., 2019, pp. 124–129.)

According to a systematic literature review by Reiss (2013), children and adolescents aged 4–18 from low SES families are two to three times more likely to have mental health issues than their peers with high SES. Out of SES indicators, low levels of household income and parental education had the best predictive power. There were no big gender differences between SES and mental health, but the association was found in all ages. Children under 12 years had even stronger association with low SES and mental health disorders than older children. Stronger association with low SES and externalising disorder was found than with SES and internalising disorders in many studies, although not all results were consistent. (Reiss, 2013.)

Often these studies include data from only one country, but some cross-country studies have been made on mental health inequalities. Over 16 000 child-parent pairs were studied in 11 European countries, to examine the association between parental education level, family affluence scale and mental health state of children aged 8–18. They found consistent mental health differences among socioeconomic groups in the studied countries. (Rajmil et al., 2014.)

Although associations between socioeconomic position and mental health are widely documented, there is no consensus on causality. No causal effects between changing family income during childhood and adolescence and severe mental health diagnoses among Finnish young adults were found when sibling-comparison models were added to the analysis (Sariaslan et al., 2021). This study, however, received criticism because of its use of sibling design as a tool to study causality of family income (Rod et al., 2021). Moreover, no causal chain was found between parental education, mental health disorders of children and the child's educational attainment (Mikkonen et al., 2020).

Family income is often found to have a negative association with mental health. American researchers studied poverty and mental health and found support to social causation theory. After a poverty intervention, American Indian children, whose families left poverty, had fewer (behavioural) mental health symptoms. (Costello et al., 2003.) Poor family economy was also associated with a higher amount of all mental health disorders among Norwegian adolescents aged 11–13, whereas a lower level of parental education predicted more strongly children's externalising disorders, such as conduct and hyperactivity disorders (Bøe et al., 2012). Family poverty in later childhood and adolescence had an association with higher levels of anxiety and depression in adolescence and young adulthood also in an Australian study (Najman et al., 2010).

Similar results were found in a study using Danish data, where a lower level of family income in childhood was associated with a higher risk for developing mental health disorders and getting a diagnosis in secondary care during ages 15–37. This association was especially strong for substance misuse and personality disorders and weaker for mood and anxiety disorders. The longer the low-income status of the family lasted, the higher was the risk for mental disorder diagnosis. Children, whose families experienced a downward mobility from the richest income quintile to the poorest, also had a higher risk for disorders. There was one exception to the pattern, which was that lower family income did not predict more eating disorder diagnoses. (Hakulinen et al., 2020)

Specific psychiatric disorders have also been studied. For example, even though ADHD is a disorder with a strong genetic association, the risk for a child to develop it increased with parental unemployment, relative income poverty and low education. The risk was higher when the forms of disadvantage accrued. (Keilow et al., 2020.)

As mentioned above, several measures for socioeconomic status have been used in these studies. A German longitudinal study found that out of parental education, household income and parental unemployment, parental education had the best predictive power to mental health of children. Children of higher-educated parents had lower chances of developing mental health issues than children with lower-educated parents. (Reiss et al., 2019.)

Another important aspect of SES and mental health of children is the use of healthcare services. In a German study, children with lower SES used more mental healthcare services than children with higher SES. However, parental education, income and parental occupation were not statistically significant moderating predictors between mental health symptoms and the usage of health services. These results suggested that socioeconomic status had no impact on receiving care and help for mental health problems. (Reiß et al., 2021.) Mental health services and inequalities will be discussed more in a later section of this chapter.

3.3 Parental mental disorders as risk factors

Parental mental health disorders are risk factors for a child's mental health (Dean et al., 2010). They can also mediate and moderate between SES and a child's mental health (Reiss, 2013). For example, parental ADHD might moderate between the association of socioeconomic disadvantage and a child's ADHD because social gradient for children's mental health was found to be stronger among families with no parental ADHD than those with it (Keilow et al., 2020).

Associations between parental mental health and a child's mental health have been studied in Nordic register-based studies. For example, in a Swedish study, children of mothers with intellectual disability (ID) were more likely to develop a mental health disorder, ID and to encounter violence and child abuse in early childhood than children whose mothers did not have ID. (Wickström et al., 2017.)

Finnish intergenerational associations have been studied as well. Children aged 0–12 years, whose mothers had psychiatric disorders and substance abuse problems, had a higher risk for developing emotional, behavioural and psychological development mental health disorders than those children whose mothers did not have these problems. The risks were higher for boys than for girls and for children whose mothers were socioeconomically disadvantaged. The greatest risks for developing mental health disorders were for children whose mothers had both psychiatric and substance abuse problems. (Ranta and Raitasalo, 2015.)

Even though parental mental disorders are not the main focus of this thesis, they will be used as control variables, since these associations are important when children are the focus of the research.

3.4 Regional differences in mental disorders

Regional differences in health are often studied by looking at the role of urbanisation, geographical position of the regions or different deprivation indexes that measure the relative disadvantage of the region.

Differences between urban and rural contexts in mental health are consistently found. A Finnish follow-up register study on the use of special psychiatric outpatient healthcare found that children and adolescents from urban areas used services more often than children from rural areas. In addition, regional variation in the use of psychiatric specialised healthcare was found: both outpatient and inpatient services were used more in the southern capital area and outpatient services less in the north. (Paananen et al., 2013.)

International literature reports similar results. A study, which covered many developed countries, found that psychiatric disorders, as well as mood and anxiety disorders, appeared more frequently in urban than rural areas (Peen et al., 2010). All psychiatric disorders, except intellectual disability and behavioural and emotional disorders with onset in childhood, occurred more often for people who were born in large cities than in rural areas in Denmark (Vassos et al., 2016). Similar results were found for psychiatric morbidity in Great Britain (Paykel et al., 2000).

Since the data used in this thesis is based on visits in specialised health care, also the aspect of service supply over regions has to be considered. Services for mental health and substance use problems have been developed at different paces over regions in Finland, which might have caused differences in organising the services (Viertiö et al., 2017). Regional differences have also been found in seeking special healthcare for psychiatric problems among families with 5–12-year-old children (Huikko et al., 2017). In addition, large differences in mental health personnel resources have been found among Finnish municipalities in primary health care (Sadeniemi et al., 2014).

These findings combined form an interesting setting for multilevel analysis, where contextual differences between municipalities could occur. This literature review will be used overall as a base to interpret the findings of empirical models, and I will also compare results to existing literature. In the following chapter, I will continue with presenting the data and variables of my study.

Chapter 4

Data, sample and study design

This thesis uses Finnish register data, which has been shown to be of high-quality with good validity and coverage (Gissler and Haukka, 2004). Register data, which Nordic countries have been producing since the 1960s, is based on administrative sources, which are not usually produced or collected for statistical or research purposes. This might lead to challenges in research use, since the variable or population definitions might not always be optimal. Thus, register data often requires editing and merging. However, the data quality is generally good. (Tønder, 2008; United Nations Economic Commission for Europe, 2007.)

An important aspect of register data are the unified personal identification numbers, because they enable linkages between different registers. For research, this offers numerous possibilities; for example, because information on a person's income, education, household, family members can be combined from different registers. (Tønder, 2008; United Nations Economic Commission for Europe, 2007.)

In this chapter, I present the register-based data and variables of the empirical part of the thesis. The data sources and used variables are introduced in detail. In addition, descriptive statistics are shown and the main characteristics of the data are discussed. Finally, a brief summary about how healthcare services are organised in Finland is given to understand the institutional context.

4.1 Data source and study sample

This thesis uses individual-level register data of the total population in Finland. Data on psychiatric health information is received from the Care Register for Heath care (Hilmo) administered by the Finnish Institute of Health and Welfare. It contains information on visits in public specialised healthcare services and ICD-10 codes (International Classification for Diseases) of psychiatric diagnoses. I also use Statistics Finland's data of individual socioeconomic information on an annual level. The data is pseudonymous, and it is edited and analysed remotely via a system provided by Statistics Finland.

The analysis sample consists of all children aged 4–17 years living in Finland in the year 2018. Younger children were excluded due to a low prevalence of mental disorders. Information on children's socioeconomic status is from 2018. In addition, household-level data on family income is combined with individual-level data. To obtain information on parents, children and their biological or adoptive parents were linked to each other with pseudonymous individual identification numbers.

In the year 2018 there were 849 233 children aged 4–17 years living in Finland. I excluded children whose one or both parent were missing an identification number (n=21 245) and children who were not living in the same household with neither of their biological or adoptive parents (n=13 818) from the analysis sample. For the former group, no parental information could be found, and the latter consist of special groups of children living, for example, in foster homes or in custody and adolescents living on their own.

In 2018, Finland had 311 municipalities, which are used as the Level 2 units. However, based on the simulation from Moineddin et al. (2007), the number of children in the municipalities was allowed to be no less than 50. All municipalities with under 50 individuals were islands belonging to Åland. Therefore, all six municipalities belonging to subregion Åland's archipelago were joined together as one municipality.[1]

After this modification, the number of individuals in municipalities varied from 57 to 76 703 with the mean 2665. The final analysis sample consists of 815 616 individuals, who were nested in 306 Level 2 units based on their municipality of residence in 2018.

4.2 Dependent variable

In this thesis, the dependent variable is a dichotomous variable indicating mental disorder (based on ICD-10 F-class Mental and behavioural disorder) that was treated in a public specialised healthcare visit. If the child had a health contact in specialised healthcare with any mental disorder diagnosis during 2018, the variable takes on the value one, otherwise the value zero. In addition, if the child had visited a specialised psychiatric care with an empty diagnosis field, they were given the value one. These visits are often part of an evaluation period of psychiatric symptoms before the patient is given a diagnosis.

The dependent variable includes various psychiatric disorders, however, some diagnoses in F-class were excluded based on psychiatrist recommendation. The aim with this variable was to get information on the overall pattern of mental disorder inequalities. In the context of multilevel logistic model, with which too low prevalence of the studied

[1] Brändö, Föglö, Kumlinge, Kökar, Sottunga and Vardö

event is not recommended, models with single disorders would not be possible with this data. The full list and exclusion criteria of F-class diagnoses is given in Appendix A.

4.3 Independent and control variables in Level 1

Within-cluster effects are studied with two main explanatory variables in individual Level 1. They both are indicators of the child's family's socioeconomic status.

I use the child's household income to describe the child's childhood living environment. Household income is defined as a household's disposable income in 2018; more specifically as income after taxes and income transfers. The household size is taken into account by dividing the disposable income by OECD consumption unit. Incomes are presented as quintiles, which are calculated based on the study sample.

The highest completed degree by the year 2018 is used for maternal education and it is split into three categories: lower secondary or less, upper secondary education and tertiary education. I chose to use maternal education instead of paternal education, because it is in most cases used in the literature and allows making straightforward comparisons with previous literature. The reason why many studies choose to use maternal education might be due to some practical reasons and data availability. However, I also use paternal education in a robustness check.

In addition, the child's age and gender are controlled for. Age is used as a categorical variable (4–6, 7–12 and 13–17 years) instead of a continuous variable because the prevalence of mental disorders varies by age and gender, but the variation is not linear. Gender is a dichotomous variable (male, female), since register data is based on administrative records and therefore does not offer information on gender identity. Information on the child's family structure, categorised as whether the child lives with both parents, only mother, or only father is also controlled for.

Parental mental disorder is controlled separately for both mother and father and coded as a dichotomous variable similar to the main dependent variable. However, all F-class diagnoses were included from the years 2014–2018.

4.4 Independent variables in Level 2

Four Level 2 variables will be used in the analyses. Between-cluster effects are studied with these variables.

First, the level of urbanisation of the municipality is used, divided into three categories: urban, semi-urban and rural.

Second, the variable on the geographical location of the municipalities is utilised. These are based on Statistics Finland's Major regions classification. The five values of this variable are Åland, Southern Finland, Helsinki-Uusimaa, Western Finland and Northern and Eastern Finland.

The variables urbanisation and major region are obtained from Statistics Finland's register data. In addition, there are two municipality-level variables retrieved from Sotkanet, which is an open source indicator bank by THL that offers regional level health and welfare information. These variables are used as deprivation indices of the municipalities.

The first deprivation variable is the share of persons with higher education qualifications in the municipality's over 20-years-old population (THL, 2022b). The second one is the share of children under the age of 18, who live in households considered at-risk-of-poverty (THL, 2022a). At-risk-of-poverty households are those whose disposable income is less than 60 per cent of the annual population median, using the OECD household consumption unit.

4.5 Descriptive statistics

Descriptive statistics of categorical independent variables are shown in Table 4.1. They present both all children and children who have a mental disorder. Both distributions among all children and those with a mental disorder, in addition to prevalence of mental disorder in each category of independent variables, are presented.

The overall prevalence of mental disorders in the sample is 4.7 per cent (n=38 404). The prevalence of mental disorders is slightly greater for males (5.1%) than for females (4.3%). The prevalence also increases by age; for ages 4–6 it is 1.7 per cent, for ages 7–12 it is 4.4 per cent and for ages 13–17 it is 7.0 per cent.

Family structure has an association with the child's mental disorder. Children who are living with only one of their parents have a greater prevalence (8.2% for mother, 8.6% for father) of mental disorders than children who live with their both parents (3.3.%). However, there are 424 (0.05%) missing values in this variable.

In addition to living circumstances, parental mental disorders are also clear risk factors for the child's mental disorder. The prevalence is 12.0 per cent among children of mothers with a mental disorder compared to 4.1 per cent among those without it. For paternal mental disorder the pattern is similar, just slightly weaker (10.2% for children with paternal mental disorder and 4.1% for those without).

The prevalence of mental disorders seems to decrease when mothers are higher-educated. Only 3.8 per cent of children with mothers with post-secondary and tertiary education have a mental health disorder, when the corresponding value for children with the lowest maternal education is 6.3 per cent. The association is linear, since the prevalence of children with upper secondary maternal education is 5.5 per cent.

However, the relationship between mental disorders and household income is not as

Table 4.1: Descriptive statistics of mental disorder by categorical background variables.

	All children	Children with a mental disorder	
	Distribution	**Distribution**	**Prevalence**
Level 1			
Gender			
Male	51.2%	55.3%	5.1%
Female	48.4%	44.7%	4.3%
Age group			
4–6	21.5%	7.8%	1.7%
7–12	44.3%	41.5%	4.4%
13–17	34.3%	50.7%	7.0%
Family structure: lives with			
Both parents	71.6%	50.0%	3.3%
Mother	24.1%	42.1%	8.2%
Father	4.2%	7.9%	8.6%
Maternal mental disorder			
No disorder	92.1%	80.0%	4.1%
Has a disorder	7.9%	20.0%	12.0%
Paternal mental disorder			
No disorder	94.6%	88.3%	4.4%
Has a disorder	5.4%	11.7%	10.2%
Maternal education			
Lower secondary or less	9.4%	12.5%	6.3%
Upper secondary	38.6%	45.1%	5.5%
Post-secondary or tertiary	52.0%	42.5%	3.8%
Household Income Quintile			
1 The lowest	20.0%	22.8%	5.4%
2	20.0%	24.2%	5.7%
3	20.0%	20.3%	4.7%
4	20.0%	17.6%	4.2%
5 The highest	20.0%	15.1%	3.6%
Level 2			
Urbanisation			
Urban	69.5%	71.8%	4.9%
Semi-urban	17.1%	15.9%	4.4%
Rural	13.3%	12.4%	4.4%
Major region			
Åland	0.6%	0.8%	7.0%
Southern Finland	19.5%	24.8%	6.0%
Helsinki-Uusimaa	30.4%	29.9%	4.6%
Western Finland	25.4%	19.7%	3.7%
Northern and Eastern Finland	24.2%	24.8%	4.8%
Observations	815 616	38 404	4.7%

straightforward as with education. Children from the three highest-earning quintiles have lower and decreasing prevalence than the two poorest ones, but the poorest quintile diverts from the linear pattern. 5.4 per cent of children from the poorest quintile and 3.6 per cent of children from the richest quintile have mental disorders. There are 14 036 (1.72%) missing values in this variable.

The prevalence of mental disorders hardly differs by the level of urbanisation. There is only a small difference in prevalence, it is 4.9 per cent for urban and 4.4 percent for both semi-urban and rural.

For major regions, there are notable differences. The prevalence of mental disorders is the greatest in southern parts of Finland. It is 7.0 per cent in Åland and 6.0 per cent in Southern Finland. Helsinki-Uusimaa and Northern and Eastern Finland have similar prevalence, 4.6 per cent for the former and 4.8 per cent for the latter. The smallest prevalence, 3.7 per cent, is in Western Finland.

Table 4.2: Descriptive statistics of mental disorder by continuous background variables.

	Mean	**Std. dev.**	**Median**	**N**
Level 2				
All children				
Share of higher-educated	31.74%	8.06	31.3%	815 616
Share of at-risk-of-poverty children	12.14%	3.29	12.4%	815 616
Children with a mental disorder				
Share of higher-educated	31.66%	7.70	31.3%	38 404
Share of at-risk-of-poverty children	12.30%	3.15	12.4%	38 404

For continuous independent variables, descriptive statistics are presented in Table 4.2. The mean and median shares of both higher-educated and at-risk-of-poverty children in municipalities do not differ significantly between all children and those with a mental disorder. The mean share of the higher-educated is 31.74 per cent, and the median is 31.3 per cent among all children. The corresponding shares are 31.66 per cent and 31.3 per cent for children with a mental disorder.

For the share of at-risk-of-poverty children, the mean is 12.14 per cent and median 12.4 per cent for all children, and same shares are 12.30 per cent and 12.4 per cent for children with a mental disorder.

In addition to distributions and prevalence of single independent variables, I will take a look at the correlations of variables. They are shown in Appendix C Table C.1. Notable correlations are between household income and maternal education (0.408), and household income and family structure (-0.274). Level 2 variables urbanisation and major region also have a correlation (0.291).

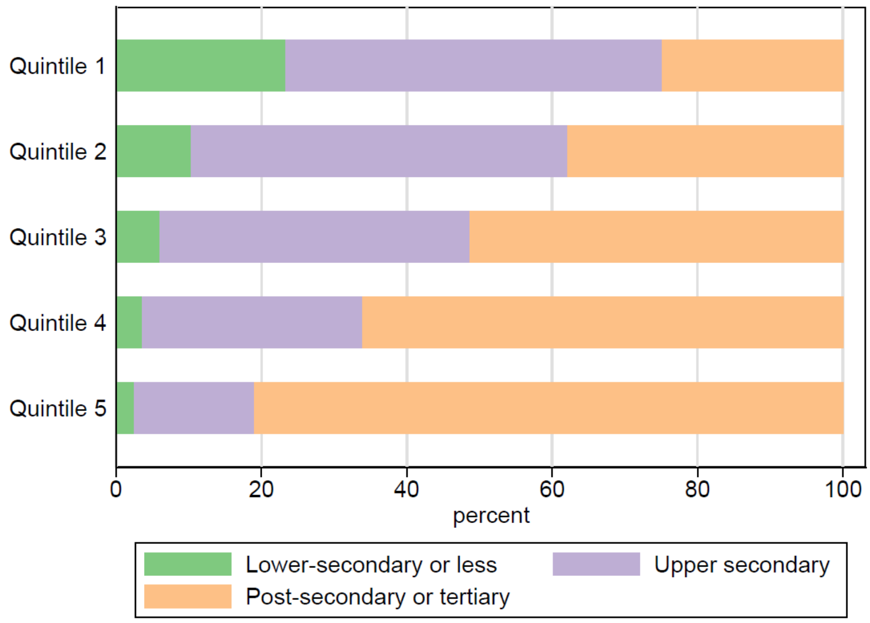

Figure 4.1: Share of maternal education levels in household income quintiles.

Figures 4.1 and 4.2 illustrate more detailed associations of these Level 1 correlated variables. For maternal education and household income quintile the proportion of the highest educated mothers strongly increases in higher income households (Figure 4.1). This is supported by previous literature, which has consistently found that high education is associated with higher income (e.g. Koerselman and Uusitalo, 2014).

In addition, the share of children living only with their mothers decreases by higher earning households (Figure 4.2). About half of the children in the poorest quintile live with only one of their biological or adoptive parents, whereas in the richest quintile more than 80 per cent live with both parents. This finding is rather intuitive, because single-parent families are more likely to have lower income than two-parent families. However, it is interesting how strong this association is, even though the household size is taken into account in the income variable with the use of OECD consumption unit.

This thesis has a geographical perspective on mental disorders, because the Level 2 units are Finnish municipalities. Keeping this point of view in mind, Figure 4.3 illustrates how the prevalence of mental disorders varies in municipalities. Higher-prevalence municipalities seem to center in Eastern and Southern Finland and Åland, whereas in most of the municipalities in Western and Middle Finland the prevalence is lower. A few municipalities in the map are presented as missing values due to data protection rules by

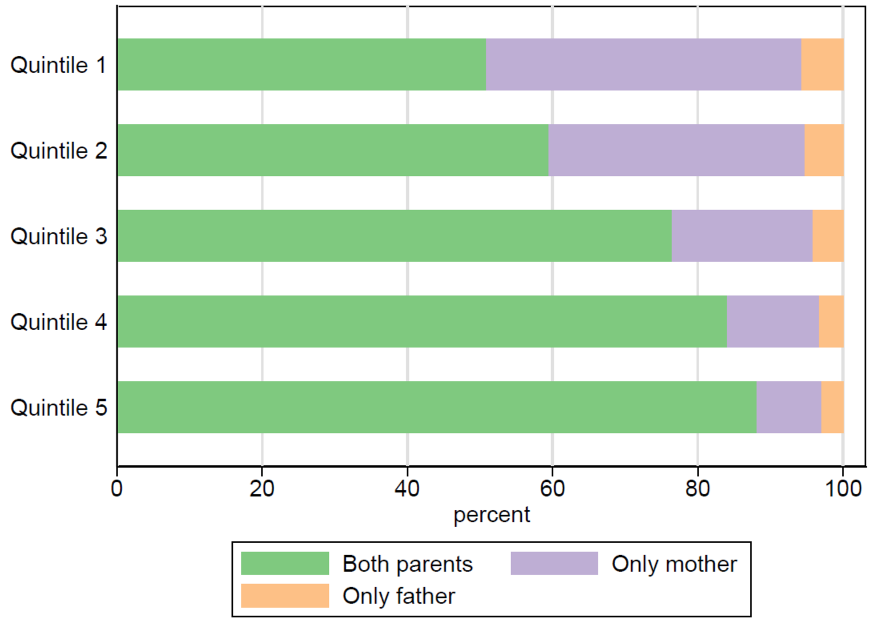

Figure 4.2: Share of family structure categories in household income quintiles.

Statistics Finland. However, their information is still used in other descriptive statistics and models of this thesis where it cannot be identified.

4.6 Healthcare services in the Finnish context

The data of this thesis is based on records of the use of public specialised healthcare services. Next, I will briefly discuss how these services are organised and used in Finland.

Finland is a Nordic welfare state, where comprehensive public health care is offered to all citizens. Specialised healthcare services are provided in public hospitals, and psychiatric specialised care is offered to children and adolescents when symptoms are severe and primary or school healthcare are not able to offer adequate help.

Expenses of healthcare are mainly paid by the citizens' home municipalities and specialised services are organised by hospital districts. Customer fees in hospitals are modest and have an annual payment ceiling, hence the individual's or family's earnings should not impact the seeking of treatment for illness. In addition, most of the services are free of charge for the population under 18 years.

However, this data contains mainly the more severe psychiatric cases, because primary, school, and private healthcare are excluded. Another aspect about data coverage is that a

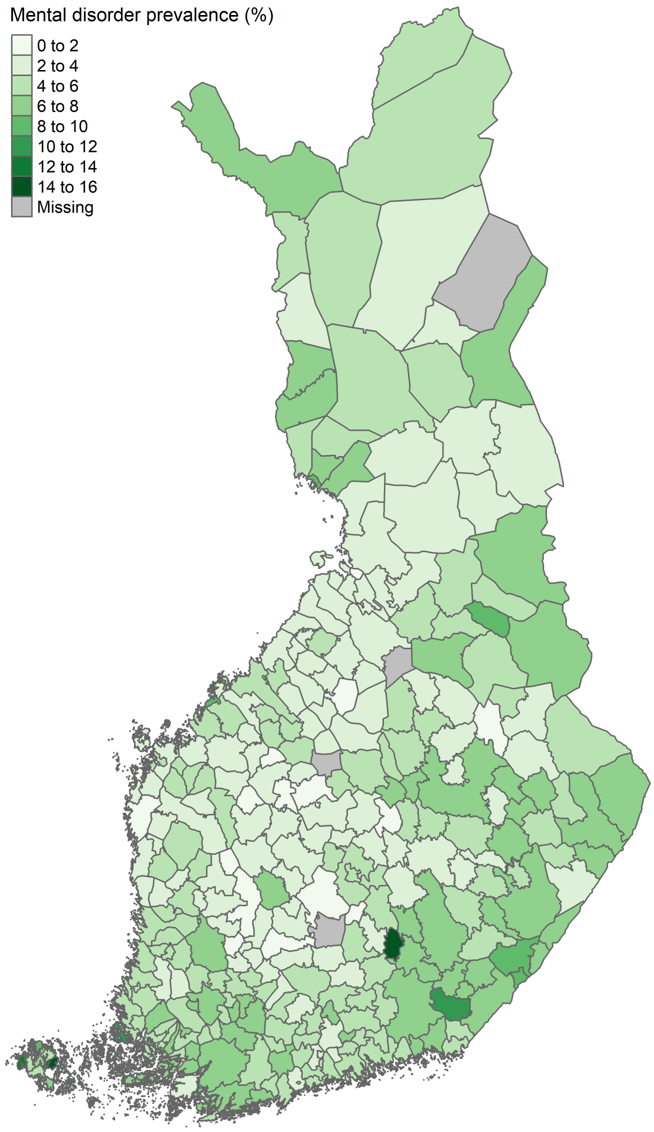

Figure 4.3: Prevalence of mental disorders in Finnish municipalities among children aged 4–17 in 2018.

large number, about half of the Finnish children, have a supplementary health insurance, and parental education level explains the choice of taking an insurance (Valtonen et al., 2014). Therefore, it is possible that the data is missing mental disorders of children who have highly educated parents. However, Valtonen et al. (2014) also found out that both children with and without health insurance used public healthcare, and therefore children with health insurance are not necessarily completely left out of public records.

In addition, education is free of charge in Finland from comprehensive school until tertiary and doctoral education, and income inequality is low compared with many other European countries. Nevertheless, socioeconomic health inequalities persist at the national level.

Now that the data is presented, the next chapter will present and discuss the empirical models and results. However, when interpreting the results, both the data source and the context of the Finnish society should be taken into account.

Chapter 5

Empirical application of the multilevel logistic model

In this chapter the empirical models and their interpretations are discussed. I start by fitting a single-level logistic model and move subsequently to a multilevel logistic model. I will follow the bottom-up analysis strategy by Hox et al. (2010) introduced in section 2.3.2 and go through the results step by step.

In the equations, the modelled probability is whether the child has a mental disorder, notated as MD_{ij} for individual $i = (i = 1, \ldots, n_j)$ in municipality $j = (j = 1, \ldots, J)$. The mathematical form of the modelled probability is MD_{ij}=Pr(mental disorder=1).

The models are run in Stata version 17.0 with the logit and melogit commands. In the following model equations 5.1, 5.2 and 5.3, shortened versions of model variable names are used to cut down the long equations. For clarification, these are listed in Appendix B.

5.1 Single-level logistic regression

I begin the modelling by fitting a single-level logistic regression model. This modelling was done in three stages, in models 0a, 0b and 0c. First, model 0a contains household income quintile, maternal education and control variables age group and gender. Second, model 0b also controls for parental mental disorders and family structure. Finally, model 0c includes urbanisation and major region. Results of these three models are presented in Table 5.1.

Boys have 1.19 times higher odds for mental disorder than girls (models 0a–0c). Also adolescents have higher odds than younger children, the odds are 4.01 times higher for 13–17-year-old children compared to 4–6-year-old children (models 0b–0c). The addition

Table 5.1: Logistic regression model odds ratios.

	Model 0a	Model 0b	Model 0c
Gender			
Ref. Female	1.00	1.00	1.00
Male	1.19*** (0.013)	1.19*** (0.013)	1.19*** (0.013)
Age group			
Ref. 4–6	1.00	1.00	1.00
7–12	2.71*** (0.055)	2.54*** (0.052)	2.54*** (0.052)
13–17	4.37*** (0.088)	4.01*** (0.081)	4.01*** (0.081)
Maternal education			
Ref. Post-secondary or tertiary	1.00	1.00	1.00
Lower secondary or less	1.63*** (0.030)	1.39*** (0.026)	1.37*** (0.026)
Upper secondary	1.37*** (0.017)	1.26*** (0.015)	1.26*** (0.015)
Household income quintile			
Ref. 5 - the highest	1.00	1.00	1.00
1 - the lowest	1.26*** (0.024)	0.84*** (0.017)	0.85*** (0.017)
2	1.43*** (0.026)	1.03 (0.019)	1.04* (0.020)
3	1.24*** (0.023)	1.07*** (0.020)	1.08*** (0.020)
4	1.13*** (0.021)	1.06** (0.020)	1.06** (0.020)
Maternal mental disorder			
Ref. No disorder		1.00	1.00
Has disorder		2.59*** (0.037)	2.59*** (0.037)
Paternal mental disorder			
Ref. No disorder		1.00	1.00
Has disorder		1.71*** (0.030)	1.71*** (0.030)
Family structure: lives with			
Ref. Both parents		1.00	1.00
Only mother		2.07*** (0.025)	2.04*** (0.025)
Only father		1.78*** (0.039)	1.77*** (0.038)
Urbanisation			
Ref. Rural			1.00
Semi-urban			1.02 (0.021)
Urban			1.10*** (0.019)
Major region			
Ref. Helsinki-Uusimaa			1.00
Southern			1.28*** (0.019)
Western			0.80*** (0.013)
Northern & Eastern			1.07*** (0.016)
Åland			1.55*** (0.098)
N	801 580	801 436	801 436

* p<0.05, ** p<0.01, *** p<0.001, standard errors in parentheses
Model 0a: Maternal education, income quintile and controlled for gender and age group
Model 0b: Model 0a + controlled for family structure and parental mental disorders
Model 0c: Model 0b + urbanisation and major region

of control variables only weakens the association of age and mental disorder by little.

Children whose mothers have an education of lower level have higher odds for mental disorder than children of the highest educated mothers. The odds are 1.63 times higher for the lowest level compared with the post-secondary or tertiary education (model 0a). The association declines a bit when control variables are added in model 0b, but not greatly. In addition, the effect of education seems to be linear because the odds ratio of upper secondary education is 1.26 and of the lowest education is 1.39 (model 0b).

Interestingly, the association between household income and mental disorder is not as straightforward as with maternal education. In model 0a, children from less-earning quintiles have higher odds for mental disorder than children from the richest quintile. Nevertheless, the association is not linear among quintiles, and the odds are highest for quintile 2 (OR=1.43). However, when the control variables parental mental disorder and family structure are included, the odds ratios for quintiles 2–4 decline nearly to one (model 0b). Moreover, the poorest quintile 1 has the odds ratio of 0.84 (model 0b). This is interpreted as that children from the poorest families have lower odds for mental disorder than those from the richest quintile. Further modelling (not shown), where the model was otherwise the same as model 0b, but the variable family structure was excluded, that was conducted suggests that it is the one control variable causing this complex effect of income in the model.

Both parental mental disorders and living with only one parent are strong risk factors for a mental disorder. Children with a maternal mental disorder have 2.59 times higher odds for a mental disorder themselves than children whose mother do not have a disorder. The effect is similar but weaker for paternal mental disorder with 1.71 times higher odds (models 0b–0c). Moreover, children who live only with their mother have 2.07 times higher odds, and those living only with their father have 1.78 times higher odds for mental disorder than children who are living with both of their parents (model 0b).

Children from urban municipalities have just slightly higher odds (OR=1.10) for a mental disorder than rural children, whereas semi-urban municipalities do not statistically significantly differ from the rural ones. For the major region, Helsinki-Uusimaa is used as the reference category. Higher odds for a mental disorder are for municipalities of Southern Finland (OR=1.28), and Northern and Eastern Finland (OR=1.07) and Åland (OR=1.55). Municipalities of Western Finland have lower odds (OR=0.80) compared with Helsinki-Uusimaa.

As a whole, the models stay quite stable through this three-step modelling process. From model 0a to model 0b, odds do weaken, and especially income quintile odds ratios come close to one. The additions of Level 2 variables in model 0c do not greatly change any of the odds ratios from model 0b.

This single-level logistic modelling was conducted to elaborate the overview of the statistical associations of these variables. Next, I move on to multilevel logistic modelling, with the focus on the dependent Level 1 and 2 variables.

5.2 Intercept-only and variance component two-level models

Before starting a multilevel modelling, centering of variables is a common modification, as written in the section 2.3.1. However, most of the independent variables in my empirical models are categorical, and practical issues in their centering appeared in Stata. Stata does not allow categorical variables to have non-integer values and therefore does not allow grand mean centered variables in models, so only continuous variables are centered in my analyses.

I begin the multilevel modelling by conducting an empty intercept-only model shown in equation 2.4 to estimate the intraclass correlation coefficient ρ of the model. Results of this model 1 are shown in Table 5.2. The most important coefficient $\sigma^2_{\mu_0}$ of this model is used in the ICC formula 2.8.

Therefore, we get $\rho = 0.156/(0.156 + (\pi^2)/3) = 0.045$ [SD=0.004, 95% CI 0.037–0.055]. We interpret this as that 4.5 per cent of the variation is explained by the grouping structure. It can be considered to be quite a small level of group-level variation. However, the likelihood ratio test rejects the null hypothesis, which implies that group differences, even if comparatively small, exist.

In addition, a median odds ratio is calculated as in definition 2.9, and it is 1.46, which indicates the size of variation among Finnish municipalities. The contextual effect is not large in size, but some variation still exists. Therefore I decide to move forward with the multilevel logistic model.

After the empty intercept-only model, model 2 with all Level 1 independent and control variables, which assumes fixed regression slopes, is run. The formula of this model is

$$\begin{aligned} MD_{ij} = \text{logistic}(&\gamma_{00} + \gamma_{10} education_{ij} + \gamma_{20} income_{ij} + \gamma_{30} gender_{ij} \\ &+ \gamma_{40} agegroup_{ij} + \gamma_{50} mMD_{ij} + \gamma_{60} fMD_{ij} + \gamma_{70} familystructure_{ij} + \mu_{0j}). \end{aligned} \tag{5.1}$$

The odds ratios of dependent variables education and income quintile of model 2 are presented in Table 5.2. The model 2 is otherwise same as model 0b but it also includes the random term for constant. All control variables from Level 1 are included in the model, but they are left out of the results table because they are not the main interest here.

Odds ratios of model 2 for both maternal education and income are very similar to the ones of the single-level logistic model 0b. However, the difference of this model compared

Table 5.2: Multilevel logistic variance component model odds ratios.

	Model 1	Model 2	Model 3
Fixed part			
Level 1			
Maternal education			
Ref. Post-secondary or tertiary		1.00	1.00
Lower secondary or less		1.38*** (0.026)	1.37*** (0.026)
Upper secondary		1.28*** (0.016)	1.28*** (0.016)
Household income quintile			
Ref. 5 - the highest		1.00	1.00
1 - the lowest		0.84*** (0.017)	0.84*** (0.017)
2		1.03 (0.020)	1.03 (0.020)
3		1.06** (0.020)	1.06** (0.020)
4		1.05* (0.020)	1.05* (0.020)
Level 2			
Urbanisation			
Ref. Rural			1.00
Urban			1.04 (0.054)
Semi-urban			0.99 (0.050)
Major region			
Ref. Helsinki-Uusimaa			1.00
Southern			1.18* (0.092)
Western			0.71*** (0.053)
Northern & Eastern			0.90 (0.067)
Åland			1.50** (0.209)
Random part			
$\sigma^2_{\mu_0}$	0.156*** (0.016)	0.134*** (0.014)	0.092*** (0.010)
Model fit			
Deviance	366 189	281 868	281 776
LR-test p-value	0.00	0.00	0.00
MOR	1.46	1.42	1.34
N	815 616	801 436	801 436

* p<0.05, ** p<0.01, *** p<0.001, standard errors in parentheses

Model 1: Intercept-only model

Model 2: Maternal education, household income quintile and controlled for gender, age group, family structure and parental mental disorders

Model 3: Model 2 + urbanisation and major region with the single-level one is the random part. $\sigma^2_{\mu_0}$ is 0.134, which indicates the size of the intercept variation.

The model fit measure deviance is 281 868, and the likelihood ratio test is significant. The deviance is smaller than the one in the empty model 1, which indicates an improvement in model fit. Nevertheless, because of different sample size due to missingness in some variables of model 2, the models are not straight comparable. The MOR is 1.42, indicating a rather low level of heterogeneity between municipalities. However, it is larger than the odds of maternal education or income quintile.

Next, I proceed in building the fixed part of the model by also including the first Level 2 variables in model 3. This model is defined as

$$\begin{aligned}(5.2)\quad MD_{ij} = \text{logistic}(&\gamma_{00} + \gamma_{10}education_{ij} + \gamma_{20}income_{ij} + \gamma_{30}gender_{ij}\\ &+ \gamma_{40}agegroup_{ij} + \gamma_{50}mMD_{ij} + \gamma_{60}fMD_{ij}\\ &+ \gamma_{70}familystructure_{ij} + \gamma_{01}urban_j + \gamma_{02}majorregion_j + \mu_{0j}).\end{aligned}$$

The results of model 3 are also shown in Table 5.2. The categories of the urbanisation of the municipality are not statistically significant, meaning that there are no statistical differences between urban and rural municipalities. For major region, the odds ratios of Åland, Southern and Western Finland remain similar to the single-level model 0c. The category of Northern and Eastern Finland is not statistically significant in this model. Random term for constant $\sigma^2_{\mu_0}$ declines from previous model and is now 0.092.

Furthermore, I also run model 3a, shown in Appendix Table C.2, which also includes the Level 2 variables the share of higher-educated and the share of at-risk-of-poverty children. As these were continuous variables, they were included in a grand mean centered form. Nevertheless, the odds ratios of these two variables are almost one and statistically insignificant. Therefore, they do not add any value to the model, as the odds ratios of the other variables remain similar as in model 3, and goodness of fit measures stay almost the same. This is why I decided to drop these two Level 2 variables from my further modelling, as it seemed that there was no statistical association between them and child's mental disorder.

The fixed part of the model is now built. By this stage, only the model intercept was allowed to vary between the Level 2 municipalities. Next, I will move to test random slopes for the independent variable maternal education.

5.3 Random coefficient two-level model

In this section, I build the random part of the model. First I have model 4, where maternal education is assumed to vary between municipalities. The equation of this model is:

$$MD_{ij} = \text{logistic}(\gamma_{00} + \gamma_{10} education_{ij} + \gamma_{20} income_{ij} + \gamma_{30} gender_{ij} + \gamma_{40} agegroup_{ij} + \gamma_{50} mMD_{ij} + \gamma_{60} fMD_{ij} + \gamma_{70} familystructure_{ij} + \gamma_{01} urban_j + \gamma_{02} majorregion_j + \mu_{0j} + \mu_{1j} education_{ij}). \tag{5.3}$$

The results of model 4 are shown in Table 5.3. The odds ratios of fixed terms in Level 1 are in line with the previous ones from model 3. However, the Level 2 odds ratios seem to have a slightly greater effect in the random coefficient model. In urban municipalities, the odds are 1.22 and in semi-urban 1.39 times greater for children's mental disorders than in rural ones. In addition, the odds for major region categories are also greater in size. These sudden changes, nevertheless, raise some suspicion of the validity of model fit, because the odds ratios were stable in previous models.

In the random part, there are now terms $\sigma^2_{\mu_0}$, which is still indicating the size of variation for the intercept and $\sigma^2_{\mu_{1a}}$ and $\sigma^2_{\mu_{1b}}$, which indicate the size of variation of the maternal education slopes between municipalities. Moreover, we also have covariance structure terms. $\sigma_{\mu_{1a1b}}$ is covariance between the maternal education slopes, and $\sigma_{\mu_{01a}}$ and $\sigma_{\mu_{01b}}$ are covariance terms between the intercept and the slopes for maternal education. However, all the covariance terms are small in size and statistically insignificant. This suggests that the slopes of maternal education categories do not differ significantly among municipalities.

When model 4 is compared to model 3, we see that the model fit does not improve. The deviance is greater than in the previous models 2 and 3, and the likelihood ratio test is insignificant. This implies that the inclusion of random slopes in maternal education does not improve goodness of fit. The MOR of this model is 1.32, so there is only a slight decline from model 3.

I tried to run a model with random slopes for income quintiles, but this model did not converge, which might imply that the data did not fit this model well (model not shown). However, because the odds of household income quintiles differed only little in models 2 and 3, it may not be necessary to test random slopes for income. Since the differences between income quintiles were small, testing the random part can quite likely be assumed to give insignificant results.

It can thus be concluded that the best multilevel logistic model fit was found in model 3. I will continue discussing this model in more detail.

5.4 Final model

The final model of this thesis is chosen as model 3, where intercept is allowed to vary between municipalities but the slopes of dependent variables are fixed. This model is

Table 5.3: Multilevel logistic random coefficient model odds ratios.

	Model 4
Fixed part	
Level 1	
Maternal education	
Ref. Post-secondary or tertiary	1.00
Lower secondary or less	1.35*** (0.027)
Upper secondary	1.28*** (0.016)
Household income quintile	
Ref. 5 - the highest	1.00
1 - the lowest	0.86*** (0.017)
2	1.05* (0.020)
3	1.08*** (0.020)
4	1.06** (0.020)
Level 2	
Urbanisation	
Ref. Rural	1.00
Urban	1.22*** (0.045)
Semi-urban	1.39*** (0.064)
Major region	
Ref. Helsinki-Uusimaa	1.00
Southern	1.29*** (0.021)
Western	0.87*** (0.017)
Northern & Eastern	1.22*** (0.021)
Åland	1.80*** (0.255)
Random part	
$\sigma^2_{\mu_0}$	0.087 (0.030)
Maternal education: Lower secondary or less	
$\sigma^2_{\mu_{1a}}$	0.068 (0.029)
Maternal education: Upper secondary	
$\sigma^2_{\mu_{1b}}$	0.074 (0.030)
Covariance	
$\sigma_{\mu_{1a1b}}$	0.066 (0.027)
$\sigma_{\mu_{01a}}$	0.012 (0.025)
$\sigma_{\mu_{01b}}$	0.002 (0.025)
Model fit	
Deviance	290 445
LR-test p-value	1.00
MOR	1.32
N	801 436

* p<0.05, ** p<0.01, *** p<0.001, standard errors in parentheses

Model 4: Model 3 + random slopes for maternal education

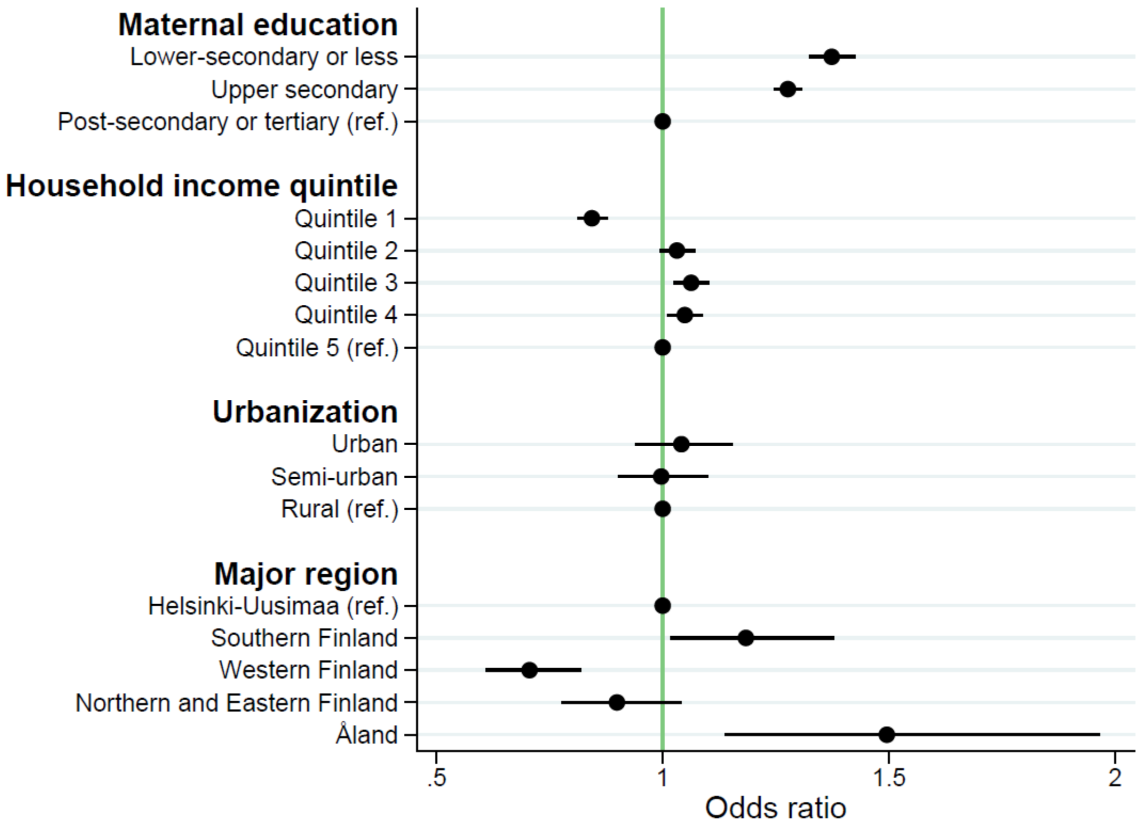

Figure 5.1: Model 3 plotted odds ratios and 95% confidence intervals.

shown to have the best goodness of fit out of the tested models.

The plotted odds ratios and their 95% confidence intervals of model 3 are visualised in Figure 5.1. The clearest associations are among maternal education categories where also intervals are small. For household income and urbanisation, the odds are close to one and for urbanisation the intervals overlap the value one. For major regions, the confidence intervals are larger than for other variables. Åland has an especially large interval, which probably is caused by the small number of individuals in the region.

In many ways, these results are expected and in line with the previous literature discussed in Chapter 3. Perhaps the most surprising result is the weak association between income and mental disorder and especially that the poorest quintile 1 has lower odds for mental disorder than the richest quintile 5. There could be multiple explanations to this result, which I will discuss later in the conclusions. Also, urbanisation does not have a significant effect on mental disorder, unlike in the literature review.

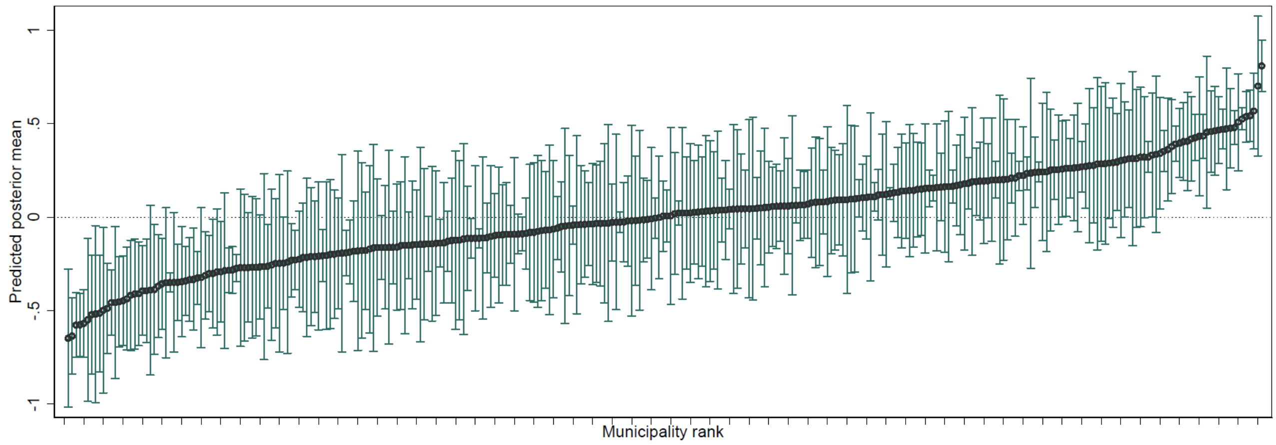

Figure 5.2: Model 3 predicted posterior means of random effects.

As a robustness check I also ran a model that was the same as model 3, but paternal education was used instead of maternal education. The results of this model are shown in Appendix Table C.3. The odds ratios of paternal education are slightly weaker compared with maternal education in model 3. Goodness of fit declines a bit. This additional model implies robustness of the final model.

Considering the variability among municipalities in model 3, the MOR value 1.34 gives us some insight. The contextual effect may be rather small, but it exists, since the median odds would increase by 1.34 when moving from a lower-risk municipality to a higher-risk municipality. This is similar in size to the odds of having a mother with lower secondary or less education (OR=1.37), compared with having a mother with post-secondary or tertiary education.

Moreover, Figure 5.2, where the predicted posterior means of model 3 are ranked by municipalities illustrates variation among the Level 2 units. Significant differences are seen between the municipalities, as the confidence intervals vary on both sides of zero. The size of confidence intervals varies also quite a lot. This may be caused by the large differences in municipality sizes, as the smallest municipality has 55 children whereas the largest municipality has 74 561 children.

This modelling process also answers the first research question, which asked whether the association between SES and mental disorder varies between the child's municipality of residence, and which regional factors explain the possible differences. Since random slopes in model 4 did not improve the model fit, it can be concluded that socioeconomic inequalities in mental disorders among children aged 4–17 do not vary statistically significantly in Finnish municipalities. However, this does not denote that the Level 2 inclusion in the model would be unnecessary. The second research question of this thesis asked if the multilevel model provided additional value to the context. As model 3 results highlight, variation among municipalities exists and, therefore, Level 2 provides additional information to the context of mental disorders among children overall.

Chapter 6

Conclusions

As mental health inequalities of children and young people have been in the interest of both researchers and policy makers and also a widely discussed concern in public media, this thesis aimed to look at mental disorder inequalities through childhood at the municipality level. Mental disorders in childhood are associated with many negative outcomes for individuals, families and society, and they should therefore be given more detailed research attention.

Keeping the statistical perspective of this thesis in mind, I chose to study this phenomenon with a multilevel logistic model, using Finnish municipalities as the Level 2 units. The statistical argument behind this method was the fact that single-level models assume observations to be independent from each other, which might not hold in hierarchical data. The first research question was whether mental disorder disparities would vary between Finnish municipalities and if so, which regional factors would explain this variation. Finnish register data and public specialised healthcare visits from the year 2018 were used as main data sources.

I began by looking at two measures of socioeconomic status in Level 1; maternal education level and household income quintile. I found that mental disorder disparities occurred and low maternal education was a significant risk factor for the child's mental disorder. This supports the existing literature where high maternal education is shown to protect children from mental disorders compared with the children of lower-educated mothers.

However, the results were more complex with household income, and the effect between income quintiles disappeared when control variables were added to the model. Interestingly, the odds for a mental disorder were lower in the poorest income quintile than in the reference category, which was the richest quintile. One possible explanation could be that the poorest families did not seek or failed to receive help for their child's mental condition and therefore were not reached in the data. Other possible explanation might be related to the association between mental disorder and family structure, that is, whether the child lives with both parents or one parent. These variables were also correlated and the effect of household income disappeared when family structure was included in the model. Some missingness (1.72%) was also seen in the income variable, which might contribute partly and affect some unreliability to the results.

The Level 2 variables urbanisation and major region also revealed interesting results. Unlike in the previous literature, urbanisation did not have a significant association with mental disorder in the final model. This result might indicate that urban-rural differences in mental health only appear later in life.

For major region, higher odds for mental disorder were found for Åland and lower odds for Western Finland, when Helsinki-Uusimaa was used as the reference category. The results of Southern, Northern and Eastern Finland were not significant in the final model, and no difference compared with Helsinki-Uusimaa was found. These results are partly in line with THL's Morbidity Index 2019, which covers all population, includes seven disease groups and is standardised for age. In this index, Western and Southern Finland were also the healthiest areas, and many municipalities in Åland had a healthier population than the Finnish average (Parikka et al., 2022). Interestingly, mental disorders among children in Åland seem to divert from the general health pattern of the region. However, the large standard error of Åland's odds ratio adds some uncertainty to this finding.

Multilevel modelling revealed that mental disorder disparities did not vary between municipalities. There was variation in mental disorders among municipalities, but it was caused by other factors, which were not included in this study. Considering the larger question of regional health inequalities, this is a hopeful finding. Regional health inequalities in Finland have been found among the adult population, but it is an encouraging result that inequalities in childhood mental disorders are not shown to be stronger in some regions than others. Although health policies should still target lower socioeconomic groups, at least regional differences do not seem to be associated with differences in disparities. Even though the variation in organising healthcare services was not separately examined in this thesis, since no regional variation in inequalities was found, it can be assumed that they are not causing differences during childhood.

However, the multilevel model demonstrated that variation in mental disorders in childhood among municipalities exists, and the multilevel approach was therefore a useful element in this study, although no detailed information about this variation was discovered. To find out which factors cause this variation, more research is needed.

This study utilised high-quality Finnish register data on total population, which is produced in validated and stable methods. The SES variables are reliable, since the amount of errors and non-response is negligible. A unique feature in register data is the anonymous identification number system, which, for example, allows combining different data sets from several administrative sources and also information of both children and their parents. This thesis exploited this data characteristic as well. Considering the good quality and total population coverage of the data, the results can be generalised at least in the Finnish context.

Nevertheless, the used register data only includes the individuals who had sought and received mental disorder treatment in specialised healthcare during 2018. This includes mainly those children whose symptoms were severe, since many mental health conditions are treated in school and primary healthcare. Moreover, the data includes neither families who used private healthcare, which is quite common due to high health insurance rate among children (Valtonen et al., 2014), nor families who failed to receive help. These data aspects limit the accuracy of the findings to some extent.

Keeping the limitations in mind, one future research idea would be to expand this study data-wise and to include primary and school healthcare data. Another option would be to include Kela's data of reimbursements for medicine expenses, where those individuals who did not have a healthcare contact during that year but were receiving medication would also be included as part of the dependent variable.

Another future research idea would be to examine mental health services at a deeper level and perhaps include the young adult population. If regional disparities in mental disorders do not exist in childhood, as the results of this thesis suggest, one possible option would be to switch the focus to the older population. One could ask whether different treatment admissions and other service differences in municipalities have an association with mental disorder inequalities. Since the health and social services reform will move the responsibility of health service organisation from municipalities to wellbeing services counties in 2023, this opens a fruitful research setting where the time before and after the reform can be compared. Multilevel methods can contribute to studies in which not only individual characteristics are assumed to affect the topic at hand but societal context is assumed to play a role as well.

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Appendix A

Mental disorder diagnostic groups

Diagnosis groups included in the dependent variable, based on ICD-10 F-class codes.

- Alcohol and other substance use disorders (F10–F19)
- Schizophrenia spectrum disorders (F20–F29)
- Bipolar disorders (F30, F31, F34.0)
- Depressive disorders (F32, F33, F34.1)
- Anxiety disorders (F40, F41, F42)
- Trauma- and stress-related disorders (F43)
- Eating disorders (F50)
- Autism spectrum and other disorders of psychological development (F85, F88, F89)
- ADHD / Hyperkinetic disorders (F90)
- Conduct disorders (F91, F92)
- Emotional disorders with onset specific to childhood (F93)
- Other childhood onset disorders (F94–F98)

Groups Organic, including symptomatic, mental disorders (F00–09), Intellectual disability (F70–F79) and Developmental disorders of speech, language, learning and motor coordination (F80–83) were excluded based on psychiatrist consultation. These disorders are usually congenital or caused by a serious medical illness during childhood and are typically treated in other specialised fields than psychiatric services.

Appendix B

Terms used in model equations

MD = mental disorder
$education$ = maternal education
$income$ = household income quintile
$gender$ = gender
$agegroup$ = age group
mMD = maternal mental disorder
fMD = paternal mental disorder
$familystructure$ = family structure
$urban$ = urbanisation
$majorregion$ = major region

Appendix C

Additional tables

Table C.1: Correlations of independent variables.

	Age group	Gender	Maternal educa-tion	Household income quintile	Maternal mental disorder	Paternal mental disorder	Family struc-ture	Urban-isation	Major region
Age group	1								
Gender	-0.002	1							
Maternal education	0.026	-0.001	1						
Household income quintile	0.006	-0.002	0.408	1					
Maternal mental disorder	-0.011	-0.002	-0.010	-0.111	1				
Paternal mental disorder	0.001	0.001	-0.079	-0.118	0.099	1			
Family structure	0.128	-0.008	-0.188	-0.274	0.166	0.148	1		
Urbanisation	0.022	-0.002	-0.059	-0.098	-0.006	-0.008	-0.034	1	
Major region	0.010	-0.001	-0.007	-0.146	0.003	0.003	-0.020	0.291	1

Table C.2: Multilevel logistic variance component model odds ratios. Level 2 continuous variables included.

	Model 3a	
Fixed part		
Level 1		
Maternal education		
Ref. Post-secondary or tertiary	1.00	
Lower secondary or less	1.37***	(0.026)
Upper secondary	1.28***	(0.016)
Household income quintile		
Ref. 5 - the highest	1.00	
1 - the lowest	0.84***	(0.017)
2	1.03	(0.020)
3	1.06**	(0.020)
4	1.05*	(0.020)
Level 2		
Urbanisation		
Ref. Rural	1.00	
Urban	1.00	(0.067)
Semi-urban	0.97	(0.052)
Major region		
Ref. Helsinki-Uusimaa	1.00	
Southern	1.21*	(0.096)
Western	0.73***	(0.057)
Northern & Eastern	0.95	(0.077)
Åland	1.50**	(0.209)
Share of higher-educated	0.99	(0.006)
Share of at-risk-of-poverty children	1.00	(0.005)
Random part		
$\sigma^2_{\mu_0}$	0.092	(0.010)
Model fit		
Deviance	281 774	
LR-test p-value	0.00	
MOR	1.34	
N	801 436	

* p<0.05, ** p<0.01, *** p<0.001, standard errors in parentheses

Model 3a: Model 3 + share of higher-educated and share of at-risk-of-poverty children

Table C.3: Multilevel logistic variance component model odds ratios. Robustness check using paternal education.

	Model 3b	
Fixed part		
Level 1		
Paternal education		
Ref. Post-secondary or tertiary	1.00	
Lower secondary or less	1.33***	(0.022)
Upper secondary	1.19***	(0.016)
Household income quintile		
Ref. 5 - the highest	1.00	
1 - the lowest	0.89***	(0.018)
2	1.06**	(0.020)
3	1.08***	(0.020)
4	1.05**	(0.020)
Level 2		
Urbanisation		
Ref. Rural	1.00	
Urban	1.05	(0.067)
Semi-urban	1.00	(0.052)
Major region		
Ref. Helsinki-Uusimaa	1.00	
Southern	1.18*	(0.091)
Western	0.70***	(0.053)
Northern & Eastern	0.90	(0.067)
Åland	1.50**	(0.209)
Random part		
$\sigma^2_{\mu_0}$	0.091	(0.010)
Model fit		
Deviance	281 943	
LR-test p-value	0.00	
MOR	1.33	
N	801 436	

* p<0.05, ** p<0.01, *** p<0.001, standard errors in parentheses

Model 3b: Model 3, but paternal education used instead of maternal education