# Determinants of children's mental health: Relative contributions when accounting for endogeneity, self-selection and unobserved heterogeneity

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***ABSTRACT***

We investigate the relative contribution − sign, magnitude and significance levels − of individual and neighbourhood characteristics associated with children's mental health when accounting for endogeneity, self-selection in neighbourhoods of different socio-economic status, and unobserved heterogeneity. We use two waves of data extracted from the Lifelines Cohort Study of children between 7 and 15 years of age in the North of the Netherlands. We distinguish and explain internalising and externalising behaviour using a random effects model in space and time and a cross-sectional model reformulated in first-differences. Our empirical results show that children living in adverse neighbourhood and household conditions present worse externalising and internalising behaviour symptoms. We also find that controlling for endogeneity leads to notable differences. Although present, accounting for self-selection does not appear to be as crucial as endogeneity. These findings are helpful for future prevention policies on the prevalence of mental health problems in children and adolescents.

**Key words**: mental health, inference, neighbourhood effects

## *1. INTRODUCTION*

Mental health disorders are one of the main threats to today's children (Currie & Rossin-Slater, 2015). Poor mental health in childhood can lead to worse quality of life due to health loss over the individual life course (Klaufus *et al.*, 2022; Prinz *et al.*, 2018). Generally, mental health in children is classified into externalising and internalising behaviour. Externalising behaviour is characterised by impulsivity, disruptive behaviour, rule violation and hyperactivity (e.g., Attention Deficit Hyperactivity Disorder (ADHD)), while symptoms of anxiety, social withdrawal and depression characterise internalising behaviour (Achenbach & Edelbrock, 1978). Following Bronfenbrenner's (1979) ecological systems theory, much research has focused on studying the role of the family environment on internalising and externalising behaviour (Cobham *et al.,* 2016). A vast number of studies have shown that children living in unstable family environments (i.e., lower income) tend to present worse mental health status than those living in comfortable family conditions (Zilanawala *et al.,* 2019). However, the idea that neighbourhood can also determine children's mental health was not explored until the 1980s-1990s (Diez-Roux, 2001). Instead of focusing on how shared individual-life-risk factors contribute to health inequalities in a particular area, literature on the so-called *neighbourhood effects* aims to understand how neighbourhood characteristics influence health and what mechanisms underlie this (van Lenthe *et al.,* 2007; Diez-Roux, 2001). Being able to understand the potential link between the neighbourhood and children's mental health is crucial as the environment in which children are growing up today is characterised by an ongoing rise of socioeconomic inequalities (Minh *et al.*, 2017) and segregation (Musterd *et al.*, 2016).

Until now, studies have shown that children living in deprived neighbourhoods are associated with higher adverse childhood experiences, resulting in overall poorer mental health (Nieuwenhuis *et al.,* 2021; Leventhal & Dupéré, 2019; Minh *et al.,* 2017; Caughy *et al.,* 2013; Flouri *et al.,* 2012, 2013). For instance, Caughy *et al.* (2013) show that poor physical environmental conditions in US neighbourhoods are associated with higher behavioural problems of children aged 5-13, while Flouri *et al.* (2013) find that children aged 3-16 living in more deprived UK neighbourhoods present higher emotional and behavioural problems, even after adjusting for family and individual covariates. These findings align with the so-called "triple jeopardy" hypothesis, which asserts that individuals with lower socioeconomic status (SES) or ethnic-population minorities face (i) higher adverse exposures, (ii) increased risk to poor health due to material deprivation and psychosocial stress, and (iii) present higher health disparities due to higher susceptibility to the exposures (Grönqvist *et al.,* 2020; Verbeek, 2019; Jans *et al.,* 2018; O'Neill *et al.,* 2003).

Despite the increasing evidence on the association between children's mental health and their neighbourhood, Galster (2012) argues in his overview of the neighbourhood effects literature that "to ascertain *quantitatively their relative contributions* to the outcome of interest" (p.27) remains a challenge (see also Chyn & Katz, 2021; van Ham *et al.,* 2018; Musterd *et al.*, 2016) and that "given the complexity of the topic there is far too little scholarship to make claims about which causal links dominate for which outcomes" (p.45). To determine these relative contributions, measured in this study as sign, magnitude and significance level, three potential properties of the data need to be addressed: endogeneity, self-selection and unobserved heterogeneity. Ignoring any of them may bias the results. Although this is not a treatment effect study that is used to evaluate a program − mental health problems do not occur due to an intervention but due to unpleasant circumstances children are unwittingly exposed to − several problems are similar. Endogeneity in single-equation studies occurs when a determinant of the outcome variable is correlated with the error term. In social research this may happen if this determinant is influenced by other observable or unobservable confounding variables that also influence the outcome variable but which are not part of the regression equation. There are two main econometric techniques to account for this: propensity score methods (Liu *et al.,* 2016; Tchetgen & VanderWeele, 2010) and instrumental variables (Deryugina & Molitor, 2021; Chetty & Hendren, 2018). Since we do not have sufficient data to construct as good as randomly assigned instruments for those variables that are potentially endogenous, neither at the individual level nor at the neighbourhood level, we use a propensity score approach. A more detailed explanation is provided in section 3.

Self-selection refers to the phenomenon that individuals choose their neighbourhood based on affinity with their individual characteristics. This selection process might inflate the coefficient estimates of the neighbourhood characteristics due to multicollinearity between these individual and neighbourhood characteristics (van Ham *et al.,* 2018). Although several studies in the past decade have proposed different econometric techniques to explain self-selection − such as instrumental variables and multi-level modelling (Chen *et al.,* 2022) − evidence on how to adequately control for it is still scarce (van Ham *et al.*, 2018).

Since propensity score matching can only account for endogeneity caused by observable and not for unobservable confounding variables that are not part of the equation, we not only estimate regression equations in levels but also in first-differences. This model also accounts for unobservable variables (or unobserved heterogeneity), assuming that these variables are not time-varying.

Using data from the Lifelines Cohort Study (Scholtens *et al.*, 2015), we analyse which individual and neighbourhood characteristics are associated with children's mental health. The aim of this paper and contribution to the existing literature is to investigate to which extent their relative contribution is influenced by potential endogeneity, self-selection and unobserved heterogeneity. A more detailed description of the data is provided in section 2 and of the applied model designs in section 3. In section 4 we present and discuss the results, while section 5 concludes.

## 2. DATA AND METHODS

### 2.1. STUDY DESIGN AND SAMPLE

For this study, we use data from Lifelines, a three-generation population based-cohort study that aims to assess biomedical, socio-demographic, behavioural, physical, and physiological factors that may potentially contribute to the health and health-related aspects of 167,729 participants from the Northern Netherlands (Warmink-Perdijk *et al.,* 2020; Scholtens *et al.,* 2015). The Lifelines study is conducted according to the principles of the Declaration of Helsinki and approved by the Medical Ethics Committee of the University Medical Centre Groningen (the Netherlands).

Our study sample is derived from the Child Behavior Checklist (CBCL) questionnaire, within the underage Lifelines Child Cohort data. Children are recruited with their parent's permission, and an informed consent is signed prior to their start. Data collection was carried out following a 2001 revised version of the questionnaire, CBCL6/18, and it was collected across two periods: the first wave (2010-2013) and the second wave (2014-2017). We consider participants that are present in both waves and who are 7 to 15 years old, resulting in a final sample size of two times 1662 participants. Figure A.1 in the appendix provides a more detailed description of the selection procedure.

### *2.1.1. OUTCOME*

We extract data on internalising and externalising behaviour from the CBCL6/18, which is included in the underage Lifelines Cohort. The CBCL6/18 is a well-grounded assessment tool to assess emotional and behavioural problems in children aged 6-18 years (Achenbach *et al.*, 2001), which has been translated into more than 90 languages, including Dutch. The CBCL6/18 consists of 118 items, answered by the parents, with a response format of 0 (“not true), 1 (“somewhat or sometimes true”) and 2 (“true”). The final score can be grouped into eight domains: anxious/depressed, withdrawn/depressed, somatic complaints, social problems, thought problems, attention problems, rule-breaking behaviour, and aggressive behaviour. By aggregating the items from rule-breaking and aggressive behaviour we obtain an overall score on externalising behaviour, while we derive such score on internalising behaviour by aggregating the items on anxiety, depression, withdrawal, and somatic complaints (Achenbanch & Edelbrock, 1978; Achenbach *et al.*, 2001). We use the raw scores from internalising and externalising behaviour in our analysis as outcome variables, which range from 25-75 and 21-72, respectively.

Among all potentially relevant determinants of both types of behaviour, we have chosen to focus on a set of key characteristics that previous work in the literature has already highlighted as important for children’s mental health. We first introduce the neighbourhood characteristics and then the individual characteristics of the child or family in which it grew up.

### *2.1.2. NEIGHBOURHOOD CHARACTERISTICS*

The neighbourhood level considered in the study is according to the *Buurt* definition from the *Central Bureau voor de Statistiek* (Statistics Netherlands) (CBS, 2017). This is the lowest level of scale at which CBS collects data. Our sample region, the North of the Netherlands, covers a total of 805 different neighbourhoods. We extract data on SES, demographic and environmental characteristics (*Kerncijfers Wijken en Buurten*) and link it to our main database through IBM SPSS Statistics (V 28.01.1 (15)).

As neighbourhood income indicators, we include the percentage of population with the highest 20% income households and the percentage of population with the lowest 20% income households (Zhu *et al.*, 2021). To assess the household distribution of the neighbourhood, we include the percentage of people aged 0 to 15 years in the neighbourhood (Milias & Psyllidis, 2022). Furthermore, we control for information whether the child has experienced emotional stress due to the physical environment associated with housing deprivation in the past two years. As a proxy for exposure to violence, we distinguish the possibility that the child is exposed to environmental stressors in the neighbourhood (e.g., crime, noise) in the past two years (Chyn & Katz, 2021). Finally, we include the percentage of Western (Europe, USA, Canada and, Japan) and non-Western inhabitants with a migration background (born abroad) as information on the ethnic composition of the neighbourhood (Erdem *et al.*, 2019).

### 2.1.3. INDIVIDUAL CHARACTERISTICS

On the individual level, we include the possibility of whether the child is exposed to financial or divorce stress within the family (Flouri *et al.*, 2010) in the last two years before the first or the second questionnaire took place. We include these two stress variables to provide information on family adversity. As control variables, we further include the sex and age of the participants (Singh & Gandhour, 2012). Information about the mother is used to characterize the family background. We include the age of the mother when the questionnaire took place, as well as her country of birth (Erdem *et al.*, 2019). Family SES is assessed through the mother's educational attainment (Angelini *et al.*, 2021; McGrath *et al.*, 2006), which is categorised into: "low"- up to junior general secondary education, "middle"- secondary vocational education or senior general secondary education, and (3) "high"- higher vocational education or university education. Unfortunately, we are unable to include parental income as it is often not observed. Note however that parental income is most likely related to parental education and therefore an acceptable alternative. In addition, we control for the lowest and highest 20% income at the neighbourhood level.

### 2.2. DATA PREPARATION

All the analyses are performed using RStudio (V 4.1.2.) (R Core Team, 2021). Descriptive statistics of the study population are reported in Table 1. Possible multicollinearity of the covariates is investigated using the *olsrr* package (Hebbali, 2020). Variables with a variance inflation factor (VIF) higher than 10 are excluded.[1] Because some key variables in our study are characterized by

[1] Average income per inhabitant and neighbourhood unemployment rate were discarded for this reason.

a low number of missing values (<10%), we conduct a single imputation with the *missForest* package (Stekhoven, 2011).

<< Table 1 about here >>

Our final sample consists of two waves with 1662 participants each. 50.10% are females and 49.90% are males. Their average age is 8.82 years. Most of the participants' mothers were born in the Netherlands (>90%) and have middle to high education. The percentage of the participants exposed to divorce or financial stress within the family or within the neighbourhood (housing, crime or noise) is relatively limited. However, in each of these cases the mean of the outcome variable, the level of externalising or internalising behaviour, appears to be significantly higher relative to that of reference group not experiencing stress. We also observe that there are significant differences between groups. Males report significant higher levels of externalising behaviour than females. The same applies to children who grew up in families with less educated mothers.

## *3. MODELLING DESIGN*

We depart from a random effects panel data model formulated in levels to explain children's internalising and externalising behaviour. In section 3.3 we introduce our specification in first-differences. The level equation reads as:

$$\mathrm{w_{ijt}y_{ijt}} = \mathrm{w_{ijt}x_{it}}\beta + \mathrm{w_{ijt}z_{jt}}\gamma + \lambda_i + \xi_t + \mu_{ij} + \varepsilon_{ijt}, \qquad (1)$$

where $\mathrm{y_{ijt}}$ refers to internalising or externalising behaviour of individual $i$ in neighbourhood $j$ and wave $t$, $\mathrm{x_{it}}$ is a vector of individual characteristics and $\mathrm{z_{jt}}$ is a vector of neighbourhood characteristics. The impact of these two sets of explanatory variables is captured by the vectors of parameters $\beta$ and $\gamma$, respectively. In addition, we add individual random effects, $\lambda_i$, and wave random effects, $\xi_t$, to control for both time-invariant and individual-invariant factors that potentially lead to differences in the outcome variable. We use random rather than fixed effects since the participants form a random draw from a larger population and since they are interviewed at different moments in time over a three-year period for each wave, dependent on their age. This set-up also prevents individual specific effects and personal characteristics as well as wave-specific effects and neighbourhood characteristics from overlapping so much that these characteristics become redundant. $\varepsilon_{ijt}$ denotes the normally distributed error term of the model. The symbol $w_{ijt}$ is used to control for endogeneity and the symbol $\mu_{ij}$ to control for self-selection. They are further explained in the next two sections.

### *3.1 INVERSE PROBABILITY WEIGHTING*

An important issue to investigate is whether or not some individual or neighbourhood characteristics are endogenous. The individual characteristics divorce stress within the family and the mother's educational attainment may not only influence the behaviour of her children, these determinants and the outcome variable may also be affected by confounding variables not part of the equation causing endogeneity. These confounding variables can also force a family or part of it to move to a poorer neighbourhood, causing the percentage of households with the lowest 20% income to be potentially endogenous. To adjust for possible statistical bias due to the endogeneity, we apply inverse probability weighting (IPW), using the ipw package (van der Wal & Geskus, 2011). We assign each potential endogenous characteristics per participant a weight equal to the inverse of the conditional probability of the observed exposure, known as propensity score (Mansournia & Altman, 2016). Following Forastiere et al. (2020), we estimate wave-specific separate weights for divorce stress, the mother's educational attainment and the percentage of households with the lowest 20% income, and then obtain the final weight, denoted by $\mathrm{w}_{\mathrm{ijt}}$ in Equation (1) as the product of these separate weights.

We apply a logit model to explain the probability of observing 1 versus 0 for divorce stress and an ordered logit model for observing a certain level of educational attainment (low, medium or high). If the potential endogenous variable is denoted by $\mathrm{x}_{\mathrm{it}}^{\mathrm{En}}$, the exogenous characteristics by $\mathrm{x}_{\mathrm{it}}^{\mathrm{E}}$ and the probability to observe a particular value $\bar{x}$ by $\mathrm{p}(x_{it}^{E})=\mathrm{Pr}(x_{it}^{E}=\bar{x}|\mathrm{U})$, where U is a set of observed characteristics, then the weight is given by:

$$w_{it}=\left[\frac{\bar{x}}{\hat{p}_i(x_{it}^{E})}\right] / \left[\sum_{l=1}^{L}\frac{\bar{x}}{\hat{p}_l(x_{lt}^{E})}\right] + \left[\frac{1-\bar{x}}{1-\hat{p}_i(x_{it}^{E})}\right] / \left[\sum_{l=1}^{L}\frac{1-\bar{x}}{1-\hat{p}_l(x_{lt}^{E})}\right], \tag{2}$$

where $\hat{p}$ is the estimated logit probability, and $L$ is the total number of individuals (indexed by $l$) in wave $t$. A similar kind of expression applies to the mother's education, except that it can take three instead of two values. Since the percentage of households with the lowest 20% income is a continuous instead of a discrete variable, the weight is slightly different:

$$w_{jt} = \left[\frac{\bar{z}}{f(z_{jt}^{E})}\right] / \left[\sum_{k=1}^{K} \frac{\bar{z}}{f(z_{kt}^{E})}\right], \quad (3)$$

where $f$ is the conditional probability density function, and $K$ is the number of neighbourhoods (indexed by $k$). Further note that in this equation, every x (individual characteristic) is replaced by z (neighbourhood characteristic) and that $i$ is replaced by $j$ accordingly. As observed characteristics $U$ to determine the propensity weights of the individual and neighbourhood characteristics, we use the remaining individual and neighbourhood exogenous characteristics, as listed in Table 1. The regression results of these propensity score models are recorded in **Table A1-A3** of the appendix.

Two key assumptions underlie the use of IPW: (*i*) *common support* and (*ii*) *unconfoundedness*. The *common support* assumption asserts that the propensity scores are bounded away from zero and one (see Figure A.2.-A.4.). The unconfoundedness assumption requires that confounding variables that are correlated with both the outcome and the potential endogenous characteristics are observable. Propensity score methods aim to adjust for such observed confounders, such that potential endogenous characteristics become as good as randomly assigned conditional upon them (Rosenbaum & Rubin, 1983). Although the assumption that all variables affecting both outcome and endogenous characteristics are observable is strict and non-refutable, our data contains sufficient information on a number of important and diverse factors to support this assumption. The data used for children whose mental health is good or worrying is extracted from the same source, the number of observations and the number of observations with both types of behaviour are sufficiently large, and all the children are living in the North of the Netherlands, which is a homogenous region and in economic terms slightly below the average compared to the whole of the Netherlands. Figure A.5. in the appendix illustrates this. The percentage of households with the highest 20% income in our study region tends to be below 20% in most neighbourhoods and only in a limited number of areas between 20-40%.

Instrumental variable methods do not require the uncounfoundedness assumption, but require instrument-error independence and an exclusion restriction. The instrument-error independence implies that the potential outcomes are independent of the instrument, possibly after conditioning on covariates. The exclusion restriction holds if the instrument can only affect the outcome through its effect on the endogenous variable. This implies that there is no effect of the instrument on the outcome. Instrumental variables methods have been used in neighbourhood analyses. Both Chetty & Hendren (2018) and Deryugina & Molitor (2021) exploit the variation in the age of children when families move as an instrument for the children's economic opportunities shaped by the neighbourhoods in which they grow up. However, in our data we observe too few moves to use a similar instrument. Unfortunately, no other possible instruments that satisfy the exclusion restriction, variables that influence the potential endogenous characteristics but not the potential outcomes, are available in our data set.

### *3.2 SELF-SELECTION*

To determine the relative contribution of neighbourhood effects on children’s behavioural development, we also need to control for self-selection into certain neighbourhoods. In the past decade, several studies have proposed different methods to account for this. More specifically, it is key to understand which individual and neighbourhood characteristics influence this selection process (van Ham *et al.*, 2018; Hedman & Galster, 2013). For this purpose, we combine a two-step framework based on Van Ham *et al.* (2018) and Ioannides & Zabel (2008), which first dismantles the self-selection process and then adds correction terms for this process to the regression equation.

We first estimate the probability that a participant chooses one of a set of randomly selected neighbourhoods, based on interaction effects between individual (mother’s age, educational attainment, and country of birth) and neighbourhood characteristics. Contrary to Van Ham *et al.* (2018), we do not consider the full choice set of neighbourhoods, because it is not feasible to compute the probability for all the neighbourhoods (805) in our dataset. Instead, we follow Ioannides & Zabel (2008) and estimate the probabilities from a random neighbourhood selection. For each individual, we randomly select fifteen different neighbourhoods from the same municipality, including the neighbourhood where the child really lives. We then estimate a conditional logit model for each individual, using the *clogit* function from the survival package (Therneau & Lumley, 2022) to estimate the probability values of living in one of the fifteen randomly selected neighbourhoods, using the interactions between the individual and neighbourhood characteristics as selection variables. Table A.4 in the appendix reports the regression results over all 1662 individuals and the two waves.

The estimated probabilities obtained from the logit model are used subsequently to determine Inverse Mills ratios (IMR), defined as the density divided by the cumulative density of the conditional logit model (McFadden, 1973). This yields a matrix of order 3324×805 with individual IMRs for each participant for all neighbourhoods in each wave

$$\lambda_{ijt}=\exp(-\alpha x_{it} z_{jt}) \tag{4}$$

where $\alpha$ represents the coefficient for each interaction term between an individual characteristic ($x_{it}$) and a neighbourhood characteristic ($z_{jt}$) in wave t, as reported in Table A.4.

Since participants with similar individual characteristics will have similar probabilities to live in a certain neighbourhood, the full matrix presents a high degree of multicollinearity and for this reason is not suitable to correct for self-selection in Equation (1) by means of $\mu_{ij}$. Principal component analysis (PCA) allows us to reduce the degree of collinearity and the number of correction terms, without losing significant information from the obtained matrix. We use the *pcromp* function from *stats* package (R Core Team, 2021) for this purpose. This resulted in three principal components that explain up to 98% of the total variance. The principal components, denoted by PCA1 up to PCA3, are eventually used as correction terms $\mu_{ij}$ to adjust for potential self-selection. Coefficients of PCAs significantly different from zero in (1) point to the existence of self-selection. For a more detailed explanation of this framework, we refer to Van Ham *et al.* (2018).

### 3.3 Unobserved heterogeneity

It might be that accounting for endogeneity of some characteristics or self-selection into certain neighbourhoods is not sufficient to determine the relative contribution of the different determinants of children's mental health due to variables omitted from the model. It may concern family or neighbourhood characteristics unknown to the researcher or which are unobservable due to lack of data. Although we do control for individual and wave random effects in the level equation, this may still not be fully effective since the random error terms, just as the regular error term, should not correlate with the explanatory variables $x_{it}$ and $z_{jt}$. Assuming that these non-observable variables do not change over time, we can control for them by reformulating Equation (1) in first-differences, to get

$$w_{ij}\Delta y_{ij} = w_{ij}\Delta x_i \beta + w_{ij}\Delta z_j \gamma + \mu_{ij} + \varepsilon_{ij}, \qquad (5)$$

where $\Delta \cdot_{ij} = (\cdot_{ij,2} - \cdot_{ij,1})$, and the index 2 and 1 denote the value of a variable for individual *i* at the second and the first wave. Due to taking first-differences, this equation can only be estimated based on a cross-section of 1662 observations. This explains why the index t has been removed from Equation (5). If a personal characteristic $x_i$ in this equation changes from the first to the second wave (the child and the mother both get older, financial or divorce stress occurs or is solved), the coefficient $\beta$ of this characteristic really measures its marginal effect, as time-invariant background variables unobservable to the researcher have been removed from the model by taking first-differences. The same applies to the coefficients $\gamma$ of the neighbourhood characteristics $\Delta z_j$. The relative contribution of individual characteristics that do not change over time cannot be determined anymore when using this approach. It concerns the sex of the children and the mother's education.

Just as in Equation (1), we can again control for potential endogeneity of some individual or neighbourhood characteristics by $w_{ij}$ and for self-selection into certain neighbourhoods by $\mu_{ij}$ because there might be also be time-varying background characteristics. As long as they are observable, they can again be controlled for by propensity score.

## *4. RESULTS*

For comparison and to gain insight into the impact of potential endogeneity of included explanatory variables and of self-selection, we present and discuss the results of three models. Model 1 is a `standard' random effects model ignoring both endogeneity and self-selection, Model 2 extends this model by also accounting for endogeneity using IPW, while Model 3 further extends this second model by also accounting for self-selection. This latter model represents the model proposed in this paper. Table 2 reports the estimation results of all three models.

<< Table 2 about here >>

First, we discuss the estimation results for Model 1 (first column of Table 2), starting with the impact of neighbourhood characteristics on externalising and internalising behaviour of children. Increased levels of stress appear to significantly affect problem behaviour. When the parents of the children experience housing stress externalising behaviour increases with 1.5 points and when they experience neighbourhood stress internalising behaviour increases with 1.3 points (only weakly significant). Conversely, neither the percentage of children, nor the percentage of non-western population or the percentage of low-income households (statistically) significantly affects problem behaviour.

Financial stress within the household plays an important role in explaining problem behaviour of children. We find a significant 1.4 points higher score for externalising behaviour and 2.4 points higher score for internalising behaviour. The sex of the child is a significant indicator of problem behaviour, with male children having a 1.2 higher score for externalising behaviour but a 0.4 lower score for internalising behaviour (though only weakly significant). A higher educated mother lowers problem behaviour, although significant only for medium educated mothers: 1.1 point lower for externalising behaviour and 1.3 point lower for internalising behaviour. These findings are in line with the literature (e.g., Saha et al, 2020). When the mother is born abroad her children show more problem behaviour: a significant 1.1 points higher score for externalising behaviour and a 1.8 point higher score for internalising behaviour. The age of the child only affects internalising behaviour, with a lower score of 0.2 for older children. An older mother decreases the score of her children on externalising behaviour (0.06 lower). Divorce stress only affects internalising behaviour (0.7-point higher score).

When we compare the estimated coefficients of the standard model (Model 1) with the estimated coefficients of a model accounting for the endogeneity of some individual and neighbourhood characteristics (Model 2, see Table A1-A3 in Appendix A for the estimated coefficients of the propensity score models), we notice several important differences. First of all, the impact of (endogenous) mother's education on externalising behaviour decreases: children with mothers with medium education have a 0.9-point lower score instead of 1.1. Conversely, the impact of housing stress increases from 1.5 to 2.1 points. For externalising behaviour using IPW to account for endogeneity also affects the estimated coefficients. The impact of the percentage of non-western population in the neighbourhood increases from 0.01 to 0.04 and becomes significant, the impact of the sex of the child for male children increases from 1.2 up to 1.6, the impact of financial stress in the household slightly falls down from a 1.4 to 1.3 points increase and the impact of whether the mother is born abroad falls down from a 1.15 to a 1.0 point higher score. For internalising behaviour accounting for endogeneity has a large effect on the estimated coefficients of financial stress (from 2.4 down to a 1.5-point increase), divorce stress (from 0.7 up to a 1.5-point increase), neighbourhood stress (from a weakly significant 1.3 up to a significant 2.4 point increase), and whether the mother is born abroad (from a significant 1.8 down to an insignificant 0.5-points increase). Finally, the age of the child has not a significant effect on internalising behaviour anymore.

Next, when comparing the estimated results from the IPW model (Model 2) with the model also accounting for selective neighbourhood choice (Model 3) we hardly see any differences. This is because only one principal component for externalising behaviour appears to be statistically significant. In sum, we find that accounting for possible endogeneity is important and leads to substantial changes in some parameters, while additionally accounting for self-selection of individuals into neighbourhoods does not seem to matter for the parameter estimates. This result differs from a recent Dutch study of Boderie *et al.* (2023) for which there is one geographical and one methodological reason. Our study focuses on a peripheral region located in the north of the Netherlands, where the unemployment is above-average compared to the rest of this country as illustrated in Figure A.5, whereas their study focuses on the city of Rotterdam, an urban area belonging the core of the Dutch economy with the largest harbour around the world. The methodological explanation is that we control for both endogeneity and self-selection, whereas the Boderie *et al.* (2023) only control for self-selection, perhaps because they only selected people who moved house. In line with this, the age of the respondents is also different.

Using a model formulated in first-differences instead of levels is an alternative approach for accounting for endogeneity (compared to IPW) in observational studies. However, a first-differences model cannot include any characteristics (personal or neighbourhood) that do not change over time, such as mother's education. The parameters of a first-differences model also have another interpretation. They tell how much the change in a covariate explains the change in problem behaviour (external or internal) within a household rather than between households.

According to the estimated first-difference models (Table 3), the only (statistically significant) factor explaining the change in externalising behaviour is the change in the percentage of young children in the neighbourhood; a one percentage point change would lead to an 0.12-points decrease for externalising behaviour. Although negative, this coefficient was not significant for any of the models in Table 2 with respect to externalising behaviour. The only (statistically significant) factor explaining the change in internalising behaviour is the change in financial stress, which would lead to a 1.4-points decrease rather the positive and significant results found in Table 2. This means that financial stress causes problematic behaviour in general, but that children with the household are apparently better able to deal with this stress when they get older.

<< Table 3 about here >>

Just as in Table 2, we do not find any change in parameter estimates when we account for self-selection in the first-difference model.

## *4. DISCUSSION*

This study shows that housing stress and financial stress are important factors explaining externalising behaviour problems, while neighbourhood stress, financial stress and, divorce stress are important factors explaining internalising behaviour problems. The role of financial and divorce stress fits with evidence from previous studies that have shown that unstable family environments are associated with higher problem behaviour and emotional distress in children (Zilanawala *et al.*,2019). Other studies have suggested that children in stressful family environments are more susceptible to the negative effect of neighbourhood adversity in their development and behavioural outcomes (Zhu *et al.*,2021; Callahan *et al.*, 2011) and cannot benefit from the neighbourhoods' resources.

In line with previous studies (Brandlistuen *et al.*, 2020; Loyd *et al.*, 2019; Maschi *et al.*, 2008), we find that male children present worse externalising behaviour than females. We find that children living in neighbourhoods with a higher percentage of non-Western migrants are associated with externalising behaviour scores, which is in line with the "triple-jeopardy" hypothesis. We also find that externalising behaviour problems decrease with the age of the mother and with their mother's education. Internalising behaviour problems also increase with the percentage of children in the neighbourhood and decrease with mother's education.

This study also shows that it is important to account for endogeneity of included explanatory variables in neighbourhood analysis of children's mental health, using an IPW method both on a personal level and a neighbourhood level. Accounting for selection into the neighbourhood, by including the principal component of the inverse Mills ratios of residing in a neighbourhood, seems less important.

Using a model formulated in first-differences instead of levels the only factor explaining the change in externalising behaviour is the change in the percentage of young children in the neighbourhood and the only factor explaining the change in internalising behaviour is the change in financial stress. This is due to the fact that the parameters in this model have a different interpretation.

Although our study has provided interesting findings on the determinants children's mental health, it still has some limitations. First, as in all observational studies, even though we control for self-selection and endogeneity, we are cautious about a causal interpretation of our results (Jacob & Ganguli, 2016). Second, our results could be influenced by self-reported bias (Althubaiti, 2016), especially considering that the answers are from the parent's perspective. Lastly, most children in our dataset are from middle to high-SES families, which can affect our results since children from high-SES families may not (i) rely so much on neighbourhood resources and (ii) be more protected from the exposures because of their own resources. Further research should focus on exploring the causal pathways in which neighbourhood effects might act, as well as the role of self-selection in these pathways.

## ***5. CONCLUSION***

In this study we tackle two main challenges in the neighbourhood literature (of mental health of children in particular). First, we control for endogeneity of both individual and neighbour characteristics through an IPW approach and, second, we account for self-selection into the neighbourhood. This study shows that both personal and neighbourhood characteristics determine the mental health of children (7-15 years). Our empirical analyses, based on a large survey in the Northern part of the Netherlands, suggest that both stress on the neighbourhood level (housing or neighbourhood stress) and stress on the household level (financial or divorce stress) are important factors that increase mental health problems of children.

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Table 1. Descriptive statistics.

| | | % / mean | Externalising mean | Internalising mean |
|---|---|---|---|---|
| Sex | Male | 49.90 | $42.56^{+}$ | 40.64 |
| | Female | 50.10 | $40.98^{+}$ | 40.95 |
| Children's age | | 8.826 | | |
| Mother's age | | 38.92 | | |
| Mother's birthplace | The NL | 92.80 | 41.77 | 40.78 |
| | Outside the NL | 2.90 | 42.46 | 42.08 |
| Mother's educational attainment | Low | 13.30 | $42.38^{+}$ | 41.30 |
| | Medium | 44.00 | $42.02^{+}$ | 40.99 |
| | High | 39.10 | $41.30^{+}$ | 40.40 |
| Financial stress | Yes | 3.20 | $43.50^{+}$ | $45.48^{+}$ |
| | No | 96.80 | $41.68^{+}$ | $40.64^{+}$ |
| Stress divorce | Yes | 8.50 | 42.72 | $42.34^{+}$ |
| | No | 91.50 | 41.68 | $40.65^{+}$ |
| Stress housing | Yes | 1.50 | $45.20^{+}$ | $44.52^{+}$ |
| | No | 98.50 | $41.72^{+}$ | $40.74^{+}$ |
| Stress neighbourhood | Yes | 1.10 | 43.39 | 43.33 |
| | No | 98.90 | 41.75 | 40.77 |
| Western population | | 5.51 | | |
| Non-Western population | | 3.81 | | |
| % household with lowest 20% income | | 41.34 | | |
| % household with highest 20% income | | 15.95 | | |
| % children aged 0-15 years | | 18.85 | | |

Characteristics of the study population (n =3324) by externalising and internalising behaviour at baseline. Welch two sample t-tests (binary variables) and Kruskal Wallis tests (>2 groups) were performed to test differences between groups, $^{+}$ $p<0.05$.

Table 2. Results random effects models.

| | Externalising behaviour | | | Internalising behaviour | | |
|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 |
| *Neighbourhood characteristics* | | | | | | |
| % of children aged 0-15 | -0.020 | -0.014 | -0.013 | 0.026 | 0.059** | 0.059** |
| | (0.022) | (0.018) | (0.018) | (0.024) | (0.021) | (0.021) |
| % Non-western | 0.014 | 0.038* | 0.038* | 0.021 | 0.038+ | 0.037+ |
| | (0.027) | (0.017) | (0.017) | (0.031) | (0.021) | (0.021) |
| % Households with lowest 20% income | 0.005 | 0.009 | 0.008 | 0.008 | -0.002 | -0.002 |
| | (0.013) | (0.011) | (0.011) | (0.015) | (0.014) | (0.014) |
| Stress housing[a] | 1.543** | 2.149** | 2.183** | 0.439 | 0.626 | 0.704 |
| | (0.537) | (0.476) | (0.481) | (0.585) | (0.506) | (0.513) |
| Stress neighbourhood[a] | 0.746 | 0.505 | 0.467 | 1.313+ | 2.383** | 2.402** |
| | (0.631) | (0.688) | (0.690) | (0.686) | (0.726) | (0.728) |
| *Personal characteristics* | | | | | | |
| Children's age | -0.119 | -0.101 | -0.099 | -0.190** | -0.152+ | -0.156+ |
| | (0.082) | (0.077) | (0.077) | (0.044) | (0.086) | (0.087) |
| Children's sex[a] | 1.205** | 1.579** | 1.573** | -0.415+ | -0.261 | -0.262 |
| | (0.195) | (0.192) | (0.192) | (0.226) | (0.243) | (0.243) |
| Mother's age | -0.055* | -0.055* | -0.054* | -0.017 | -0.046 | -0.047 |
| | (0.024) | (0.023) | (0.023) | (0.027) | (0.029) | (0.029) |
| Mother medium edu[a] | -1.069** | -0.884** | -0.891** | -1.342** | -1.373** | -1.374** |
| | (0.306) | (0.305) | (0.305) | (0.354) | (0.384) | (0.384) |
| Mother high edu[a] | -0.378 | -0.357 | -0.364 | -0.626+ | -0.715+ | -0.713+ |
| | (0.299) | (0.298) | (0.298) | (0.346) | (0.375) | (0.375) |
| Mother's birthplace[a] | 1.141* | 0.982+ | 0.972+ | 1.846** | 0.512 | 0.514 |
| | (0.576) | (0.533) | (0.533) | (0.666) | (0.671) | (0.671) |
| Financial stress[a] | 1.406** | 1.303** | 1.279** | 2.423** | 1.490** | 1.501** |
| | (0.445) | (0.456) | (0.456) | (0.488) | (0.502) | (0.502) |
| Stress divorce[a] | 0.417 | 0.287 | 0.296 | 0.700* | 1.456** | 1.436** |
| | (0.271) | (0.272) | (0.272) | (0.301) | (0.305) | (0.305) |
| Intercept | 48.419** | 48.083** | 48.018** | 47.196** | 47.909** | 48.052** |
| | (1.629) | (1.538) | (1.541) | (1.649) | (1.755) | (1.761) |
| Variance random effect (wave) | 0.154 | 0.083 | 0.083 | 0.000 | 0.098 | 0.101 |
| Variance random effect (individual) | 12.741 | 13.120 | 13.098 | 19.662 | 27.433 | 27.414 |
| *Principal component* | | | | | | |
| Principal component 1 | | | -0.005* | | | 0.0003 |
| | | | (0.002) | | | (0.003) |
| Principal component 2 | | | 0.0005 | | | -0.004 |
| | | | (0.004) | | | (0.004) |
| Principal component 3 | | | 0.008 | | | -0.005 |
| | | | (0.012) | | | (0.013) |

[a] Reference category: no stress housing, no stress neighbourhood, female, no financial stress, no stress divorce, mother's edu(cation) low, mother's country of birth the Netherlands. n=3324. Standard error in brackets. +p<0.1, *p<0.05, **p<0.01

*Table 3. Estimated coefficients of first difference model for externalising and internalising behaviour in children aged 7 to 15 years old.*

| | Externalising behaviour | | Internalising behaviour | |
|---|---|---|---|---|
| | Model 4 | Model 5 | Model 4 | Model 5 |
| | | *Neighbourhood characteristics* | | |
| % of children aged 0-15 | -0.121** | -0.120** | 0.026 | 0.026 |
| | (0.038) | (0.038) | (0.043) | (0.043) |
| % Non-western | 0.005 | 0.003 | 0.026 | 0.024 |
| | (0.075) | (0.076) | (0.085) | (0.085) |
| % households with the | 0.025 | 0.027 | -0.006 | -0.005 |
| lowest 20% income | (0.031) | (0.031) | (0.035) | (0.035) |
| Stress housing | -0.693 | -0.715 | 0.751 | 0.718 |
| | (0.631) | (0.634) | (0.711) | (0.713) |
| Stress neighbourhood | -0.362 | -0.381 | -0.439 | -0.448 |
| | (0.729) | (0.730) | (0.821) | (0.821) |
| | | *Personal characteristics* | | |
| Children's age | -0.165 | -0.177 | -0.231 | -0.234 |
| | (0.225) | (0.226) | (0.253) | (0.254) |
| Mother's age | 0.055 | 0.059 | -0.044 | -0.043 |
| | (0.205) | (0.205) | (0.230) | (0.231) |
| Financial stress | -0.502 | -0.507 | -1.433* | -1.435* |
| | (0.531) | (0.562) | (0.632) | (0.633) |
| Stress divorce | -0.379 | -0.389 | -0.392 | -0.391 |
| | (0.394) | (0.394) | (0.443) | (0.444) |
| Intercept | -0.783* | -0.762+ | 0.143 | 0.145 |
| | (0.397) | (0.398) | (0.447) | (0.448) |
| | | *Principal component* | | |
| Principal component 1 | | -0.003 | | -0.003 |
| | | (0.003) | | (0.003) |
| Principal component 2 | | -0.002 | | -0.001 |
| | | (0.004) | | (0.005) |
| Principal component 3 | | 0.009 | | -0.00004 |
| | | (0.014) | | (0.016) |

n=3324. Standard error in brackets. +p<0.1, *p<0.05, **p<0.01