The evolution of health outcomes from childhood to adolescence

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Abstract

Using data from the Canadian National Longitudinal Survey of Children and Youth (NLSCY), this study examines how and why health outcomes exhibit persistence during the period from childhood to adolescence. We examine the distribution of health outcomes and health transitions using descriptive analysis and explore the determinants of these distributions by estimating the contributions of family SES, unobserved heterogeneity and state dependence and also allowing for heterogeneity of state dependence parameters across categories of neighborhood status. Our analysis indicates that children living in poorer neighborhoods, in neighborhoods with lower education levels and in neighborhoods with more families headed by lone-parents tend to experience poor health status for longer after a transition to it, while children tend to experience multiple health drops living in poorer neighborhoods, in neighborhoods with more families headed by lone-parents and in neighborhoods with more families headed by lone-parents tend to experience poor health status for longer after a transition to it, while children tend to experience multiple health drops living in poorer neighborhoods, in neighborhoods with more families headed by lone-parents and in neighborhoods with more families headed by lone-parents and in neighborhoods with more families living in poorer neighborhoods.

Keywords: child health; health dynamics; Canadian panel data; neighbourhood effects

JEL classification: C5; I12

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1. Introduction

Health development during the period of childhood to adolescence is important because, for most individuals, initial health in adulthood and attitudes towards health promoting or risky behaviors are largely formed during this transition period (see e.g. Heckman 2006). Furthermore, evidence documents that pre-adult health is positively correlated with achievement over the lifespan (see e.g. Case et al 2005). While the association of child/youth health and economic, institutional and environmental factors has been examined by various studies within a static framework, few studies have focused explicitly on health dynamics from childhood to adolescence. On both efficiency and equity grounds, it is important to quantify both the mobility and persistence of health over time and to identify systematic differences in mobility across subgroups. Knowing the systematic differences in the dynamics of health across different subgroups helps to disentangle how different factors determine the health transition from childhood to adolescence within a population. Furthermore, if we observe that reductions in health status are more permanent than transitory in nature for particular groups, we may be more concerned about this than cross-sectional variation in health; more efficient improvement of average health status of the whole population can be made possible if social support programs are targeted at individuals who are more likely to have multiple periods of ill-health and equity objectives likely require us to be more concerned about children who suffer prolonged ill health.

This study draws on two streams of health outcomes research. The first stream focuses on the association of child/youth health and economic, institutional and contextual factors. A positive relationship between high family SES and good child health status has been recorded in various studies. Using cross-sectional data sets of U.S children, Case et al. (2002) pointed out children's health is positively related to household income and the income-health gradient has deepened as children age. They also investigated the extent to which the gradient can be explained by other characteristics of children and parents, including child health at birth, parental health, genetic ties, health insurance and maternal labor supply. Following Case et al. (2002), Currie and Stabile (2003) used the Canadian NLSCY to confirm the deepening gradient, and to test two hypotheses of the underlying mechanisms that cause the deepening gradient. They concluded that the mechanism of the deepening gradient is not that children with poorer health lack the resources to respond to health shocks, but they are subject to more shocks. Curtis et al. (2001) explored data from the Ontario Child Health Study (OCHS) to estimate the association between child health and both low-income and family status. They find that child health is much more strongly (and negatively) related to low-average-income than to low-current income, while lone-mother status is negatively associated with child outcomes. Contovannis and Dooley (2010) examined the relationship between childhood health problems and various young adult outcomes and the role that health status plays in the intergenerational correlation of economic outcomes using the Ontario Child Health Study (OCHS). Specifically, they examined the association between parental socio-economic status and the prevalence of a childhood chronic condition, a functional limitation, or a conduct or emotional disorder and reported for each case an income effect that is modest in size. They also found that parental health is strongly related to childhood health outcomes, but the effect of family income on child health is not mainly a proxy for parental health. Another two studies have provided evidence of the health-SES gradients among adolescents (Graeme Fort et al. 1994, Chris Power and Sharon Matthews 1997). The above examples largely identified the potential SES factors that are correlated with and may contribute to the health of children and adolescents. However, it is worth mentioning that few of these studies are implemented in a panel data framework and dealt with individual unobserved heterogeneity. The only study we are aware of which involves the transition of health outcomes from childhood to adolescence is Currie and Stabile (2003). In order to test one of the two hypotheses in explaining the deepening SES-health gradient recorded by Case et al. (2002), they investigated whether low-SES children deal with bad "health shocks" as effectively as high-SES children by examining if the negative impacts of previous chronic conditions onset differ by family SES. While their results are in line with ours in the sense that poor health status in the previous period has persistent negative effects on current child health, the study did not focus on how state

dependence systematically determine the dynamics of child health over time and how state dependence of child health differ across neighborhood types as in our study. In their study, only two periods of data are used and the onset of chronic conditions in the first period are controlled as the "health shocks" for health state in the second period; while in our study all six cycles are used and self-assessed health status in the previous period is controlled for in modeling current self-assessed health status.

The positive association between SES and health is difficult to untangle for adults, due to the likelihood of a reverse causal relationship. Although the channel that runs directly from health to income can be eliminated for the case of children, possible unobserved factors that can affect child health outcomes and are also correlated with family SES make identification of a causal relationship difficult. Dooley and Stewart (2004) used data from the Canadian NLSCY and cautiously estimated the size of the effect of income on child's cognitive outcomes by attempting to separate out the variation in outcomes caused by potential unobserved heterogeneity and that caused by regressors. They implemented four empirical strategies using panel data and reported a smaller income effect on child outcomes than from conventional estimates which are obtained from weighted least squares regressions with pooled data. This difference in estimates reveals the benefit of exploiting a panel data structure when unobserved individual heterogeneity contributes substantially to child outcomes.

Other studies have focused on the social contextual influences on child outcomes. Boyle et al. (2007) used multilevel models to examine longitudinal associations between contextual influences (neighborhood and family) and educational attainment in a cohort of 2,355 children. The results showed that while 33.64% of the variation in individual level educational attainment can be explained by their model, 14.53% of the variation is attributable to neighborhood and family-level variables versus 10.94% to child-level variables. Several other studies have provided consistent evidence that neighborhood or community level socioeconomic advantage is positively associated with better child outcomes (Brooks-Gunn, Duncan, Klebanov and Sealand 1993; Garner and Raudenbush 1991). Leventhal and Brooks-Gunn (2000) provide a comprehensive review of research on the effects of neighborhood effects on child and adolescent well-being. By summarizing the existing evidence of neighborhood effects on child and youth outcomes, they conclude that high SES is of great importance for school readiness and achievement while low SES and residential instability are determinants of poor behavioral/emotional outcomes. Therefore, social contextual or environmental characteristics should be considered as other important factors related to child and youth health.

The second stream of studies on health outcomes focuses on modeling adult health distributions in a dynamic framework. Studies have addressed the question of why some adults experience persistently good or bad health. The persistence could be explained by pure state dependence, particular individual socio-economic characteristics, or environmental characteristics (Jones, Rice and Contovannis 2006). Some empirical health dynamics studies have examined the relative contributions of pure state dependence and unobserved heterogeneity, and the conditional effect of socio-economic status in explaining observed health status variation (Contoyannis, Jones and Rice 2004a, Contoyannis, Jones and Rice 2004b), while other empirical health dynamics studies have provided evidence of associations between observed health *persistence* and SES positions. In particular using the British Household Panel Survey (BHPS), Hauck and Rice (2004) found evidence of substantial mental health mobility and that the extent of mobility varies across SES categories with greatest persistence in lower income groups and less educated individuals. In a different framework, Buckley et al. (2004) examined the influence of SES position on transition probabilities from good health to poor health for older Canadians. The results showed that the probability of remaining in good health is higher in the highest quartile of income and education, which also indicated a positive association between good health and SES.

Our study aims to contribute in the following ways. Firstly, this study contributes to the health dynamics and child health literature. As discussed above few studies have been focused on modeling

the evolution process of health outcomes from childhood to adolescence, particularly in Canada. Secondly, as this paper uses information on both family SES positions and neighborhood level characteristics into the dynamic panel data framework, it contributes by examining the impact of contextual factors in the health dynamics literature.

This paper proceeds as follows. Section 2 describes the data set we used for the study and presents some descriptive analysis of the data. Section 3 introduces the theoretical rationale and empirical framework of the study. In section 4, the regression results are reported and analysed while in section 5 some conclusions are provided.

2. Data

As this study considers both the effects of family SES positions and neighbourhood characteristics on child health dynamics, two data sets are explored in our study. The first data set is the Canadian National Longitudinal Survey of Children and Youth (NLSCY) cycles 1 to 6, which contains rich information on child outcomes and family SES positions. The second data set is the Census profile data of Canada 1996 and 2001, which contains information on neighborhood characteristics. We construct and use the following four sets of variables throughout this study: 1) child general physical health outcome measures, e.g. Self-Assessed Health (SAH) of the child reported by the Person Most Knowledgeable(PMK) about this child; 2) family socio-economic variables, e.g. total household income, parental education, family structure (family size, whether the child is living with two parents) etc.; 3) Other variables for the child and the parents such as age, whether the PMK is the biological parent of the child and maternal age at birth of the child; 4) neighborhood level variables, e.g. mean household income, percentage of population with university degree, etc.

2.1 Sample and variables

The National Longitudinal Survey of Children and Youth (NLSCY) is the main data source used in this study to examine the contribution of individual and family level variables in determining health transitions. The NLSCY is a survey "designed to collect detailed information every two years about the factors influencing a child's cognitive, emotional and physical development and to monitor the impact of these factors over time" (NLSCY user guide). With the main purpose of following up a group of children over time, the survey began to collect information with one large cohort of 0-11 year- olds in 1994, and followed up every two years till 2004 (Cycle 6). All the available waves so far (from Cycle 1 to Cycle 6) are used in this study.

As stated in the NLSCY User's Guide, the NLSCY is divided into four components: the household component, adult component, child component, and youth component. The household component is used to determine the relationship between all household members. It also identifies the person most knowledgeable (PMK) about the child in the household. The PMK provides the information for all selected children in the household and then gives information about himself/herself and his/her spouse/partner. A child component was created for each selected child between 0 and 17 years of age. The PMK about children and youth answered the child component questions. The child component provides information on the child demographic information and child health measures. But the only sections of the Child Questionnaire asked about youth aged 16 and 17 are the Aspirations and Expectations section, Custody and the Socio-Demographics section. Therefore, the relevant child health measures for the children/youth aged 16 and older in the Youth Questionnaire, as the youth component is used for selected respondents aged 16 to 21 years old. However, the respondent of the Youth Questionnaire answer questions about themselves so we suspect that the reporting would be systematically different from the responses from the PMKs. An adult component was created for the

PMK and his/her spouse or partner, if the selected child is 17 years old or younger. This component collects information for the PMK and the spouse of the PMK about their age, education, income, labor force participation and health condition etc. From this information, the family structure and parental characteristics with potential impacts on child's health development are extracted.

With respect to child health, the variable of general health assessed by the PMK is used in the analysis. The survey question requires the respondent to rank the child's health as excellent, very good, good. fair or poor. This measure falls into the category of a subjective measure of self-assessed health (SAH) which provides ordinal rankings of the respondents' perceived health status. Although the reliability of this subjective measure of health has been questioned by some literature (see Crossley and Kennedy 2002), the child health measure is confined to this variable in our study for the following reasons. Firstly, measures of self-assessed health are commonly used in the literature and have generally been found to be powerful predictors of mortality (see Idler and Kasl 1995; Idler and Benyamini1997; Burström and Fredlund 2001), and to be good predictors of subsequent use of medical care (see van Doorslaer et al. 2000, 2002). Also, since SAH has been consistently defined across different datasets based on which most empirical studies are conducted, using the same measure makes our results more comparable to the others. The study from Crossley and Kennedy (2002) has provided evidence that this measure suffers from the non-random measurement error in terms of reporting, and the perceptions of the respondents' own health systematically vary by age and some socioeconomic status. However, our study is limited by the availability of other suitable measures of health¹. Other concerns about this measure are related to the reporting heterogeneity in the ordered responses which may invalidate group comparisons and measures of health inequality (Lindeboom and van Doorslaer 2004; Murray et. al 2001). More objective measures of health are suggested and methods to overcome this problem are discussed in this literature (see discussion in Contoyannis, Jones and Rice 2004b).

In order to investigate the relationship between family SES and child health outcomes we use the total household income in the past 12 months and a set of variables for parental educational achievements. Case et al. 2002 found that while there still exists a large and significant correlation between income and child's health, the addition of parental education levels to the regression controls had a substantial impact on the estimated income coefficients (reducing the magnitude of the positive correlation). This suggests that household income and parental education are two important factors in determining the child's health and they affect child's health through different pathways. In the NLSCY, information about educational attainment, labor force participation etc. are collected for the PMK and the spouse of PMK, but the PMK and the spouse of PMK are not necessarily the biological parents of the child. They can be step parents, adopting parents or even unrelated persons. This brings in complexity in interpretation because mother's education may influence child health through both her childcare skills after birth and the health of the child at birth, while a PMK who is not the mother will likely exert a much larger influence(relative to the birth mother) on child health through childcare. Moreover, mother's education and father's education level are expected to have different impacts on child's health in that, in most cases, it is the mother who takes care of the child and their behavior would shape child's health to a larger extent, especially for the children at younger ages. Therefore, we separate mother's education from father's education level. In this study, mother's education was obtained from the PMK's (or the spouse of PMK) education level if PMK (or the spouse of PMK) is the biological mother of the child. Otherwise, female caregiver education was obtained from the closest female figure in the household (defining the biological mother as the closest female figure overall), i.e. it was obtained from the information of the PMK (or the spouse of PMK) if PMK (or the spouse of PMK) is female but not the biological mother of the child. If there is no education information for the closest adult female figure in the household, female caregiver education was set to

¹ The McMaster Health Utility Index Mark 3 (HUI3) is often deemed a more objective measure of general health but this measure is only available for children aged 4 or 5 years old in the NLSCY. Other existing measures of self-reported chronic conditions in NLSCY do not provide us a global measure of general health of children. It is worth noting that even the self-reported objective measures of health on the incidence of chronic conditions are criticized for the significant measurement error. Details see Michael Baker, Mark Stabile and Catherine Deri 2004.

missing. The variable for male caregiver education was derived in the same way. In order to capture the difference between the effects of education for a biological mother and another female figure, a dummy indicating the PMK (or spouse of the PMK) is the biological mother of the child is included in the regression and interacted with mother's education level. Also, a dummy indicating PMK is female is included in the regression to account for the response "bias" by gender. Other than the main SES variables, family structure characteristics have a potential impact on child health. A variable for family size indicating the total number of persons living in the household and a dummy variable indicating whether or not a child lives with both parents are included in the regression too². Table 1 in the Appendix A lists the definitions of the main variables we used in this study.

To explore the relationship between neighborhood characteristics and child health dynamics, we split our sample by a set of neighborhood level variables indicating the "affluence" status and "socioeconomic disadvantage" status of the neighborhood the child resides in. In our study, "neighborhood" is defined by census tract (CT) boundaries within all census metropolitan areas (CMAs) and part of census agglomerations (CAs) where a CT boundary exists, while by Enumeration Area (EA) or dissemination areas (DAs) boundaries within more rural areas where a CT boundary does not exist. Census tracts (CTs) are small geographic units representing urban or rural neighborhood-like communities within all CMAs and CAs with an urban core population of 50,000 or more at the previous census. In most CTs, there are 2,500-8,000 people living within them (Statistics Canada, 1992). An EA is the smallest level of geographical aggregation used by Statistics Canada: it contains at least 375 dwellings in urban areas and 125 dwellings in rural areas. To attach neighborhood information to every child in each cycle, we firstly matched the neighborhoods identities within NLSCY and Census profile data through Enumeration Area (EA) or Dissemination Area (DA) code which exist in both data sets. Since the neighborhoods are mostly defined by CT boundaries, we then used the Geography Tape File (GTF) to map from EA/DA boundaries to CT boundaries when CT boundaries are used to define neighborhoods. At the end, the neighborhood variables aggregated at the CT boundary level are used for the neighborhoods defined by CTs; while the neighborhood variables aggregated at the EA or DA boundary level are used for the neighborhoods defined by EAs or DA s. In our study, the "affluence" status of the neighborhoods is measured by two variables: average household income and the percentage of the adult population with university or college degrees; while the "socioeconomic disadvantage" status of the neighborhoods is measured by another two variables: percentage of families headed by lone parents and the percentage of families living in rental accommodations. These specific concepts of community characteristics have been established and used in studies examining the neighborhood influence on educational attainment of children (Boyle et al. 2007). Since we are using a longitudinal cohort and the respondents might have moved from one neighborhood to another across cycles, we mapped the respondents into neighborhoods for each cycle based on the most up-to-date available census profile data at that time. In other words, the neighborhood characteristics are drawn from the census profile data 1996 for the first four cycles of NLSCY, while these values are drawn from the census profile data 2001 for the last two cycles of NLSCY.

2.2 Data description

As we focus on the longitudinal transition of the child health distribution over time, our study employs data on the original longitudinal cohort in NLSCY over six waves. There is considerable attrition in the longitudinal cohort of the NLSCY. According to the NLSCY Cycle 7 User Guide, by cycle 6, "the cumulative, longitudinal response rate for children in the original cohort was 57.6%"³. Because of the

 $^{^2}$ For the same reasons, we discriminate between the scenario of "child living with both biological parents" and the scenario of "child living with both parental figures but not the biological parents" and included both variables in our analyses.

³ In order to adjust for total non-response, the NLSCY employs weighting procedures to produce two longitudinal (funnel and non-funnel) weights at each cycle. Specifically, these weights are calculated by taking the child's design weight and making adjustments for survey non-response and post-stratification to ensure that the final survey weights

sample attrition, around 11,000 children aged 10 to 21 years old from the original longitudinal cohort remained in the sample. Several sample selection criteria have been used for the investigation of family SES and child health dynamics association in our study. Firstly, we only included children aged 0-15 (including age 15) in all cycles. As discussed earlier, in the NLSCY the self-assessed general health (SAH) status is reported in the Child Questionnaire by the Person Most Knowledgeable (PMK) about the child for children aged 0 to 15; while this health measure is reported in the Youth Ouestionnaire by the youth themselves for children aged 16 and older. The PMK is an adult figure, usually the mother/father of the child. We believe the response from the PMKs and the response from the children themselves are systematically different so we excluded the children aged 16 and older. This leads to a reduction of our study sample to 6,611 children. Secondly, we only included children who had information with respect to all of our main variables listed in Table 1 in Appendix A in all six cycles. In other words, only a balanced panel sample is used for both descriptive and regression analysis. This leads to a further reduction of the study sample to 3,752 children. Thirdly, we excluded children with obvious errors in their data, e.g. we excluded children who had multiple gender values across cycles. We ended up with 22,398 observations for 3,733 children with 6 time periods as our study sample. For the subgroup analysis with different neighbourhood status, we then only included children with complete information with respect to the four neighbourhood variables in all six cycles. This leads to a further reduction of sample to 21,726 observations for 3,621 children with 6 time $periods^4$.

2.2.1 The study sample

Child SAH

Originally the health status variable is a categorical variable with 5 ranks. However, we regrouped this variable in the descriptive analysis by merging the fair health group and poor health group because of the constraint imposed by the data confidentiality requirement from Statistics Canada⁵. After the merge, the number of observations in the fair/poor health group is big enough for data disclosure. Figure 1 (see all figures in Appendix A) shows the health dynamics of children over 6 cycles. The proportion of children in excellent health was decreasing and the proportion of children in very good health was increasing slightly between cycles 1 and 3. Between cycles 4 and 6 there does not appear to be a discernible trend in the proportions reporting excellent and very good health. In all cycles there are only a very small proportion of children reported as in fair or poor health with no apparent trend in this proportion or for the proportion in good health.

Figure 2 displays the distribution of child's health status pooled over 6 cycles by household income categories. From the figure, it can be seen that children's health status is better in households with higher incomes than those in households with lower incomes. As we move from low income group to high income groups, the proportion of children in excellent health increases while the proportion of children in fair or poor health decreases.

sum to known counts of children by age, sex and province (See the NLSCY User's Guide in references) for the attrition rate and the weighting procedure which attempts to adjust for total non-response). Accordingly, we applied the funnel weights to our final sample in the descriptive analysis because funnel weights are assigned to children who have responded at every cycle.

⁴ We lost 112 children from our analyses for neighborhood effects on child health dynamics because a) some of the EA or DA codes are missing from the NLSCY; or b) some of the EA or DA codes of our NLSCY sample cannot be found in the Census profile data; or c) at least one of the four neighborhood variables are missing values in the corresponding Census profile data.

⁵ Statistics Canada's data confidentiality restriction requires that—"Data users must not release or publish any estimate that would allow the identification of a specific respondent or reveal any individual's responses. For this reason, estimates (for example, the cells in a cross-tabulation) should have at least five contributing respondents" (NLSCY cycle 7 User's Guide). As only a small proportion of children in our sample reported poor health in all cycles, we had to regroup the two categories of "poor" and "fair" health together to reach the minimum cell size.

Figures 3 displays the distribution of child's health status pooled over 6 cycles, by mother's education attainment. The figure shows very similar patterns of child health variation as to household income level. The proportion of children with excellent health increases and the proportion of children with fair or poor health decreases as we move up from lower maternal education level to higher maternal education level. The pattern can be observed as well in the distribution of child's health by father's education attainment.

State Dependence

State dependence in health has been explored by the literature on health dynamics (e.g Contoyannis et al. 2004) and it is expected to explain a substantial proportion of health variation. Without conditioning on other variables, the degree of mobility/persistence of health outcomes can be assessed descriptively by the probability distribution conditioned on the previous health distribution. Figure 4 shows the distribution of child's health status in cycle 2 by the previous health status in cycle 1. It can be seen from the figure that given the child was in excellent health in cycle 1, the probability of transiting from excellent health to fair or poor health is very close to zero and the probability of staying in excellent health is very high. Similarly, for the children who had fair or poor health in cycle 1, the probability of transiting from fair or poor health to excellent health is very low while the probability of staying fair or poor health is high. In general, this figure shows that children are much more likely to stay in their health status of origin than moving away from it. The same pattern can be seen for all the cycles from a transition matrix in table 1. The elements of the table can be interpreted as the conditional probabilities under a Markov model. The table shows that conditioning on being in excellent or very good health states, children are much more likely to stay within the states than moving away from them in the current period; while conditioning on being in good health or lower than good health, children are more likely to move one level up in the current period. It indicates that the persistence mainly operates around the state of excellent health and very good health while the health status is pretty mobile around the states of good and fair/poor health.

Family SES and other variables

In order to examine the association between family SES characteristics and child health dynamics, we compared the means of the family SES variables across a set of child health transition scenarios. Tables 2 and 3 present the means for the main family SES and other demographic variables for the study sample and for a set of interesting sub-samples by health transition patterns. Column 1 in table 2 lists the mean values for the whole balanced sample. The second column shows the average characteristics for the children who had excellent or very good health for all 6 cycles and the third column shows the average characteristics for the children who always had less than good health. Column 4 presents the mean values for the children who had a single transition from excellent or very good health to worse health status without recovering to the original health status, while column 5 shows the mean of variables for the children who had a single transition from less than good health to better health and stayed healthy since then. From the comparison between the second and third columns, it can be seen that children who were always in excellent or very good health tend to be living in a smaller household and be brought up in a richer family than the children who were always in good or less than good health. Also, mother's age at the birth of the child is lower for the children with excellent health or very good health than for the children with good or less than good health. Surprisingly, there is no systematic difference in the parents' education level for these subgroups. No specific pattern is found comparing the subgroup of children who had a single transition from excellent to very good health and did not recover and the subgroup of children who had a single transition from good to poor health, except that household income and parents' education level are slightly higher for the first subgroup than for the second subgroup.

In table 3, we show the mean values of these variables for the subsample of children who had few

health drops⁶ versus the subsample of children who had multiple drops, and for the subsample of children whose health drop lasted for only 1 cycle versus the subsample of children whose health drop lasted for multiple periods. Columns 1-4 show the mean values for the groups of children who had 0, 1, 2, 3 or 4 drops during our study period, respectively. Children with lower household income and lower parental education tend to experience multiple health drops relative to the children with higher family SES. This observation is in line with the result from the study by Currie and Stabile (2003) which indicates that children brought up in families with lower SES are subject to more health shocks than the children with higher family SES. Columns 5-8 show the mean values for the groups of children who had 1 drop and this drop lasted for only 1 cycle, for 2 cycles, for 3 cycles and for 4 cycles. A slight negative association is discernable from the comparison among these neighborhood subsamples, with children who experienced short health drops are brought up in families with slightly higher income. The basic descriptive statistics shows a negative association between family SES and the number of health shocks the children experienced while a much weaker negative association exists between the family SES variables and the persistence of health shocks.

2.2.2 Sub-samples by long-term neighbourhood status

State Dependence

Another goal of this study is to identify which neighbourhood characteristics contribute to the persistence of poor health states. To examine the heterogeneity of the state dependence across neighbourhood characteristics, we divide the study sample into four subgroups for each of the four neighbourhood variables and constructed the transition matrices for each subgroup⁷. When we split the sample into subgroups, we divide them into quartiles based on the simple average of a neighborhood variable across 6 cycles. This allows us to include both movers and stayers in our study sample and does not restrict classification according to the neighborhood variable at an arbitrary period of time for all individuals (e.g cycle 1). We can see some general patterns over a set of transition matrices presented in table 4. The first panel of table 4 shows the transition matrices for neighborhoods with lowest, second lowest, middle and highest levels of average household income, respectively. It shows that the less than good health state is more persistent in lower income neighborhoods than in higher income neighborhoods. In particular, in the highest income neighborhoods children with less than good health in the last period are most likely to move up one rank, while in the lowest income neighborhoods they are most likely to continue to have less than good health. The second panel shows the transition matrices for neighborhoods with less educated people and for neighborhoods with more educated people. Being in the less than good health state is more persistent in neighborhoods with less educated people than in neighborhoods with more educated people. The third panel presents the transition matrices for neighborhoods with larger proportions of families headed by lone-parents and for neighborhoods with smaller proportions of families head by lone-parents. The last panel shows the transition matrices for neighborhoods with larger proportions of families living in rental accommodations with smaller proportions of families living in rental accommodations. The similar pattern in these four panels indicates that, without conditioning on any other family-level variables, the persistence level of ill health is different across neighborhoods with different socio-economic conditions. In particular, the ill health state is more mobile in neighborhoods with higher income, in neighborhoods with more educated people, in neighborhoods with fewer families headed by lone-parents and in neighborhoods with fewer families living in rental accommodations.

⁶ A "health drop" here is defined as a decrease of SAH from any health status (e.g. excellent to fair or very good to poor). The decrease could be 1 category or more.

⁷ Here we regrouped the five ranks into three ranks because of the confidentiality restriction from Statistics Canada noted above. We combined poor, fair and good health into a category of "equal or less than good health" so that for all cross-tabs the cell size is greater than 5. Accordingly, we have only three categories of health status for the descriptive statistics in the subgroup analysis: excellent, very good and equal or less than good health.

3. Empirical Methods

A widely used economic model (Currie 2000) for child health determination will be followed in this study. In the standard model, parents are assumed to maximize an intertemporal utility function, which trades off child's health stock and their consumption of other goods and leisure, subject to a series of budget and time constraints. The solution to the maximization problem gives the demand function for child health stock. Unfortunately we do not know the health production function which makes it impossible to specify the complete structural model and, in any case, it is difficult to estimate convincingly. Therefore, an alternative representation is used instead in which child health outcomes depend on a set of family SES factors (mainly family income, family structure), child characteristics, parental characteristics and some initial conditions such as maternal age at birth.

Empirically, this study will examine the effects on child health outcomes of SES position, neighbourhood characteristics, pure state dependence and unobserved heterogeneity. Taking into account neighbourhood characteristics is expected to reduce estimates of unobserved heterogeneity. State dependence will be taken into account by controlling for the lag of the health status of the child, while unobserved heterogeneity will be controlled for by using random effects models. Previous empirical studies have been implemented using either pooled approaches or dynamic nonlinear panel data approach with random effects (Contoyannis et al. 2004a, b, Hauck and Rice 2004). This is because, with a nonlinear fixed effect model, the MLE estimator is not consistent in a panel setting with small T (# of time periods) and large N (# of individuals), due to the incidental parameters problem from estimating the fixed effects.

As in most of the micro-level panel data cases, our data is a short panel of large cross-sections (large N but small T). Econometricians have attempted to find fixed-T consistent estimators in modelling discrete choices with individual effects but, in general, fixed-T consistent estimators for nonlinear panel models are not available for most models with unobserved heterogeneity treated as fixed effects. As in static models, there is a trade-off between choosing fixed and random effects approaches for the dynamic nonlinear panel data models we consider in this study, in the sense that achieving fixed-T identification with a less restricted conditional distribution of individual effects usually requires a more restrictive specification of the conditional distribution for y given variables of interest and individual effects.(e.g. logit type)

Fixed effects models are more robust without imposing restrictions on the conditional distribution of individual effects but it suffers from the incidental parameter problem. There are no general solutions for nonlinear models with fixed effects, and in some cases, although a specific solution is available, it is not root-N-consistent. For example a dynamic logit fixed T- consistent estimator is available but it converges slowly and does not allow for time dummies. (see Honore and Tamer 2006).

Arellano (2003) pointed out that there are random effects models that achieve fixed T consistency subject to a particular specification of the form of the dependence between the explanatory variables and the effects, but they rely on strong and untestable auxiliary assumptions. For example, the random effects dynamic nonlinear panel data approach advocated by Woodridge (2005), which is one of the approaches we implement in our study, can generate consistent estimators only when the specified distribution of the individual effects is correct. Even though fixed T consistency is achievable for less restrictive random effects specifications, identification is often out of reach (see Honore and Tamer 2006).

3.1 Baseline dynamic panel ordered probit model without individual effects

A basic approach to estimating the effect of family SES variables in explaining the health transition is to estimate a dynamic panel model without dealing with individual specific effects at all. We denote this the pooled model. The regression model can be simply specified as below:

$$H_{it}^{*} = \theta' H_{it-1} + \beta' X_{it} + \mathcal{E}_{it} \quad (i=1,...,N; t=2,...,T)$$
(1)

where H_{it}^{*} is the latent variable of health outcome, H_{it-1} is a vector of indicators for the child's health status in the previous period, X_{it} is a set of observed family SES variables. ε_{it} is a time and individual-specific error term which is assumed to be normally distributed and uncorrelated across individuals and waves. The latent variable H_{it}^{*} relates to the observed health outcome H_{it} as follows:

$$H_{it} = j$$
 if $\mu_{j-1} < H_{it}^* < \mu_j, j = 1,...,m$ (2)

where $\mu_0 = -\infty, \mu_i \le \mu_{i+1}, \mu_m = \infty$.

3.2 Dynamic panel ordered probit model with random effects

The empirical specification incorporating the family SES effect and unobserved heterogeneity can be written as:

$$H_{it}^{*} = \theta H_{it-1} + \beta X_{it} + \alpha_{i} + \varepsilon_{it} \quad (i=1, ..., N; t=2, ..., T)$$
(3)

where α_i is an individual-specific and time-invariant random component, and the idiosyncratic component ε_{ii} is assumed to be uncorrelated with α_i . The latent variable H_{ii}^* specification is the same as in 3.1.1.

This study follows the approach of Wooldridge (Wooldridge 2005), Contoyannis et al. (2004b) which attempts to deal with the initial conditions problem in non-linear dynamic random effects models; the individual specific effect is specified as the following:

$$\alpha_i = \alpha_0 + \alpha'_1 H_{i1} + \alpha'_2 X_i + u_i \tag{4}$$

where \overline{X}_i is the average over the sample period of the observations on the time-varying exogenous variables and u_i is assumed to be normally distributed. When the error process is not serially independent and the initial observations are not the true initial outcome of the process thus are not exogenous in nature, treating the lagged dependent variables as exogenous leads to inconsistent estimators in non-linear dynamic random effects models. Equation 4) deals with this initial conditions problem by directly modeling the distribution of the unobserved effect as a function of the initial value and any exogenous explanatory variables. However, as discussed earlier, since this approach specifies a complete model for the unobserved effects, the consistency of the estimator can be sensitive to misspecification of this distribution.

4. Estimation Results

4.1 Family SES and child health distribution

We explore the determinants of child health distributions by estimating the contributions of family SES, unobserved heterogeneity and state dependence with the dynamic panel data models described in the previous section. Table 5 presents the coefficient estimates for the ordered probit models based on pooled and random effects specifications. Column 1 and 2 shows the estimates of coefficients and standard errors with the pooled ordered probit model, while column 3 and 4 show the estimates of coefficients and standard errors with the random effects model with the specification suggested by Wooldridge (2005). The pooled ordered probit models allow for serial correlation in the errors by using a robust estimator of the covariance matrix. Several patterns can be seen from the comparison of

the models. Firstly, there is a gradient in the effect of previous health on current health. The reference group here is the group reporting very good health (the second highest rank of health state). For both of the models, previous health is highly statistically significant and the magnitude of the coefficient is not trivial. Secondly, the child's health status does improve as family SES position increases, shown by the significant and positive coefficients on the household income variable and positive gradients on parental education level. In order to capture the differential effects of maternal education on child health through biological and other pre and postnatal effects, the interaction terms of maternal education with the dummy indicating whether the PMK is the biological mother of the child are included in the regressions. It can be seen from column 3 and column 4 that after controlling for the within-individual average of current household income and the within-individual average of parental education level, and with adjustments for unobserved heterogeneity in the estimation procedure, the original current household income variable and parental education variables are not as large and some are no longer statistically significant. This result is in line with the interpretation of regarding the mean income as a measure of long-term or 'permanent' income while regarding current income as a measure of transitory income shocks (Contoyannis et al. 2004 a, b). It shows that the long-term household income, other than the transitory income, is important for the child's health status. Other statistically significant variables are child age, and age of mother at birth of child, and family size. Thirdly, the improvement in the log-likelihood from the pooled model to the random-effects model indicates that allowing for unobserved heterogeneity can improve the goodness-of-fit of the model. Moreover, it can be seen from the ICC value in the random-effects model that about 31% of the latent error variance is attributable to unobserved heterogeneity.

As the estimated coefficients for the pooled models are not directly comparable to the ones for the random effects models, we calculated the average partial effects (APEs) on the probability of reporting excellent health. Following the approach of Wooldridge (Wooldridge 2005), Contoyannis et al. (2004b), we calculated the average partial effects (APEs) by computing the partial effect at the observed values of the regressors for each observation and averaging the estimates over all the observations⁸. The results are presented in table 6. The random-effects model results indicate that, relative to the children who reported very good health in the previous period, the children who reported excellent health in the previous period are more likely to stay in excellent health in the current period by 9.12 percentage points, while the children who reported good health, fair health and poor health previously are less likely to report excellent health in the current period by 7.23 percentage points, by 13.57 percentage points and by 27.12 percentage points, respectively.

An "empirical" transition matrix of reporting each health status given the previous health status is constructed based on the estimates of the random effects model and reported in Table 7. The way we construct the empirical transition matrix is as follows. First, the probabilities of reporting each health state are predicted and generated for each observation based on the estimated parameters. Second, all the observations are pooled together and grouped by the previous health status. For each of these groups, the means of the predicted probabilities of reporting each health status are calculated and these constitute the point estimates of the transitional probabilities. This transition matrix is comparable to Table 1 except that it shows the predicted transitional probabilities conditional on all the family-level control variables. The elements on the diagonal of table 7 are smaller than the ones of table 1. This highlights the importance of family-level characteristics and unobserved individual effects in explaining the persistence of child health status over time.

- 4.2 Neighbourhood characteristics and child health transitions
- 4.2.1 Long-term neighbourhood characteristics and child health transitions

⁸ As usual, the partial effects are obtained by taking the derivative of the ordered probit probabilities with respect to the variable in question for continuous regressors; while for discrete regressors, they are obtained by taking differences. Wooldridge (2005) shows that computing the partial effect at the observed values of the regressors for each observation and averaging the estimates over the observations provides a consistent estimate of the APE.

As in the descriptive analyses, we divide the study sample into quartiles based on the simple average across 6 cycles of each of the four neighborhood variables: average household income of the neighbourhood, the proportion of the population with a college degree, the proportion of families headed by lone-parents and the proportion of households living in rental accommodation. Since these measures are essentially the within-means of neighbourhood characteristics for each child, they can be interpreted as the long-term neighbourhood environment rather than the temporary neighbourhood characteristics. For each neighbourhood subsample, we estimated a pooled ordered probit model and random effect ordered probit model with the specification suggested by Wooldridge (2005). The corresponding average partial effects (APEs) of reporting excellent health status for the random effects specification are presented in Part A of Table 8a, 8b, 8c and 8d for each of the four neighbourhood characteristics. The gradient of pure state dependence is observable across all neighbourhood subsamples. "Permanent" household income has significant positive effects on reporting excellent health for all the subgroups, but the magnitudes of the effects indicate different interaction patterns between "permanent" household income and different neighbourhood characteristics. For example, the positive effect of "permanent" household income on child health is stronger in richer neighbourhoods and also more educated neighbourhoods. This shows the average household income level and education level of neighbourhood are positive moderators of a "permanent" family income effect. On the contrary, the positive effect of "permanent" household income on child health is weaker in neighbourhoods with less lone-parents families and also in neighbourhoods with less families living in rental accommodations. Maternal education has significant positive effects on reporting excellent health for most of the subgroups, while the neighbourhood characteristics have negative moderating effects on the effect of maternal education. Maternal education plays a more important role in the most disadvantaged neighbourhoods relative to better neighbourhoods. No discernable pattern can be found for the effect of paternal education on child health distributions.

To illustrate that living in different types of neighborhood leads to significantly different health dynamics in the long term, we conducted a one-to-one comparison on the average partial effects (APE) of each health lag term across all neighborhood quartiles, and we implemented a simple test that examines whether each pair of the APE estimates are significantly different. The test-statistic and the p-values are presented in Part B of table 8a, 8b, 8c and 8d for each of the four neighborhood characteristics. The results from the tests confirm that the persistence level differs systematically across different neighborhood status except for neighborhood living arrangements.

A set of empirical transition matrices of reporting each health status given the previous health status for different types of neighbourhoods are constructed based on the estimates of the random effects model and reported in Table 9. These transition matrices are comparable to the ones in the descriptive analysis except that they are the predicted probabilities conditional on all the control variables. In the table, previous health status is presented in rows while current health status is presented in columns. Like the transition matrices in the descriptive analysis, the low health state is more persistent in neighborhoods with lower income, in neighborhoods with less educated people and in neighborhoods with more families headed by lone-parents than in neighborhoods with better conditions. Nonetheless, there is no discernable pattern across neighborhoods with different living arrangements defined by the proportion of families living in rental accormodations. It indicates that controlling for family level characteristics neighborhood income, neighborhood education and neighborhood lone-parents status remain important in explaining the heterogeneity of persistence levels of ill-health over time.

In order to show the magnitude of the difference in the transition probabilities across different neighborhood quartiles, we constructed 95% confidence intervals for each estimate of the transition probabilities for all empirical transition matrices in table 9. The point estimates and the 95%

confidence intervals of the transitional probabilities⁹ are presented by figure 5 to figure 8 for each of the four neighborhood characteristics. These figures illustrate which neighborhood characteristics contribute to the difference in the dynamics and to what extent the transition probabilities differ across quartiles by these neighborhood characteristics. From the figures, we see that the difference in health transitions across quartiles of neighborhood income is most obvious. Five out of the nine transitions of health status have systematically different transitional probabilities across quartiles of neighborhood lone-parents status, but in only three out of the nine transitions. No difference in health transitions is observed across quartiles of neighborhood living arrangements. Overall, the transitional probability of being in "less than good health" and stuck in this poor health status in the next period is systematically lower in richer neighborhoods, neighborhoods with more educated people and in neighborhoods with fewer families headed by lone-parents. The transitional probability of being in excellent health and staying in excellent health in the next period is systematically lower with more educated people and in neighborhoods with more educated people and in neighborhoods, neighborhoods with more educated people and in neighborhoods with more educated

Furthermore, we calculated the predicted probabilities of trajectories of some specific health transition scenarios¹⁰ based on these transition matrices. Figure 9 shows the predicted probabilities of health drops lasting for only 1 period versus health drops lasting for multiple periods across different neighbourhoods. The first panel compares the probabilities across neighbourhoods with different levels of average household income. The second, third and fourth panel compares the probabilities across neighbourhoods with different proportions of highly-educated people, across neighbourhoods with different proportions of lone-parents families and across neighbourhoods with different proportions of families living in rental accommodations. Figure 10 shows the predicted probabilities of children having 0 drop, 1 drop, 2 drops, 3 or 4 drops during 6 cycles across different neighbourhoods. It is observable that children tend to experience multiple health drops living in poorer neighborhoods, in neighborhoods with less educated people, in neighborhoods with more families headed by lone-parents and in neighborhoods with more families living in rental accommodations.

To test if there is any effect of current neighborhood characteristics on child health dynamics, we also estimated the same pooled ordered probit and random effects ordered probit models with our full sample on an alternative specification which includes interaction terms between the health lags and the concurrent neighborhood variables¹¹. The regression results show that the gradient in the estimated effect of previous health on current health (estimated coefficients of the health lag dummies) are still clear and significant, while most of the estimated coefficients of the interaction terms are insignificant. In order to test the hypotheses that (at least some) current neighborhood characteristics do affect the transition dynamics of child health, we conducted a Wald test on the joint significance of each set of the interaction terms, e.g. interactions terms between health lag dummies, initial health status and the neighborhood income quartiles. The results from the Wald tests indicate that current neighborhood characteristics in general do not moderate the transition dynamics in a significant way, except for neighborhood living arrangement condition. In summary, the regression results from this model

⁹ There are 9 types of transitions in our case here: transition from "<=Good health" to "<=Good health", transition from "<=Good health" to "Excellent health", transition from "Very Good health" to "Excellent health", transition from "Very Good health" to "Second health", transition from "Very Good health" to "Excellent health", transition from "Very Good health" to "Excellent health", transition from "Excellent health" to "Excellent health". ¹⁰

 $^{^{10}}$ These health transition scenarios correspond to the ones listed in table 2 and table 3.

¹¹ We constructed the interaction terms for our random effect model as follows. For each neighborhood characteristic (i.e. income, education, lone-parents status and living arrangement) the neighborhood quartiles are now constructed according to the quartile the child was in during each cycle. The four sets of neighborhood quartile dummies (4*3=12 more regressors in total) are included in the regression along with the interactions with the health lag dummies (3*3*4=36 more regressors), plus the interactions with the initial health state dummies (3*3*4=36 more regressors). So in this regression, we are using the full sample instead of the subsamples while estimating 84 additional parameters in the model.

indicate that the concurrent neighborhood characteristics do not have a significant impact on child health transitions, or that the impact (if there is indeed an impact) couldn't be detected by the random-effects model using our study sample. Given that our previous subgroup analyses by different quartiles of average neighborhood characteristics had different persistence level in health dynamics, we conclude that it is the long-term neighborhood/environmental conditions (other than concurrent conditions) that are contributing to the difference in the child health transition.

4.2.2 Neighbourhood transition paths and child health

One might argue that not only the average environment characteristics for the children could affect the transitions of child health but also particular types of change in the environment over time could lead to very different dynamics. To explore the potential effects of the change in the environment on the dynamics of child health, we conducted subgroup analyses based on different "transition paths" of neighborhood characteristics¹². At first we assigned the neighborhood quartile of each of the four neighborhood variables in every cycle to each child. As a result, every child has a sequence of environmental positions over 6 cycles. Then we group the sample based on the direction of these "transition paths": moving to better neighborhoods over time ("climbing-up" pattern), moving to worse neighborhoods at another ("bouncing" pattern), or staying in the same type of neighborhood over time¹³. Using these neighborhood subsamples, we estimated the pooled ordered probit model and random effects ordered probit model and again compared the estimated state dependence parameters to examine if there is any different dynamics across different transition paths of environment.

With the subgroup of children who stayed in the same neighborhood quartile over time, we split them into four subgroups by quartiles of neighborhood status they stayed in over six cycles and again constructed the empirical transition matrices among these four groups. Table 10 presents the empirical transition matrices by quartiles of neighborhood characteristics among these children who didn't change their neighborhood status over six cycles. Similar to the pattern showed in table 9, the low health state is more persistent in neighborhoods with lower income, in neighborhoods with less educated people and in neighborhoods with more families headed by lone-parents than in neighborhoods with better conditions, while no discernable pattern is found across neighborhoods with different living arrangements. The fact that the same pattern is preserved among the "stayers" indicates the results are robust to different study samples.

Table 11 presents the empirical transition matrices by neighborhood transition patterns. In general, all the transitional probabilities are very similar across different neighborhood transition patterns, indicating that there is no significant impact of neighborhood transition patterns on the dynamics of child health.

¹² A criticism of using simple averages of neighborhood variables to divide the sample is that it might not capture the effect of neighborhood changes on the dynamics of child health if there are a lot of changes in the environment over time for the children and these changes lead to different dynamics. Now we looked further into the "transition paths" of neighborhood and examine if we could test this hypothesis. This test is feasible because there is sufficient variation in terms of the neighborhood changes in our sample: around 43% of the children in our sample stayed within the same neighborhood income quartile over 6 cycles, about 36% of the children moved once from one quartile to another, while about 21% of them moved twice or more across different neighborhood income quartiles. These percentage figures are similar in terms of the movement across other neighborhood characteristics.

¹³ Because there are too many different "transition paths" over the six cycles according to the way we sliced our sample, (e.g. being in the highest income quartile for the first 3 cycles while moving to the second lowest quartile for the next 3 cycles), we were not able to estimate our random effects model on each subsample (due to sample size restrictions).

5. Conclusions

We explored the relative contributions of family SES, unobserved heterogeneity and state dependence in determining child health distributions. From the descriptive analysis, the positive correlation between SES and child health can be seen: children in household with higher income and more educated parents tend to be healthier in general. The results from the regression analysis indicate that the child's health status does improve as family SES position increases with household income having a large and positive effect on child health. However, after adding in the mean household income into the regression, the current household income is no longer statistically significant and the coefficient of mean household income shows a positive impact of long-term income on child health. The same pattern is found for parental education. Positive state dependence of child health is observed from the results in all dynamic models. The coefficients of health lags indicate persistence in health from childhood to adolescence. Using Wooldridge's random effects specification, unobserved heterogeneity explained approximately 31% of the latent error variance.

We also examined the potential effects of neighborhood contextual factors on the dynamics of child health by estimating the dynamic panel data models allowing for heterogeneity of state dependence parameters across categories of neighborhood status. The regression results from the subgroup analyses indicate that the positive effect of "permanent" household income on child health is stronger in richer neighbourhoods and also more educated neighbourhoods, while the positive effect of "permanent" household income on child health is weaker in neighbourhoods with fewer lone-parents families and also in neighbourhoods with fewer families living in rental accommodations. Taken together, this may highlight one of the important mechanisms through which neighbourhood contextual factors can influence child outcomes-- collective efficacy serves as a key neighborhood process likely to impact on developmental health (Sampson, Raudenbush and Earls 1997). In other words, the social exchanges of residents in richer neighborhoods and more educated neighborhoods could lead to a more efficient process which magnifies the protective effect of family income in the production of child health. The persistence level differs systematically across different neighborhood status except for neighborhood living arrangements. Specifically, the poor health status is more persistent in neighborhoods with lower income, in neighborhoods with less educated people and in neighborhoods with more families headed by lone-parents than in neighborhoods with better conditions. Results from alternative models indicate that it is the long-term neighborhood or environmental conditions, other than temporal conditions that are contributing to the difference in the child health transition. Furthermore, transition patterns of neighborhood characteristics do not explain the variability of child health dynamics over time. Accordingly, the predictions from the analyses based on long-term neighborhood status indicate that children living in poorer neighborhoods and in neighborhoods with lower education level tend to experience poor health status for longer after a transition to it, while children tend to experience multiple health drops living in poorer neighborhoods, in neighborhoods with less educated people, in neighborhoods with more families headed by lone-parents and in neighborhoods with more families living in rental accommodations.

Our study suffers from several limitations. First, our estimation results may suffer from potential bias generated by partial non-response of the NLSCY, as we are only using a balanced-sample in our study. Children are dropped from our study when some of the family-level SES measures are missing from the data. Second, the four variables we chose as measures of neighborhood characteristics might not be sufficiently comprehensive to capture the contextual factors that are important in determining the dynamics of child health. Besides neighborhood "status" indicators, characteristics representing the "capacity" and the "process" of neighborhoods are also identified as important contextual factors in child health development (Leventhal and Brooks-Gunn 2000; Sampson, Morenoff and Gannon-Rowley 2002). Our study could be extended to examine the effect of more neighborhood characteristics including the quality of institutional resources and public infrastructure in the neighborhoods and neighborhood collective efficacy. Third, the random effects model we employed in our analyses can generate consistent estimators only when the specified distribution of the individual

effects is correct. Fixed effects estimation is more robust than random effects estimation as it avoids the initial conditions problem and the specification of the relationship between the individual effects and regressors in the model, although it suffers from the incidental parameter problem. There are no general solutions for nonlinear models with fixed effects, and in some cases, although a specific solution is available, it is not root-N-consistent. A literature has been specifically focused on bias-adjusted methods of estimation of nonlinear panel data models with fixed effects. One future extension of our study is to employ a Modified Maximum Likelihood Estimation (MMLE) approach that reduces the order of the score bias from $O(T^{-1})$ to $O(T^{-2})$ regardless of the existence of an information orthogonal re-parameterization (Carro 2007) to provide more robust empirical results.

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		Fair/Poor	Good	Very Good	Excellent
		t	t	t	t
Fair/Poor	t-1	0.250	0.411	0.199	0.140
Good	t-1	0.043	0.355	0.378	0.224
Very Good	t-1	0.010	0.124	0.460	0.405
Excellent	t-1	0.005	0.042	0.219	0.735

Table 1. Transition matrix, balanced study sample

Table 2.	Mean o	f family	SES and	d other	variables
		<i>.</i>			

	(1)	(2)	(3)	(4)	(5)
Variables	Whole balanced sample	Always in excellent or very good health	Always less than good health	Single transition from excellent or very good health to worse health	Single transition from less than good health to better health
	N=22,398	N=14,676	N=120	N=15,870	N=1,416
child age	7.480	7.429	7.039	7.477	7.429
child gender	0.492	0.483	0.422	0.478	0.582
family size	4.512	4.538	5.570	4.525	4.502
mother's age at birth of child	29.346	29.626	31.842	29.534	29.055
household income	71,125.0	75,395.8	49,355.5	73,833.9	70,115.0
schoolm1	0.092	0.070	0.099	0.074	0.116
schoolm2	0.220	0.209	0.088	0.219	0.185
schoolm3	0.212	0.212	0.307	0.211	0.254
schoolm4	0.475	0.509	0.507	0.495	0.445
schoolf1	0.131	0.113	0.139	0.118	0.163
schoolf2	0.216	0.210	0.157	0.217	0.239
schoolf3	0.189	0.187	0.324	0.186	0.205
schoolf4	0.464	0.491	0.381	0.480	0.394
PMK not mother	0.074	0.079	NA	0.079	0.062
PMK female	0.928	0.922	NA	0.923	0.952
Living w/ both biological parents	0.988	0.991	NA	0.990	0.994

1. schoolm1, schoolm2, schoolm3 and schoolm4 are the percentages of female caregivers whose highest education is less than secondary, equal to secondary school graduation, some post-secondary and college or university degree, respectively.

2. schoolf1, schoolf2, schoolf3 and schoolf4 are the percentages of male caregivers whose highest education is less than secondary, equal to secondary school graduation, some post-secondary and college or university degree, respectively.

3. NA=Not available due to Statistics Canada Research Data Centre restrictions¹.

¹ According to Statistics Canada Research Data Center (RDC) program guidelines, with the NLSCY only statistics based on greater than 5 observations can be released outside of RDCs.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Had 0 drop	Had 1 drop	Had 2 drops	Had 3 or 4 drops	Had 1 drop & duration =1 cycle	Had 1 drop & duration =2 cycles	Had 1 drop & duration =3 cycles	Had 1 drop & duration =4 cycles
	N=6,480	N=9,768	N=5,370	N=780	N=3,888	N=1,248	N=522	N=174
child age	7.532	7.442	7.467	7.628	7.300	7.385	7.069	7.155
child gender	0.477	0.493	0.501	0.543	0.550	0.492	0.428	0.530
family size	4.601	4.462	4.473	4.656	4.496	4.383	4.326	4.455
mother's age at birth of child	29.656	29.355	29.027	28.777	29.262	29.170	30.575	31.351
household income	81,648.8	69,959.0	61,824.1	59,616.4	71,718.5	68,052.7	66,493.1	67,001.3
schoolm1	0.058	0.095	0.118	0.185	0.078	0.077	0.052	0.254
schoolm2	0.196	0.217	0.254	0.221	0.186	0.193	0.181	0.247
schoolm3	0.225	0.211	0.198	0.212	0.214	0.210	0.300	0.159
schoolm4	0.520	0.477	0.430	0.382	0.523	0.520	0.467	0.340
schoolf1	0.094	0.127	0.173	0.213	0.124	0.110	0.087	0.254
schoolf2	0.206	0.218	0.234	0.152	0.193	0.250	0.169	0.180
schoolf3	0.179	0.205	0.172	0.187	0.199	0.211	0.282	0.137
schoolf4	0.521	0.450	0.421	0.448	0.484	0.428	0.462	0.429
PMK not mother	0.085	0.069	0.072	0.059	0.070	0.048	0.060	0.043
PMK female	0.921	0.931	0.928	0.941	0.930	0.953	0.940	0.957
Living w/ both biological parents	0.990	0.995	0.978	0.965	0.996	0.986	NA	NA

 Table 3.
 Mean of family SES and other variables

Ι	Lowest income Second lowest income			Middle income			Highest income								
	<=	Very	Ev		<=	Very	Ev		<=	Very	Ev		<=	Very	Ev
	Good	Good	EX		Good	Good	EX		Good	Good	EX		Good	Good	EX
<= Good	0.470	0.363	0.166	<= Good	0.455	0.309	0.236	<= Good	0.481	0.285	0.234	<= Good	0.322	0.459	0.220
Very Good	0.133	0.469	0.398	Very Good	0.133	0.486	0.381	Very Good	0.149	0.453	0.398	Very Good	0.127	0.443	0.430
Excellent	0.064	0.278	0.658	Excellent	0.050	0.229	0.721	Excellent	0.053	0.236	0.711	Excellent	0.034	0.176	0.790

Table 4. Descriptive transition matrices by long-term neighborhood statusBy quartiles of mean household income of neighbourhood

By quartiles of proportion of population with university degree in neighbourhood

Lowest	% with co	vith college degree Second lowest %			Second highest %			Highest % with college degree							
	<=	Very	Ev		<=	Very	Ev		<=	Very	Ev		<=	Very	Ev
	Good	Good	EX		Good	Good	EX		Good	Good	EX		Good	Good	EX
<= Good	0.480	0.317	0.202	<= Good	0.419	0.349	0.232	<= Good	0.455	0.330	0.216	<= Good	0.346	0.443	0.212
Very Good	0.148	0.454	0.398	Very Good	0.160	0.413	0.427	Very Good	0.126	0.462	0.412	Very Good	0.118	0.494	0.388
Excellent	0.058	0.237	0.705	Excellent	0.057	0.240	0.703	Excellent	0.042	0.232	0.726	Excellent	0.039	0.184	0.777

By quartiles of proportion of families headed by lone-parents in neighborhood

Highest	t % with l	lone-pare	nts	ts Second highest %			Second lowest %			Lowest % with lone-parents					
	<=	Very	Fv		<=	Very	Ev		<=	Very	Fv		<=	Very	Ev
	Good	Good	LA		Good	Good	LA		Good	Good	LA		Good	Good	LA
<= Good	0.503	0.304	0.193	<= Good	0.395	0.377	0.229	<= Good	0.392	0.385	0.223	<= Good	0.365	0.402	0.233
Very Good	0.149	0.466	0.386	Very Good	0.133	0.443	0.424	Very Good	0.102	0.469	0.428	Very Good	0.157	0.462	0.381
Excellent	0.061	0.270	0.669	Excellent	0.046	0.196	0.758	Excellent	0.039	0.198	0.763	Excellent	0.040	0.207	0.753

By quartiles of proportion of families living in rental accommodations in neighborhood

High	hest % wi	ith rental lations		Second highest %			Second lowest %				Lowest % with rental accommodations				
	<= Good	Very Good	Ex		<= Good	Very	Ex		<= Good	Very Good	Ex		<= Good	Very Good	Ex
	Guu	Good			Good	Good			Good	0000			Good	0000	
<= Good	0.469	0.323	0.208	<= Good	0.441	0.364	0.196	<= Good	0.408	0.350	0.242	<= Good	0.356	0.423	0.221
Very Good	0.134	0.477	0.389	Very Good	0.148	0.420	0.431	Very Good	0.135	0.458	0.408	Very Good	0.121	0.483	0.396
Excellent	0.058	0.242	0.700	Excellent	0.039	0.215	0.746	Excellent	0.046	0.208	0.746	Excellent	0.042	0.199	0.759

		<u>-</u>		
	(1)	(2)	(3)	(4)
	Pooled model, w	vithout correlated	Random effects	, with correlated
	effects spe	ecifications	effects spe	ecifications
hlthc(t-1)poor	-1.9473	(0.2692)	-0.9073	(0.2619)
hlthc(t-1)fair	-1.1681	(0.0941)	-0.4432	(0.0913)
hlthc(t-1)good	-0.5473	(0.0328)	-0.2361	(0.0357)
hlthc(t-1)excellent	0.7523	(0.0218)	0.2963	(0.0266)
child age	-0.0054	(0.0028)	-0.0030	(0.0040)
child gender	-0.0415	(0.0195)	-0.0492	(0.0291)
family size	0.0292	(0.0099)	-0.0345	(0.0270)
mbirthage	-0.0077	(0.0023)	-0.0159	(0.0035)
ln(hh income)	0.1718	(0.0208)	0.0247	(0.0353)
mother school2	0.1349	(0.0376)	0.1035	(0.0550)
mother school3	0.1694	(0.0392)	0.0904	(0.0655)
mother school4	0.2255	(0.0372)	0.1250	(0.0725)
father school2	0.0676	(0.0323)	0.0146	(0.0457)
father school3	0.0578	(0.0343)	-0.0441	(0.0568)
father school4	0.0697	(0.0312)	-0.0823	(0.0634)
PMK not mother	-0.5410	(0.3185)	-0.4902	(0.7221)
mother school2*PMKnm	-0.2598	(0.1695)	-0.3210	(0.1838)
mother school3*PMKnm	-0.1644	(0.1578)	-0.1568	(0.1889)
mother school4*PMKnm	-0.1654	(0.1526)	-0.1943	(0.1793)
PMK female	-0.8001	(0.2860)	-0.8622	(0.7040)
living w/ two parents	-0.4325	(0.4166)	-0.8516	(0.5761)
living w/ biological parents	0.0900	(0.0775)	0.2713	(0.1732)
hlthc(1)poor		× ,	-1.3039	(0.3356)
hlthc(1)fair			-0.6808	(0.1385)
hlthc(1)good			-0.2170	(0.0555)
hlthc(1)excellent			0.5028	(0.0359)
mln(hh income)			0.3091	(0.0534)
magec			0.0006	(0.0096)
mfsize			0.0955	(0.0324)
mschoolm			0.0635	(0.0293)
mschoolf			0.0601	(0.0262)
mpmknm			0.7509	(1.5483)
mpmkfe			0.8813	(1.4943)
mtwopar			1.6287	(2.0270)
mlwbiopa			-0.3432	(0.2486)
msmxmpm			-0.0181	(0.1244)
cut1	-2.5054	(0.5444)	0.6633	(2.4564)
cut2	-1 5663	(0.5372)	1 7581	(2.4554)
cut3	-0.3577	(0.5351)	3.1712	(2.4552)
cut4	0.8338	(0.5351)	4.5678	(2.4554)
ICC	0.0000	(0.0001)	0.3064	(0.0135)
Log likelihood	-161	64.3	-157	48.5

Table 5. Dynamic ordered probit models estimates

1. Standard errors are reported in parentheses. These are robust to cluster effects for the pooled specification. 2. ICC is the intra-class correlation coefficient, $(\sigma_u^2/(1+\sigma_u^2))$

	(1)	(2)	(3)	(4)
	Pooled model w	vithout correlated	Random effects	with correlated
	effects sne	cifications	effects spe	cifications
	encets spe		encets spe	vinoutono
hlthc(t-1)poor	-0.4671	(0.0952)	-0.2712	(0.0340)
hlthc(t-1)fair	-0.2099	(0.0268)	-0.1357	(0.0128)
hlthc(t-1)good	-0.0635	(0.0055)	-0.0723	(0.0065)
hlthc(t-1)excellent	0.0652	(0.0015)	0.0912	(0.0074)
child age	-0.0005	(0.0002)	-0.0009	(0.0001)
child gender	-0.0037	(0.0018)	-0.0148	(0.0015)
family size	0.0026	(0.0009)	-0.0104	(0.0011)
mbirthage	0.0000	(0.0002)	-0.0048	(0.0005)
ln(hh income)	0.0011	(0.0018)	0.0074	(0.0008)
mother school2	0.0114	(0.0029)	0.0309	(0.0034)
mother school3	0.0141	(0.0029)	0.0270	(0.0029)
mother school4	0.0198	(0.0028)	0.0377	(0.0037)
father school2	0.0058	(0.0027)	0.0044	(0.0005)
father school3	0.0050	(0.0028)	-0.0133	(0.0014)
father school4	0.0061	(0.0026)	-0.0246	(0.0027)
PMK not mother	-0.0668	(0.0528)	-0.1488	(0.0161)
mother school2*PMKnm	-0.0274	(0.0210)	-0.0980	(0.0095)
mother school3*PMKnm	-0.0163	(0.0174)	-0.0476	(0.0047)
mother school4*PMKnm	-0.0163	(0.0168)	-0.0590	(0.0059)
PMK female	-0.0448	(0.0274)	-0.2278	(0.0419)
living w/ two parents	-0.0283	(0.0369)	-0.2229	(0.0413)
living w/ biological parents	0.0085	(0.0069)	0.0827	(0.0080)
hlthc(1)poor			-0.3708	(0.0579)
hlthc(1)fair			-0.2075	(0.0207)
hlthc(1)good			-0.0664	(0.0061)
hlthc(1)excellent			0.1575	(0.0103)
mln(hh income)			0.0928	(0.0097)
magec			0.0002	(0.0000)
mfsize			0.0287	(0.0030)
mschoolm			0.0191	(0.0020)
mschoolf			0.0180	(0.0019)
mpmknm			0.2254	(0.0236)
mpmkfe			0.2646	(0.0277)
mtwopar			0.4890	(0.0511)
mlwbiopa			-0.1030	(0.0108)
msmxmpm			-0.0054	(0.0006)

Table 6. Average partial effects on probability of reporting excellent health

1. Standard errors are reported in parentheses.

Table 7. T	Fransition matrix	for empirica	1 model, 1	balanced study	sample

		Fair/Poor	Good	Very Good	Excellent
		t	t	t	t
Fair/Poor	t-1	0.089	0.289	0.391	0.231
Good	t-1	0.030	0.191	0.409	0.369
Very Good	t-1	0.013	0.121	0.368	0.498
Excellent	t-1	0.004	0.058	0.274	0.664

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
	Part A	· APF estimat	es and standar	d errors by qua	rtiles of mean l	ousehold inco	me of neighbo	ourbood	
	1 41171		es une stundur	d chors by qua	tines of mean i	iousenoia mee	line of heights	Junioou	
	Lowest	income	Second low	est income	Middle i	ncome	Highest income		
hlthc(t-1)poor/fair	-0.0959	(0.0102)	-0.1691	(0.0166)	-0.1528	(0.0167)	-0.1663	(0.0155)	
hlthc(t-1)good	-0.0446	(0.0043)	-0.0401	(0.0040)	-0.0961	(0.0102)	-0.1025	(0.0106)	
hlthc(t-1)excellent	0.0868	(0.0071)	0.1201	(0.0090)	0.0756	(0.0077)	0.0760	(0.0087)	
child age	-0.0011	(0.0001)	0.0007	(0.0001)	-0.0047	(0.0006)	0.0015	(0.0002)	
child gender	-0.0003	(0.0000)	-0.0046	(0.0005)	-0.0151	(0.0018)	-0.0322	(0.0045)	
family size	-0.0147	(0.0015)	0.0108	(0.0011)	-0.0093	(0.0011)	-0.0272	(0.0038)	
mbirthage	-0.0052	(0.0005)	-0.0068	(0.0007)	-0.0010	(0.0001)	-0.0062	(0.0009)	
ln(hh income)	0.0000	(0.0000)	-0.0177	(0.0019)	0.0380	(0.0045)	-0.0032	(0.0004)	
lwbiopa	0.0984	(0.0108)	0.1241	(0.0127)	-0.0363	(0.0044)	0.1159	(0.0121)	
mother school2	0.0165	(0.0017)	0.0388	(0.0044)	0.0477	(0.0060)	0.0124	(0.0018)	
mother school3	-0.0244	(0.0025)	0.0321	(0.0036)	0.0922	(0.0120)	-0.0101	(0.0014)	
mother school4	0.0021	(0.0002)	0.0725	(0.0072)	0.0744	(0.0088)	-0.0217	(0.0032)	
father school2	0.0052	(0.0005)	-0.0021	(0.0002)	-0.0152	(0.0018)	0.0249	(0.0037)	
father school3	-0.0068	(0.0007)	-0.0019	(0.0002)	-0.0659	(0.0077)	0.0263	(0.0039)	
father school4	-0.0376	(0.0041)	-0.0242	(0.0026)	-0.0723	(0.0091)	0.0346	(0.0047)	
PMK not mother	0.0660	(0.0073)	0.1729	(0.0266)	0.1180	(0.0165)	0.2410	(0.0657)	
schoolm2*PMKnm	0.0735	(0.0082)	-0.1995	(0.0230)	-0.1537	(0.0180)	-0.4098	(0.0550)	
schoolm3*PMKnm	0.1289	(0.0162)	-0.1567	(0.0170)	-0.1422	(0.0169)	-0.2237	(0.0229)	
schoolm4*PMKnm	-0.0243	(0.0025)	-0.1444	(0.0159)	-0.0695	(0.0081)	-0.2449	(0.0287)	
hlthc(1)poor/fair	-0.0686	(0.0071)	-0.2300	(0.0236)	-0.3884	(0.0564)	-0.2846	(0.0261)	
hlthc(1)good	-0.0914	(0.0084)	-0.0810	(0.0077)	-0.0547	(0.0061)	-0.0096	(0.0013)	
hlthc(1)excellent	0.1783	(0.0109)	0.1359	(0.0098)	0.1537	(0.0133)	0.1929	(0.0148)	
mln(hh income)	0.0558	(0.0058)	0.1109	(0.0118)	0.1057	(0.0124)	0.0962	(0.0136)	
mlwbiopa	-0.0726	(0.0075)	-0.1646	(0.0175)	-0.0211	(0.0025)	-0.0559	(0.0079)	
magec	0.0012	(0.0001)	0.0093	(0.0010)	-0.0010	(0.0001)	-0.0072	(0.0010)	
mfsize	0.0395	(0.0041)	0.0045	(0.0005)	0.0167	(0.0020)	0.0566	(0.0080)	
mschoolm	0.0434	(0.0045)	0.0014	(0.0001)	-0.0148	(0.0017)	0.0337	(0.0047)	
mschoolf	0.0336	(0.0035)	0.0218	(0.0023)	0.0187	(0.0022)	-0.0027	(0.0004)	
mpmknm	-0.3190	(0.0331)	-0.0608	(0.0064)	-0.0768	(0.0090)	0.4859	(0.0685)	
msmxmpm	0.0439	(0.0046)	-0.0005	(0.0001)	0.0291	(0.0034)	-0.1498	(0.0211)	

Table 8a. Average Partial effects for the probability of reporting excellent health by neighbourhood status, random effects model-- by quartiles of mean household income of neighbourhood

Part B: Test of significance of difference in APE estimates for the probability of reporting excellent health across quartiles of mean household income of neighbourhood

	Test-statistic	p-value	Test-statistic	p-value	Test-statistic	p-value	
	Lowest inc	ome (1 st	Lowest inco	ome (1 st	Lowest inc	ome (1 st	
	quartile) vs	. Second	quartile) vs.	quartile) vs.	
	lowest inco	ome (2 nd	Middle inco	ome (3 rd	Highest inc	ome (4 th	
	quarti	le)	quarti	e)	quartile)		
hlthc(t-1)poor/fair	3.768	0.000	2.906	0.004	3.795	0.000	
hlthc(t-1)good	-0.771	0.441	4.647	0.000	5.045	0.000	
hlthc(t-1)excellent	-2.911	0.004	1.067	0.286	0.961	0.336	
			Second lowes	st income	Second lowe	st income	
			(2 nd quart	ile) vs.	(2 nd quar	tile) vs.	
			Middle inco	ome (3 rd	Highest inc	ome (4 th	
			quarti	e)	quarti	le)	
hlthc(t-1)poor/fair			-0.692	0.489	-0.125	0.900	
hlthc(t-1)good			5.118	0.000	5.503	0.000	
hlthc(t-1)excellent			3.771	0.000	3.533	0.000	
					Middle inc	ome (3 rd	
					quartile) vs.	Highest	
					income (4 th	quartile)	
hlthc(t-1)poor/fair					0.589	0.556	
hlthc(t-1)good					0.434	0.664	
hlthc(t-1)excellent					-0.032	0.975	

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
	Part A: AP	PE estimates a	nd standard er	rors by quartile	s of proportion	of population	with universit	ty degree in	
				neighb	ourhood				
	Lowest %	w/ degree	Second le	owest %	Second hi	ghest %	Highest % w/ degree		
hlthc(t-1)poor/fair	-0.1604	(0.0159)	-0.0679	(0.0065)	-0.2589	(0.0333)	-0.1238	(0.0139)	
hlthc(t-1)good	-0.0634	(0.0058)	-0.0455	(0.0043)	-0.0979	(0.0108)	-0.0786	(0.0092)	
hlthc(t-1)excellent	0.0824	(0.0067)	0.0873	(0.0072)	0.0914	(0.0095)	0.1053	(0.0114)	
child age	-0.0027	(0.0003)	-0.0041	(0.0004)	0.0004	(0.0001)	0.0026	(0.0004)	
child gender	0.0129	(0.0013)	-0.0106	(0.0011)	-0.0336	(0.0043)	-0.0217	(0.0031)	
family size	-0.0028	(0.0003)	-0.0053	(0.0005)	-0.0350	(0.0046)	0.0078	(0.0011)	
mbirthage	-0.0044	(0.0004)	-0.0048	(0.0005)	-0.0034	(0.0004)	-0.0080	(0.0011)	
ln(hh income)	-0.0120	(0.0012)	0.0133	(0.0014)	0.0251	(0.0033)	-0.0084	(0.0012)	
lwbiopa	0.0986	(0.0100)	-0.0207	(0.0021)	0.1320	(0.0162)	0.1288	(0.0147)	
mother school2	0.0203	(0.0021)	0.0539	(0.0060)	-0.0105	(0.0013)	0.0133	(0.0019)	
mother school3	0.0261	(0.0027)	0.0139	(0.0014)	0.0215	(0.0029)	-0.0046	(0.0006)	
mother school4	0.0116	(0.0012)	0.0877	(0.0077)	0.0015	(0.0002)	0.0004	(0.0001)	
father school2	0.0265	(0.0028)	0.0078	(0.0008)	-0.0448	(0.0055)	0.0361	(0.0056)	
father school3	0.0327	(0.0034)	-0.0302	(0.0030)	-0.0585	(0.0075)	0.0162	(0.0024)	
father school4	0.0096	(0.0010)	-0.0400	(0.0043)	-0.0807	(0.0118)	0.0024	(0.0003)	
PMK not mother	0.0937	(0.0114)	0.1481	(0.0186)	0.0562	(0.0080)	0.2771	(0.0806)	
schoolm2*PMKnm	0.0293	(0.0031)	-0.2124	(0.0246)	-0.0181	(0.0023)	-0.4087	(0.0634)	
schoolm3*PMKnm	-0.0741	(0.0073)	0.0228	(0.0024)	-0.1031	(0.0125)	-0.2557	(0.0312)	
schoolm4*PMKnm	-0.0770	(0.0077)	-0.0490	(0.0050)	0.0031	(0.0004)	-0.3333	(0.0482)	
hlthc(1)poor/fair	-0.2033	(0.0210)	-0.2106	(0.0215)	-0.2641	(0.0342)	-0.3071	(0.0350)	
hlthc(1)good	-0.0501	(0.0047)	-0.0940	(0.0086)	-0.0402	(0.0049)	-0.0672	(0.0082)	
hlthc(1)excellent	0.1839	(0.0106)	0.1112	(0.0084)	0.1685	(0.0141)	0.1695	(0.0156)	
mln(hh income)	0.0713	(0.0073)	0.0804	(0.0082)	0.0969	(0.0126)	0.1590	(0.0228)	
mlwbiopa	-0.1394	(0.0142)	0.0531	(0.0054)	-0.2257	(0.0294)	-0.1117	(0.0160)	
magec	0.0102	(0.0010)	0.0061	(0.0006)	-0.0020	(0.0003)	-0.0142	(0.0020)	
mfsize	0.0081	(0.0008)	0.0283	(0.0029)	0.0613	(0.0080)	0.0199	(0.0028)	
mschoolm	0.0388	(0.0040)	0.0083	(0.0008)	0.0112	(0.0015)	0.0016	(0.0002)	
mschoolf	-0.0006	(0.0001)	0.0261	(0.0027)	0.0385	(0.0050)	0.0155	(0.0022)	
mpmknm	-0.1856	(0.0189)	-0.3204	(0.0325)	0.2192	(0.0286)	0.2450	(0.0351)	
msmxmpm	0.0151	(0.0015)	0.0920	(0.0093)	-0.0639	(0.0083)	-0.0886	(0.0127)	

 Table 8b. Average Partial effects for the probability of reporting excellent health by neighbourhood status, random effects model-- by quartiles of proportion of population with university degree in neighbourhood

Part B: Test of significance of difference in APE estimates for the probability of reporting excellent health across quartiles of proportion of population with university degree in neighbourhood

	Test-statistic	p-value	Test-statistic	p-value	Test-statistic	p-value
	Lowest % w/ quartile) vs. lowest % (2 nd	degree (1 st . Second quartile)	Lowest % w/o quartile Second highe quartil	degree (1 st) vs. est % (3 rd e)	Lowest % w/ quartile Highest % w/ quarti	degree (1 st) vs. degree (4 th le)
hlthc(t-1)poor/fair	-5.377	0.000	2.668	0.008	-1.734	0.083
hlthc(t-1)good	-2.485	0.013	2.818	0.005	1.388	0.165
hlthc(t-1)excellent	-0.499	0.618	-0.780	0.435	-1.737	0.082
			Second lowe	st % (2 nd	Second lowe	est % (2 nd
			quartile) vs. Second		quartile) vs. Highest %	
			highest % (3 rd	¹ quartile)	w/ degree (4 ^t	^h quartile)
hlthc(t-1)poor/fair			5.628	0.000	3.642	0.000
hlthc(t-1)good			4.523	0.000	3.250	0.001
hlthc(t-1)excellent			-0.348	0.728	-1.338	0.181
					Second high	est % (3 rd
					quartile) vs. I	Highest %
					w/ degree (4 ^t	^h quartile)
hlthc(t-1)poor/fair					-3.745	0.000
hlthc(t-1)good					-1.364	0.172
hlthc(t-1)excellent					-0.937	0.349

	(1) (2)		(3)	(4)	(5)	(6)	(7)	(8)	
	Part A: A	PE estimates	and standard e	rrors by quartil	es of proportio	n of families h	eaded by lone	-parents in	
				neight	orhood				
	High	est %	Second h	ighest %	Second lo	owest %	Lowest %		
hlthc(t-1)poor/fair	-0.1492	(0.0160)	-0.0537	(0.0052)	-0.2530	(0.0286)	-0.1464	(0.0161)	
hlthc(t-1)good	-0.0577	(0.0052)	-0.0645	(0.0061)	-0.1151	(0.0130)	-0.0503	(0.0058)	
hlthc(t-1)excellent	0.0964	(0.0072)	0.0696	(0.0063)	0.0693	(0.0083)	0.1263	(0.0115)	
child age	-0.0004	(0.0000)	-0.0018	(0.0002)	-0.0026	(0.0004)	0.0007	(0.0001)	
child gender	-0.0290	(0.0027)	0.0053	(0.0006)	-0.0140	(0.0020)	-0.0067	(0.0009)	
family size	0.0019	(0.0002)	-0.0058	(0.0006)	-0.0088	(0.0013)	-0.0249	(0.0032)	
mbirthage	-0.0061	(0.0006)	-0.0021	(0.0002)	-0.0047	(0.0007)	-0.0071	(0.0009)	
ln(hh income)	0.0042	(0.0004)	0.0291	(0.0031)	-0.0087	(0.0012)	-0.0008	(0.0001)	
lwbiopa	0.0448	(0.0044)	0.0677	(0.0067)	0.2354	(0.0295)	-0.2998	(0.0860)	
mother school2	0.0322	(0.0031)	0.0562	(0.0067)	0.0422	(0.0066)	-0.0086	(0.0011)	
mother school3	0.0212	(0.0020)	0.0532	(0.0062)	0.0536	(0.0084)	-0.0309	(0.0039)	
mother school4	0.0559	(0.0050)	0.0513	(0.0052)	0.0681	(0.0093)	-0.0382	(0.0053)	
father school2	0.0005	(0.0001)	0.0538	(0.0061)	-0.0153	(0.0021)	-0.0229	(0.0029)	
father school3	-0.0234	(0.0022)	0.0197	(0.0022)	-0.0204	(0.0029)	-0.0247	(0.0031)	
father school4	-0.0422	(0.0042)	0.0168	(0.0018)	-0.0295	(0.0044)	-0.0486	(0.0068)	
PMK not mother	0.0613	(0.0058)	0.2071	(0.0360)	0.1462	(0.0278)	0.0418	(0.0058)	
schoolm2*PMKnm	-0.0902	(0.0094)	-0.1818	(0.0185)	-0.2226	(0.0273)	0.0722	(0.0110)	
schoolm3*PMKnm	0.1015	(0.0101)	-0.2747	(0.0336)	0.0267	(0.0040)	-0.0122	(0.0015)	
schoolm4*PMKnm	-0.0309	(0.0030)	-0.1888	(0.0213)	-0.0848	(0.0112)	0.0497	(0.0071)	
hlthc(1)poor/fair	-0.2561	(0.0335)	-0.2882	(0.0312)	-0.2370	(0.0252)	-0.1693	(0.0188)	
hlthc(1)good	-0.1209	(0.0108)	-0.0014	(0.0002)	-0.0933	(0.0112)	-0.0172	(0.0021)	
hlthc(1)excellent	0.1205	(0.0084)	0.1790	(0.0116)	0.1498	(0.0141)	0.1999	(0.0141)	
mln(hh income)	0.0952	(0.0090)	0.0926	(0.0099)	0.0961	(0.0138)	0.0846	(0.0110)	
mlwbiopa	-0.0985	(0.0093)	-0.0065	(0.0007)	-0.2204	(0.0317)	0.2425	(0.0314)	
magec	-0.0066	(0.0006)	0.0074	(0.0008)	0.0037	(0.0005)	-0.0024	(0.0003)	
mfsize	0.0263	(0.0025)	0.0151	(0.0016)	0.0276	(0.0040)	0.0444	(0.0057)	
mschoolm	0.0045	(0.0004)	0.0101	(0.0011)	0.0022	(0.0003)	0.0486	(0.0063)	
mschoolf	0.0299	(0.0028)	-0.0056	(0.0006)	0.0271	(0.0039)	0.0308	(0.0040)	
mpmknm	0.1636	(0.0155)	-0.3126	(0.0332)	-0.0622	(0.0089)	-0.1976	(0.0256)	
msmxmpm	-0.0743	(0.0070)	0.0683	(0.0073)	0.0276	(0.0040)	0.0291	(0.0038)	

Table 8c. Average Partial effects for the probability of reporting excellent health by neighbourhood status, random effects model-- by quartiles of proportion of families headed by lone-parents in neighborhood

Part B: Test of significance of difference in APE estimates for the probability of reporting excellent health across quartiles of proportion of families headed by lone-parents in neighborhood

	Test-statistic	p-value	Test-statistic	p-value	Test-statistic	p-value
	Highest % (1 vs. Second hig quarti	st quartile) shest % (2 nd le)	Highest % (1 ^s vs. Second lowe quartil	^{rt} quartile) est % (3 rd le)	Highest % (1 vs. Lowest % (4 ^t	st quartile) ^h quartile)
hlthc(t-1)poor/fair	-5.661	0.000	3.168	0.002	-0.122	0.903
hlthc(t-1)good	0.844	0.399	4.112	0.000	-0.956	0.339
hlthc(t-1)excellent	2.812	0.005	2.461	0.014	-2.206	0.027
			Second highe	est % (2 nd	Second high	est % (2 nd
			quartile) vs.	Second	quartile) vs. 1	Lowest %
			lowest % (3rd	quartile)	(4 th qua	rtile)
hlthc(t-1)poor/fair			6.864	0.000	5.494	0.000
hlthc(t-1)good			3.542	0.000	-1.688	0.091
hlthc(t-1)excellent			0.028	0.978	-4.325	0.000
					Second lowe	est % (3 rd
					quartile) vs. 1	Lowest %
					(4 th qua	rtile)
hlthc(t-1)poor/fair					-3.252	0.001
hlthc(t-1)good					-4.565	0.000
hlthc(t-1)excellent					-4.008	0.000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
	Part	A: APE estin	nates and stand	lard errors by q	uartiles of prop	portion of fami	lies living in 1	rental	
			a	s in neighborho	neighborhood				
	Highest %	with rental	Second h	ighest %	Second lo	west %	Lowest % with rental		
	accomm	odations	Becond in	ignest /o	Becond R		accommodations		
hlthc(t-1)poor/fair	-0.0928	(0.0080)	-0.1679	(0.0184)	-0.1819	(0.0220)	-0.1588	(0.0157)	
hlthc(t-1)good	-0.0529	(0.0044)	-0.0982	(0.0100)	-0.0626	(0.0081)	-0.0626	(0.0062)	
hlthc(t-1)excellent	0.0938	(0.0066)	0.0889	(0.0084)	0.0917	(0.0108)	0.0755	(0.0070)	
child age	0.0015	(0.0001)	-0.0006	(0.0001)	-0.0055	(0.0008)	0.0009	(0.0001)	
child gender	-0.0108	(0.0010)	-0.0093	(0.0011)	-0.0150	(0.0022)	-0.0160	(0.0018)	
family size	0.0127	(0.0012)	0.0018	(0.0002)	-0.0348	(0.0051)	-0.0210	(0.0024)	
mbirthage	-0.0052	(0.0005)	-0.0004	(0.0000)	-0.0119	(0.0018)	-0.0029	(0.0003)	
ln(hh income)	-0.0102	(0.0009)	0.0062	(0.0007)	0.0190	(0.0028)	0.0015	(0.0002)	
lwbiopa	0.0416	(0.0037)	0.1000	(0.0114)	0.0715	(0.0096)	-0.1688	(0.0305)	
mother school2	0.0474	(0.0047)	0.0512	(0.0067)	0.0379	(0.0060)	-0.0141	(0.0016)	
mother school3	0.0458	(0.0045)	0.0652	(0.0085)	0.0377	(0.0059)	-0.0453	(0.0049)	
mother school4	0.1020	(0.0088)	0.0501	(0.0057)	0.0501	(0.0072)	-0.0595	(0.0078)	
father school2	0.0246	(0.0023)	0.0123	(0.0015)	-0.0274	(0.0039)	-0.0046	(0.0005)	
father school3	0.0046	(0.0004)	-0.0126	(0.0015)	-0.0703	(0.0099)	0.0085	(0.0010)	
father school4	-0.0183	(0.0017)	0.0041	(0.0005)	-0.1001	(0.0170)	-0.0115	(0.0013)	
PMK not mother	0.1665	(0.0216)	0.2067	(0.0367)	0.0022	(0.0003)	0.0518	(0.0065)	
schoolm2*PMKnm	-0.1561	(0.0152)	-0.2032	(0.0254)	-0.0039	(0.0006)	-0.0685	(0.0070)	
schoolm3*PMKnm	-0.0425	(0.0038)	-0.3142	(0.0475)	0.1783	(0.0394)	-0.0470	(0.0050)	
schoolm4*PMKnm	-0.1330	(0.0130)	-0.2019	(0.0268)	0.1096	(0.0204)	-0.0236	(0.0026)	
hlthc(1)poor/fair	-0.2950	(0.0339)	-0.2549	(0.0295)	-0.2752	(0.0362)	-0.1293	(0.0122)	
hlthc(1)good	-0.0923	(0.0075)	-0.1039	(0.0107)	-0.0728	(0.0094)	0.0154	(0.0018)	
hlthc(1)excellent	0.1289	(0.0082)	0.1130	(0.0100)	0.1745	(0.0162)	0.2264	(0.0125)	
mln(hh income)	0.1165	(0.0106)	0.1282	(0.0154)	0.0995	(0.0147)	0.0707	(0.0080)	
mlwbiopa	-0.0825	(0.0075)	-0.0980	(0.0117)	-0.0827	(0.0122)	0.0541	(0.0062)	
magec	-0.0102	(0.0009)	0.0064	(0.0008)	0.0033	(0.0005)	0.0002	(0.0000)	
mfsize	0.0013	(0.0001)	0.0122	(0.0015)	0.0741	(0.0110)	0.0296	(0.0034)	
mschoolm	-0.0209	(0.0019)	0.0097	(0.0012)	0.0083	(0.0012)	0.0617	(0.0070)	
mschoolf	0.0252	(0.0023)	0.0040	(0.0005)	0.0519	(0.0077)	0.0178	(0.0020)	
mpmknm	-0.1853	(0.0169)	-0.2155	(0.0258)	0.1825	(0.0270)	-0.0139	(0.0016)	
msmxmpm	0.0272	(0.0025)	0.0681	(0.0082)	-0.1249	(0.0185)	0.0139	(0.0016)	

Table 8d. Average Partial effects for the probability of reporting excellent health by neighbourhood status, random	n
effects model by quartiles of proportion of families living in rental accommodations in neighborhood	

Part B: Test of significance of difference in APE estimates for the probability of reporting excellent health across quartiles of proportion of families living in rental accommodations in neighborhood

	Test-statistic	p-value	Test-statistic	p-value	Test-statistic	p-value	
	Highest % (1 vs. Second hig quarti	st quartile) hest % (2 nd le)	Highest % (1 ^s vs. Second lowe quartil	^t quartile) st % (3 rd e)	Highest % (1 st quartile vs. Lowest % (4 th quartile		
hlthc(t-1)poor/fair	3.752	0.000	3.804	0.000	3.756	0.000	
hlthc(t-1)good	4.155	0.000	1.049	0.294	1.276	0.202	
hlthc(t-1)excellent	0.460	0.646	0.168	0.866	1.903	0.057	
			Second highe quartile) vs. lowest % (3 rd	est % (2 nd Second quartile)	Second high quartile) vs. 1 (4 th qua	est % (2 nd Lowest % rtile)	
hlthc(t-1)poor/fair			0.487	0.626	-0.376	0.707	
hlthc(t-1)good			-2.762	0.006	-3.033	0.002	
hlthc(t-1)excellent			-0.204	0.838	1.221	0.222	
					Second lowe	est % (3 rd	
					quartile) vs. 1 (4 th qua	Lowest % rtile)	
hlthc(t-1)poor/fair					-0.852	0.394	
hlthc(t-1)good					-0.003	0.998	
hlthc(t-1)excellent					1.258	0.208	

Tuble 3. Transition matrices of tong term herginood status for empirical model
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By quartiles of mean household income of neighbourhood

Ι	Lowest income Second lowest income			Middle income				Highest income							
	<=	Very	Бv		<=	Very	Ev		<=	Very	Ev		<=	Very	Ev
	Good	Good	EX		Good	Good	ĽX		Good	Good	ĽX		Good	Good	ĽX
<= Good	0.251	0.416	0.333	<= Good	0.226	0.420	0.354	<= Good	0.272	0.389	0.340	<= Good	0.207	0.401	0.392
Very Good	0.153	0.386	0.462	Very Good	0.139	0.390	0.471	Very Good	0.133	0.355	0.512	Very Good	0.110	0.340	0.549
Excellent	0.075	0.300	0.625	Excellent	0.058	0.281	0.660	Excellent	0.067	0.275	0.657	Excellent	0.046	0.237	0.717

By quartiles of proportion of population with university degree in neighbourhood

Lowest	% with co	ollege deg	gree	Second lowest %			Second highest %				Highest % with college degree				
	<=	Very	Ev		<=	Very	Ev		<=	Very	Ev		<=	Very	Ev
	Good	Good	EX		Good	Good	EX		Good	Good	EX		Good	Good	EX
<= Good	0.252	0.409	0.339	<= Good	0.246	0.387	0.367	<= Good	0.255	0.423	0.322	<= Good	0.207	0.420	0.372
Very Good	0.143	0.373	0.484	Very Good	0.156	0.359	0.485	Very Good	0.128	0.380	0.492	Very Good	0.112	0.369	0.519
Excellent	0.069	0.283	0.648	Excellent	0.083	0.286	0.631	Excellent	0.053	0.271	0.676	Excellent	0.042	0.249	0.709

By quartiles of proportion of families headed by lone-parents in neighborhood

Highest	t % with l	lone-pare	nts	Se	cond hig	hest %		Se	econd lov	vest %		Lowest	% with l	one-parer	nts
	<=	Very	Ev		<=	Very	Ev		<=	Very	Ev		<=	Very	Ev
	Good	Good	EX		Good	Good	EX		Good	Good	EX		Good	Good	EX
<= Good	0.268	0.398	0.333	<= Good	0.215	0.400	0.385	<= Good	0.254	0.411	0.336	<= Good	0.227	0.427	0.346
Very Good	0.156	0.374	0.470	Very Good	0.132	0.365	0.503	Very Good	0.109	0.347	0.543	Very Good	0.140	0.393	0.467
Excellent	0.082	0.298	0.620	Excellent	0.066	0.282	0.652	Excellent	0.050	0.250	0.700	Excellent	0.048	0.262	0.690

By quartiles of proportion of families living in rental accommodations in neighborhood

High	hest % wi	ith rental ations		Se	cond hig	hest %		Se	econd lov	vest %		Low	vest % wi commod	th rental ations	
	<=	Very	Ex		<=	Very	Ex		<=	Very	Ex		<=	Very	Ex
	Good	Good	LA		Good	Good	LA		Good	Good	LA		Good	Good	LA
<= Good	0.233	0.393	0.374	<= Good	0.265	0.406	0.329	<= Good	0.248	0.423	0.329	<= Good	0.221	0.413	0.367
Very Good	0.146	0.365	0.490	Very Good	0.129	0.362	0.508	Very Good	0.127	0.375	0.498	Very Good	0.138	0.376	0.486
Excellent	0.074	0.284	0.642	Excellent	0.063	0.275	0.662	Excellent	0.051	0.261	0.688	Excellent	0.057	0.270	0.673

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Table	10	Transition	matrices	ov nei	ghhaiirhaac	i status te	or emr	orrical	model—st	ivers acros	S SIX CVC	les
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By quartiles of mean household income of neighbourhood

Ι	Lowest in	come		Seco	ond lowes	st income		Ν	Middle in	come		H	lighest in	come	
	<=	Very	Ev		<=	Very	Ev		<=	Very	Ev		<=	Very	Ev
	Good	Good	EX		Good	Good	EX		Good	Good	EX		Good	Good	EX
<= Good	0.252	0.433	0.315	<= Good	0.248	0.436	0.316	<= Good	0.289	0.386	0.325	<= Good	0.203	0.412	0.385
Very Good	0.152	0.403	0.445	Very Good	0.157	0.411	0.432	Very Good	0.110	0.343	0.546	Very Good	0.115	0.360	0.525
Excellent	0.074	0.316	0.610	Excellent	0.058	0.286	0.656	Excellent	0.067	0.285	0.648	Excellent	0.039	0.230	0.731

By quartiles of proportion of population with university degree in neighbourhood

Lowest	% with co	ollege deg	gree	Se	econd lov	vest %		Se	cond hig	hest %		Highest	% with co	ollege deg	gree
	<=	Very	Ev		<=	Very	Ev		<=	Very	Ev		<=	Very	Ev
	Good	Good	EX		Good	Good	EX		Good	Good	EX		Good	Good	EX
<= Good	0.271	0.410	0.319	<= Good	0.264	0.390	0.347	<= Good	0.229	0.426	0.344	<= Good	0.194	0.415	0.391
Very Good	0.149	0.376	0.474	Very Good	0.157	0.355	0.488	Very Good	0.146	0.398	0.457	Very Good	0.118	0.386	0.496
Excellent	0.068	0.281	0.651	Excellent	0.084	0.287	0.629	Excellent	0.053	0.276	0.671	Excellent	0.037	0.244	0.719

By quartiles of proportion of families headed by lone-parents in neighborhood

Highest	t % with 1	one-pare	nts	Se	cond hig	hest %		Se	econd lov	vest %		Lowest	% with l	one-parei	nts
	<=	Very	Ev		<=	Very	Ev		<=	Very	Ev		<=	Very	$\mathbf{E}_{\mathbf{v}}$
	Good	Good	EX		Good	Good	LX		Good	Good	ĽX		Good	Good	ĽX
<= Good	0.301	0.402	0.297	<= Good	0.215	0.377	0.408	<= Good	0.255	0.392	0.352	<= Good	0.245	0.442	0.313
Very Good	0.154	0.382	0.465	Very Good	0.132	0.348	0.520	Very Good	0.119	0.373	0.508	Very Good	0.142	0.397	0.461
Excellent	0.086	0.312	0.601	Excellent	0.057	0.255	0.688	Excellent	0.036	0.226	0.738	Excellent	0.044	0.257	0.699

By quartiles of proportion of families living in rental accommodations in neighborhood

High	hest % wi	ith rental lations		Se	cond hig	hest %		S	econd lov	vest %		Low	vest % wi ccommod	th rental ations	
	<=	Very	Fv		<=	Very	Fv		<=	Very	Fv		<=	Very	Ev
	Good	Good	LA		Good	Good	LA		Good	Good	LA		Good	Good	LA
<= Good	0.241	0.391	0.369	<= Good	0.268	0.379	0.353	<= Good	0.287	0.429	0.284	<= Good	0.251	0.423	0.326
Very Good	0.148	0.368	0.484	Very Good	0.107	0.317	0.575	Very Good	0.146	0.390	0.464	Very Good	0.144	0.397	0.459
Excellent	0.069	0.277	0.654	Excellent	0.065	0.260	0.675	Excellent	0.047	0.249	0.704	Excellent	0.048	0.267	0.685

	No char	nge		Slid	ling-down	n pattern		Cli	mbing-up	pattern		В	ouncing p	oattern	
	<=	Very	Ev		<=	Very	Ev		<=	Very	Ev		<=	Very	Ev
	Good	Good	EX		Good	Good	ĽX		Good	Good	ĽX		Good	Good	ĽX
<= Good	0.235	0.417	0.347	<= Good	0.231	0.418	0.352	<= Good	0.254	0.394	0.352	<= Good	0.252	0.387	0.362
Very Good	0.133	0.377	0.490	Very Good	0.131	0.380	0.489	Very Good	0.147	0.360	0.492	Very Good	0.132	0.346	0.522
Excellent	0.060	0.279	0.661	Excellent	0.052	0.267	0.681	Excellent	0.064	0.261	0.676	Excellent	0.072	0.277	0.651

Table 11. Transition matrices by neighbourhood transition patterns for empirical model—movers across six cycles

By transition patterns of neighbourhood mean household income

By transition patterns of neighbourhood education (proportion of population with university degree in neighbourhood)

	No chai	nge		Slid	ling-dowi	n pattern		Cli	mbing-up	pattern		В	ouncing j	pattern	
	<=	Very	Ev		<=	Very	Ev		<=	Very	Ev		<=	Very	Ev
	Good	Good	EX		Good	Good	EX		Good	Good	EX		Good	Good	EX
<= Good	0.231	0.408	0.361	<= Good	0.269	0.397	0.334	<= Good	0.229	0.407	0.365	<= Good	0.240	0.412	0.348
Very Good	0.137	0.376	0.487	Very Good	0.142	0.360	0.497	Very Good	0.131	0.358	0.511	Very Good	0.126	0.375	0.500
Excellent	0.058	0.271	0.670	Excellent	0.064	0.267	0.669	Excellent	0.063	0.268	0.669	Excellent	0.062	0.288	0.650

By transition patterns of neighbourhood lone-parents status (proportion of families headed by lone-parents in neighborhood)

	No chai	nge		Slid	ling-dowr	n pattern		Cli	mbing-up	pattern		В	ouncing p	oattern	
	<=	Very	Ev		<=	Very	Ev		<=	Very	Ev		<=	Very	Ev
	Good	Good	EX		Good	Good	EX		Good	Good	EX		Good	Good	EX
<= Good	0.251	0.401	0.348	<= Good	0.232	0.419	0.349	<= Good	0.255	0.409	0.336	<= Good	0.232	0.400	0.368
Very Good	0.136	0.370	0.494	Very Good	0.134	0.380	0.486	Very Good	0.138	0.363	0.499	Very Good	0.131	0.361	0.509
Excellent	0.061	0.273	0.667	Excellent	0.059	0.278	0.663	Excellent	0.057	0.256	0.687	Excellent	0.068	0.282	0.650

By transition patterns of neighbourhood living arrangements (proportion of families living in rental accommodations in neighborhood)

	No chai	nge		Slid	ling-dowi	n pattern		Cli	mbing-up	pattern		В	ouncing p	oattern	
	<=	Very	Fv		<=	Very	Fv		<=	Very	Fv		<=	Very	Fv
	Good	Good	EX		Good	Good	ĽX		Good	Good	ĽX		Good	Good	ĽX
<= Good	0.241	0.401	0.357	<= Good	0.231	0.411	0.358	<= Good	0.255	0.431	0.314	<= Good	0.240	0.388	0.372
Very Good	0.135	0.367	0.498	Very Good	0.126	0.370	0.504	Very Good	0.141	0.391	0.467	Very Good	0.139	0.350	0.512
Excellent	0.061	0.271	0.668	Excellent	0.053	0.268	0.678	Excellent	0.060	0.283	0.657	Excellent	0.071	0.271	0.657

Appendix A. Tables

Table 1. Variable names and definitions
Definition
Health status of child, 5 categories: excellent, very good, good, fair and poor; hlthc(t-1) refers to the health status in the previous period, e.g. hlthc(t-1)poor is a dummy indicating reported poor health in the last wave; hlthc(1) refers to the reported health status in the initial period, e.g. hlthc(1)good is a dummy indicating reported good health in the first wave
Age of child
Gender of child(Male=1)
Total number of persons living in the household
Age of mother at birth of the child
Total household income from all sources in the past 12 months
ln(hh income) is the log the household income.
Female caregiver education,
1= less than secondary, 2=secondary school graduation,
3=some post-secondary, 4=college or university degree
Male caregiver education,
1= less than secondary, 2=secondary school graduation,
3=some post-secondary, 4=college or university degree
Dummy indicating PMK is not the biological mother of the child
Interaction terms between mother education status (4 categories) and the dummy indicating PMK not the biological mother of child
Dummy indicating PMK is female
Dummy indicating child living with both parents (including biological parents or any other parental figures in the household)
Dummy indicating child living with both biological parents
Province of residence
Mean of the log household income variable over the sample period—within individual mean of the ln(hh income) term
Mean of the child age variable over the sample period—within individual mean of child age
Mean of the family size variable over the sample period—within individual mean of family size
Mean of the female caregiver education variable over the sample period—within individual mean of mother's education status
Mean of the male caregiver education variable over the sample period—within individual mean of father's education status
Mean of the PMK not biological mother dummy variable over the sample period—within individual mean of the "PMK not mother" term
Mean of the female PMK dummy variable over the sample period—within individual mean of the "PMK female" term
Mean of the living with two parents dummy variable over the sample period—within individual mean of the "living w/ two parents" term
Mean of the dummy variable indicating child living with both biological parents over the sample period—within individual mean of the "living w/ biological parents" term
Mean of the interactions term between mother's education and the dummy indicating PMK not the biological mother over the sample period—within individual mean of the "achealm*PMKnm" term

Appendix B. Figures



Figure 1. Health status by cycle









Figure 4. Health Status at cycle 2 by health status at cycle 1





Note: horizontal axis presents lowest income, second lowest, middle income and highest income neighbourhoods, respectively. Mean represents the point estimate of the transitional probability, the vertical line represents the 95% confidence interval of the point estimate.



Note: horizontal axis presents lowest %, second lowest %, second highest % and highest % with college degree in neighbourhoods, respectively. Mean represents the point estimate of the transitional probability, the vertical line represents the 95% confidence interval of the point estimate.



Note: horizontal axis presents highest % with lone-parents, second highest %, second lowest % and lowest % with lone-parents in neighbourhoods, respectively. Mean represents the point estimate of the transitional probability, the vertical line represents the 95% confidence interval of the point estimate.



Note: horizontal axis presents highest %, second highest %, second lowest % and lowest % with rental accormodations in neighbourhoods, respectively. Mean represents the point estimate of the transitional probability, the vertical line represents the 95% confidence interval of the point estimate.



Figure 9. Predicted conditional probabilities of different child health scenarios based on random effects model—the duration of a health drop at any time within six cycles by long-term neighborhood status

Note: the first panel represents the predicted conditional probabilities by quartiles of neighborhood average household income; the second panel represents the predicted conditional probabilities by quartiles of proportion of population with college degree in the neighborhood; the third panel represents the predicted conditional probabilities by quartiles of proportion of families headed by lone-parents in the neighborhood; the fourth panel represents the predicted conditional probabilities by quartiles of proportion of families headed by lone-parents in the neighborhood; the fourth panel represents the predicted conditional probabilities by quartiles of proportion of families living in rental accommodations in the neighborhood; respectively.



Figure 10. Predicted conditional probabilities of different child health scenarios based on random effects model—the number of health drops within six cycles by long-term neighborhood status

Note: the first panel represents the predicted conditional probabilities by quartiles of neighborhood average household income; the second panel represents the predicted conditional probabilities by quartiles of proportion of population with college degree in the neighborhood; the third panel represents the predicted conditional probabilities by quartiles of proportion of families headed by lone-parents in the neighborhood; the fourth panel represents the predicted conditional probabilities by quartiles of proportion of families headed by lone-parents in the neighborhood; the fourth panel represents the predicted conditional probabilities of proportion of families living in rental accommodations in the neighborhood; respectively.